# An Agent-Based Model of Miscommunication in Complex System Engineering Organizations

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***Abstract*—Communication in complex system design organizations affects the performance of the systems they design. *Mis*communication occurs when communication results in a "deficiency" or "problem" that hinders parties from fulfilling their individual or collective values. A recent study demonstrated widespread miscommunication in a Fortune 500 engineering firm about the definition of "an estimate" in a complex system design context. Building on that work, this study used a Monte Carlo simulation (8800 runs) of an agent-based model to demonstrate how systemic design process miscommunication may affect complex system performance. Each run of the simulation created a unique 1,000-artifact system using a network generation algorithm and converged its design through optimization. Systems where estimates communicated "current" designs outperformed systems where estimates communicated "future" projections of their designs instead. Varying the fraction of the population which uses each definition of an estimate varied system performance and uncertainty. Whether related to estimate definitions or more generally, miscommunication may affect system performance.**

## I. Introduction

"Communication problems" are some of the most frequently-cited causes of engineered system failures [1], [2] across numerous disciplines. Aerospace highlights dozens of examples [1], the most prominent of which are the Space Shuttle Challenger [3] and Columbia [4] disasters. Federal investigations of each incident similarly cite "organizational barriers that prevented effective communication of critical safety information and stifled professional differences of opinion" [4], [5]. In civil infrastructure, the recent operational failure of a civil ballistic missile alert system in Hawaii "led many residents to fear for their lives" for 38 minutes before correction [6]. Forensic software engineering often attributes software shortcomings to poor communication [7], totalling in the millions and perhaps billions of dollars in losses [8].

The previous examples all feature *complex* systems, a particularly fraught domain in engineering design [9]. *Complex (engineered) systems* are large sets of components with a well-defined purpose but with interactions between components which are "difficult to describe, understand, predict, manage, design, or change" [10]. Civil (e.g. transportation, power, water), commercial (e.g. financial, e-commerce, healthcare), and defense (e.g. aircraft, spacecraft, ballistic interception) infrastructures are all quintessential examples [11]–[13]. Significant cost and risk, extensive design cycles, protracted operational timelines, and dispersed supporting organizations fundamentally characterize complex systems [11]. These complexities plus the growing demands on these systems pose substantial challenges to the designers of such systems [11].

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Among these challenges, communication plays critical roles in engineering design processes [14]–[17]. "But just as 'good' communication produces beneficial results, 'bad' communication, 'misunderstandings' between people, too little communication, and too much communication can have serious consequences" [2]. Readers can likely recall instances in their own work where communication "failed" causing more problems than it resolved, as with "design churn" [18]. Such *miscommunication* occurs "when communication results in a 'deficiency' or 'problem' that hinders at least one of the engaged parties' abilities to fulfill their individual or collective values" [2]. Section II-A describes the nature of communication and miscommunication in further detail.

Despite evidence to the contrary, it is easy to dismiss miscommunication as exceptional instead of as a systematic feature of communication in engineering organizations [2]. Organizational communication has been shown to affect engineering team performance [19], [20] and system performance [21]–[23]. If communication affects performance, and miscommunication is characterized by communication that results in problems, then won't miscommunication also affect performance?

Demonstrating that any particular factor affects complex system performance is challenging, especially miscommunication. One option is for researchers to obtain large datasets of empirical evidence spanning statistically significant numbers of complex systems that demonstrate how specific instances of miscommunication tangibly affected system performance. However, complex system design data—let alone the design *process* data—is often extremely difficult to obtain. An alternative approach is generating large numbers of unique complex system models and simulating design processes in those complex systems, all grounded in evidence from empirically-verified phenomena. This paper furthers the latter approach by building upon the following case study.

In a recent study with a Fortune 500 engineering firm, Meluso et al. [2] demonstrated an example of systemic miscommunication about what "design parameter estimates" represented in engineering practice. Parameter estimates are core technical benchmarks which approximate some characteristic of a design such as cost, size, mass, power consumption, etc. [24]. In the Meluso et al. study, practicing engineers defined "an estimate" either as an approximation of a "current" design (representing their design at that point in time) or a "future" design (predicting their design at some future time, such as the end of system production). Engineers *communicated* estimates for system-level tracking without specifying which definition they were using, resulting in system-level aggregation of both types of estimates as though they were equivalent. Furthermore, definition use varied throughout the organization independent of organizational characteristics including participant subsystem, title, and design phase ($p > 0.3$ for all) yielding systemic miscommunication.

Estimate definitions provide an ideal case study for testing how miscommunication affects system performance. This article integrates research from network theory, agent-based modeling, design optimization, and sociolinguistics to assess the effects of organizational miscommunication on the performance of systems produced in those organizations by:

(1) generating representative complex systems,
(2) simulating human design of those systems, and
(3) modeling miscommunication between engineers exemplified by varying estimate definitions.

The article begins by summarizing the relevant research on communication theory, system modeling methods across the disciplines, and design of experiments. Then, it describes CESIUM, an agent-based model that generates and designs a unique complex system in each instance, and simulates miscommunication in the model. A Monte Carlo simulation was performed with a parameter sweep to examine 8800 such systems while varying miscommunication throughout the system. The results will show that varying estimate definitions throughout the engineering organization varied system quality and uncertainty, and therefore, that systemic miscommunication may affect system performance.

## II. Background

The model described in this paper draws from several disparate disciplines. This section recounts the literature requisite for understanding the model including communication and miscommunication, complex system modeling methods, and design of experiments.

### A. Communication & Miscommunication

Broadly defined, *communication* is “social interaction through messages” [25]. Two schools of thought shape the study of communication. Process models (or objectivist models) follow a mathematical sender-transmission-receiver structure and form the foundation of network theory [26]–[28]. Interpretive models examine linguistic and social meanings of communication through their contexts, actions, identities, and genres (or mediums) of communication [28], [29]. Both have their benefits and detriments: process models give up specific meaning for patterns at scale and vice versa for interpretive models.

In that light, reconsider the definition of miscommunication: “when communication results in a ‘deficiency’ or ‘problem’ that hinders at least one of the engaged parties’ abilities to fulfill their collective values” [2]. “Deficiencies” and “problems” are matters of interpretation in singular instances [30]; but at scale, their effects through “engagement” may harm the process of “fulfilling values” [31] which this article demonstrates.

As recounted in Section I, significant anecdotal evidence exists to suggest that miscommunication affects complex system performance. While scholars posit that miscommunication *should* do so [31], further evidence is necessary to demonstrate this connection. The model described herein adds treatment to that effect.

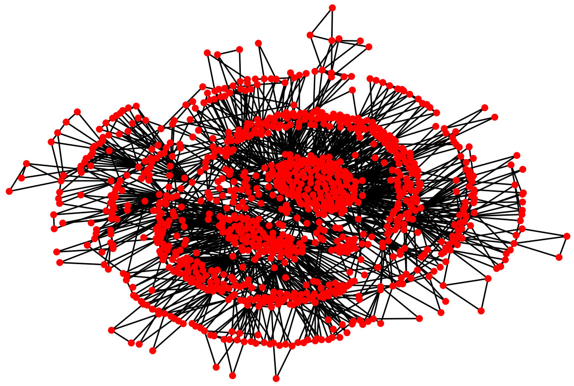
### B. Complex System Modeling Methods

The systems literature defines an *artifact* as a piece of technology designed to serve a specific purpose [10], an umbrella term for any technical product of human minds including physical parts, software, processes, information, etc. A *complex system* is “a system with components and interconnections, interactions, or interdependencies that are difficult to describe, understand, manage, design, or change” [10]. Methods for modeling complex systems include functional models, cellular automata models, game theory models, and dynamical systems models among others [32]. Most relevant to this study are network, agent-based, and design optimization models.

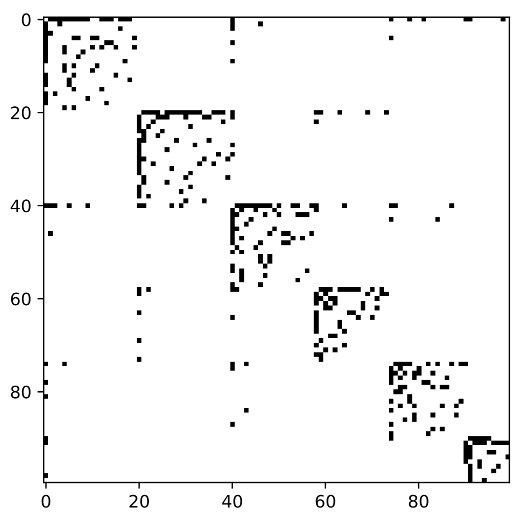
*1) Network Models:* Network theory represents systems of people or artifacts as nodes and edges, as shown in Figure 1a. *Nodes*, points connected to one another in pairs, may represent people, subsystems, artifacts, etc. in a complex system. Connections or interactions between nodes are called *edges* or *ties* and can be represented by an adjacency matrix [33] as in Figure 1b. In complex system design, interactions are *interfaces* between artifacts from which one can form a Design Structure Matrix to represent a complex system [22]. The edges of an adjacency matrix may be either unidirectional from one node to another (called *directed* edges) or bidirectional between two nodes (called *undirected* edges) [33].

The number of artifacts $j$ that each artifact $i$ interfaces with is called the degree $k_i$ of $i$. A normalized histogram of a network’s degrees is called a *degree distribution* [33]. A number of studies have shown that artifacts in many (but by no means all) complex systems follow a *scale-free* degree distribution, also called power-law or inverse exponential distributions [22], [33]–[39]. Scale-free distributions take the form $p_k = Ck^{-\alpha}$ where $p_k$ is the probability of randomly selecting a node with degree $k$, $C$ is a constant, and positive constant $\alpha$ is the exponent of the power law with typical values of $2 \leq \alpha \leq 3$ [33]. The resulting function would appear as a negatively-sloping line in a log-log plot as in Figure 1c. Studies by Braha & Bar-Yam [37], [38] and Sosa et al. [22] suggest that degree distributions of complex systems generally follow a power-law with a cut-off at some large degree. Uncertainty remains as to whether complex systems follow scale-free degree distributions [22], [39]; however, studies are sufficiently varied to suggest what may be a broader trend in complex system structures.

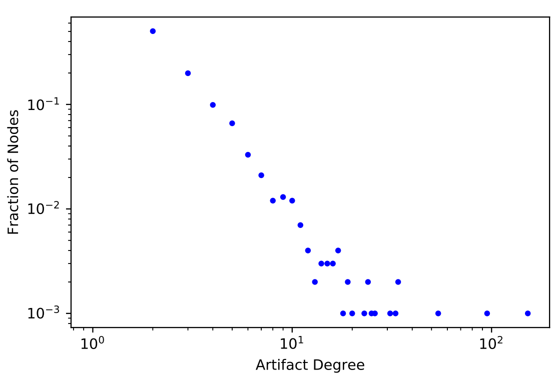
A less-popular subject in network theory with significant potential is that of generative network models that algorithmically construct a network out of basic rules [33]. One of



(a) Graph of a network with $n = 1000$ artifacts. The red dots represent nodes or artifacts, and the black lines represent edges or interfaces.




(b) An adjacency matrix or Design Structure Matrix for a network with $n = 100$ artifacts.




(c) Scale-free degree distribution of a network with $n = 1000$ artifacts. Note the approximately-linear, negatively-sloping form of the distribution on a log-log scale, characteristic of a scale-free degree distribution [33].

Fig. 1: Visual representations of undirected networks generated with a Holme-Kim preferential attachment algorithm and a clustering probability of $c = 0.9$.

the most common network generation algorithms is called preferential attachment which builds a network by connecting new nodes to existing nodes with an attachment probability proportional to the degree of the existing node [33]. Several such algorithms exist including those of Price [40], Barabsi & Albert [34], and Holme & Kim [41], all of which generate networks with scale-free degree distributions [33], [41]. Recent advances in peer-to-peer network studies allow generative algorithms to establish hard or soft cut-offs in the distribution [42], [43]. Also of value to complex engineered systems, the Holme-Kim preferential attachment algorithm includes a parameter for tuning node clustering and can be used to generate a scale-free degree distribution with nodes of degree $k_i \geq 2$ [41] by creating two edges from each new node, consistent with the minimum degree of networks identified by Sosa et al. [22].

*2) Agent-Based Modeling:* Agent-based modeling is a widely-used, effective, and tested method for simulating communication in complex systems [44]–[47]. An agent-based model (ABM) creates a system of autonomous decision-making entities called agents which individually assess their situations and make decisions based on a set of rules [46]. Agents affect their surroundings through their actions and, in doing so, self-organization, patterns, structures, and behaviors emerge from the "ground-up" that were not explicitly programmed into the models but nevertheless arise through agent-interactions [47]. This "ground up" agent-centered approach differentiates ABMs from other system modeling methods such as discrete event simulation and system dynamic models which take top-down approaches [48].

Recent applications of ABMs include systems design [49]–[52] and organization studies [53]–[56]. INCOSE, a leading systems engineering organization, promotes ABMs as one of the primary methods through which "to inform trade-off decisions" regarding "complexity in system design and development" [32]. Because complex systems are often "made up of many smaller engineered systems [that are] designed, developed, and operated by another large 'system' of dispersed, loosely connected people" [11], ABMs facilitate simulation of aggregated artifacts in ways that top-down models cannot [48].

ABMs are commonly critiqued for being too opaque or for being unrealistic "toy problems" [57]. Responses from tens of experts now provide rigorous protocols for describing and analyzing ABMs as a result [44], [45], [58], [59]. This study draws from Grimm et al.'s [45] "ODD Protocol" (Overview, Design concepts, and Details) which clarifies model descriptions and the Lee et al. ABM analysis criteria [59] to demonstrate statistical rigor. Verification of model units and structures, face and empirical validation, and model replication offer greater means of assessing the match between an ABM and the real world [60].

*3) Design Optimization:* Engineers in various disciplines use *design optimization* to maximize the performance of a system, a process of selecting the relative "best" alternative from among a set of possible designs called the *design space* [61]. They do this through *objective functions*, sets of evaluation criteria typically constructed as functions describing the relationships between independent variables (or *decision variables*) [61]. Optimization algorithms then explore the design space to find a global or local minimum (or maximum depending on problem construction) as efficiently as possible to identify a solution [62].

While the methods of constructing system objectives are beyond the scope of this paper, one method for searching design spaces remains relevant. Validated studies have shown that engineers sample their design space comparably to *simulated annealing* which can thus be used in modeling as a representation of human decision-making [63], [64].

### C. Design of Experiments

The Design of Experiments (DOE) is "the process of planning, designing, and analyzing the experiment so that valid and objective conclusions can be drawn effectively and efficiently" [65]. Recently, significant effort has gone toward documenting state-of-the-art approaches to rigorously testing and analyzing ABMs [59], [66]. Monte Carlo simulations are the quintessential method for testing ABMs and generating statistically significant outcome distributions of the assessment metrics [59]. Indeed, numerous studies to date use Monte Carlo simulations to model design teams [67]–[71] including with ABMs [52], [72], [73].

Many of the standard techniques for systematically exploring design spaces still apply to agent-based modeling, including random, factorial, and latin hypercube sampling [59], [74]; however, scholars urge caution owing to the substantially greater complexity of ABMs compared to other modeling methods [75]. For example, Lee et al. [59] theoretically and empirically determined that in order to reach statistical significance, minimum ABM sample sizes may fall in a range from 65 to 78 runs depending on the sampling distribution before standard statistical methods may then be used to analyze the results.

## III. Methodology

This section draws on the concepts in Section II to describe the model used to simulate a complex system development process.

The ComplEx System Integrated Utilities Model (CESIUM) generates and designs representative complex systems. Miscommunication of estimates was added to simulate its effects throughout an organization on system performance. A network generation algorithm was used to create a unique system for each run of the simulation. Each system was represented as a network of interdependent artifacts with individual objective functions. Each artifact was assigned to one engineer who were represented by agents in the agent-based model. Agents optimized the objective function for their artifact during each turn of the model, which terminated upon system convergence. Agents passed "estimates" (modeled after the observed definitions) to one another over the network at the end of each turn. Model assessment criteria, verification, and validation are discussed. Finally, a Monte Carlo simulation ran the model 8800 times to sweep the parameter space and detect the effects of different estimate definition proportions on system performance.

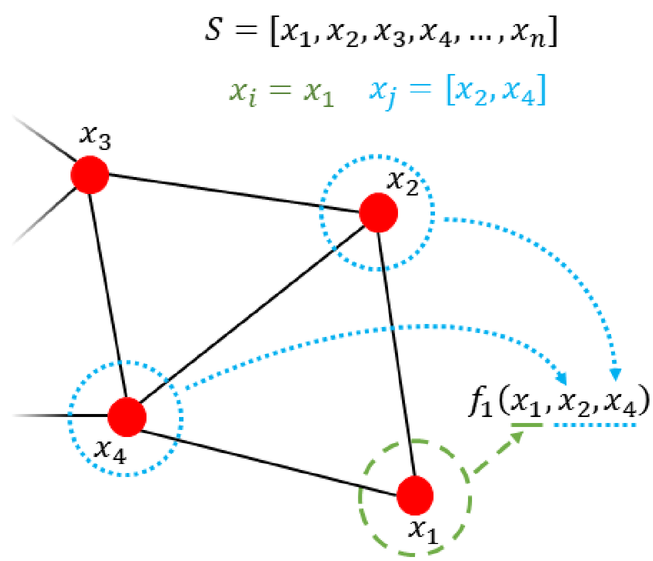


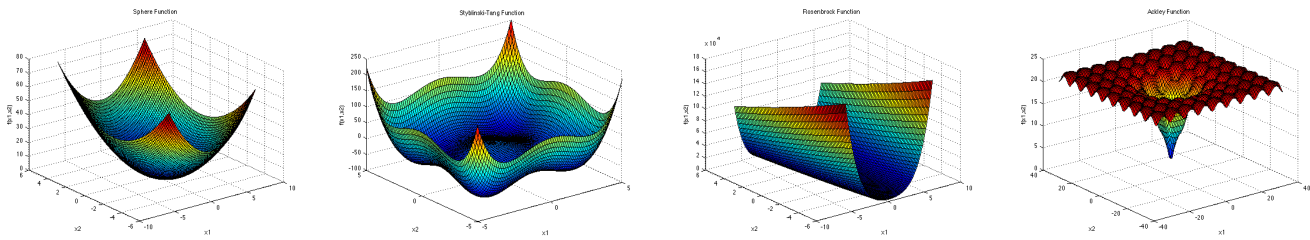

Fig. 2: An example of agent interaction. In this case, the $i^{th}$ agent is agent 1 with variable $x_i = x_1$. Agent 1 has neighbors $x_j = [x_2, x_4]$ and therefore also objective function $f_1(x_1, x_2, x_4)$.

### A. System Construction

First, assume that a complex system is composed of $n$ interacting artifacts. A complex system was represented by $n = 1000$ artifacts such that each artifact $i \in \{1, 2, \ldots, n\}$. The model assumed that $n$ artifacts interact with one other in a technical network approximated by a scale-free degree distribution, an example of which is shown in Figure 1c for a network of $n = 1000$ artifacts. Each artifact is assumed to interface with at least two other artifacts [22]. Then, each of the $i \in \{1, 2, \ldots, n\}$ artifacts has degree $2 \leq k_i \leq n - 1$. A Holme-Kim preferential attachment algorithm was used to generate an undirected network with a scale-free degree distribution and nodes of degree $k_i \geq 2$ by creating two edges from each new node $i$ with the probability of attaching to a specific node $j$ proportional to its degree $k_j$ and a clustering probability of $c = 0.5$ [41]. The result is a complex system of $n$ interacting artifacts with no formal hierarchy.

### B. Artifact Construction

In a real-world setting, the design of each artifact $i$ in the system would depend on numerous contextual and specific factors, say $\{v_{i1}, v_{i2}, \ldots\}$. Because these factors cannot be known *a priori* for thousands of real systems, the model representatively parameterized these variables such that each artifact was modeled as a single decision variable $x_i(v_{i,1}, v_{i,2}, \ldots)$. Therefore, each $x_i$ parameterized a complex set of inputs, allowing the performance of each artifact to be represented as an objective function $y_i = f_i(x_i, \mathbf{x_j})$, where $j \in \{1, \ldots, k_i\}$ represents the set of artifacts interfacing with artifact $i$, and



(a) Sphere Function (b) Styblinski-Tang Function (c) Rosenbrock Function (d) Ackley Function

Fig. 3: Graphical representations of the selected objective functions with two decision variables [76].

$\mathbf{x_j}$ is a vector of the parameterized decision variables of the $j$ artifacts. This objective function scales to incorporate the $k_i$ decision variables for each neighbor $j$ of $i$. See Figure 2 for an example.

To explore the relationship between objective function selection and the greater model construction, the researchers chose objective functions which varied both the number of global minima and the difficulty of optimization convergence. Using the combined notation $\mathbf{x} = [x_i, \mathbf{x_j}]$, the model used the following objective functions:

(a) The Sphere Function [76], an easily-converged function with a single minimum, on the recommended evaluation domain for all $x_m \in [-5.12, 5.12]$:

$$f_i(\mathbf{x}) = \sum_{m=1}^{k_i+1} x_m^2 \tag{1}$$

The optimum $\mathbf{x}^* = (0, \ldots, 0)$ minimizes $f_i$ for the Sphere Function yielding $f_i(\mathbf{x}^*) = 0$.

(b) The Styblinski-Tang Function [76], an easily-converged function with multiple minima, on the recommended evaluation domain for all $x_m \in [-5.00, 5.00]$:

$$f_i(\mathbf{x}) = \frac{1}{2} \sum_{m=1}^{k_i+1} (x_m^4 - 16x_m^2 + 5x_m - 78.332332) \tag{2}$$

with $f_i(\mathbf{x}^*) = 0$ at $\mathbf{x}^* = (-2.903534, \ldots, -2.903534)$.

(c) The Rosenbrock Function [76], a more challenging function with a single minimum, on the recommended evaluation domain for all $x_m \in [-5.00, 10.00]$:

$$f_i(\mathbf{x}) = \sum_{m=1}^{k_i} \left(100(x_{m+1} - x_m^2)^2 + (x_m - 1)^2\right) \tag{3}$$

with $f_i(\mathbf{x}^*) = 0$ at $\mathbf{x}^* = (0, \ldots, 0)$.

(d) The Ackley Function [76], a challenging function with multiple minima, on a reduced evaluation domain for all $x_m \in [-5.00, 5.00]$, $a = 20$, $b = 0.2$, and $c = 2\pi$:

$$\begin{aligned} f_i(\mathbf{x}) = &- a \exp\left(-b\sqrt{\frac{1}{k_i+1}\sum_{m=1}^{k_i+1} x_m^2}\right) + a \\ &- \exp\left(\frac{1}{k_i+1}\sum_{m=1}^{k_i+1}\cos(cx_m)\right) + \exp(1) \end{aligned} \tag{4}$$

with $f_i(\mathbf{x}^*) = 0$ at $\mathbf{x}^* = (0, \ldots, 0)$.

Figure 3 shows these functions in two dimensions. Collectively, $n$ coupled objective functions $\{f_1, \ldots, f_n\}$ compose the system being designed.

## C. *Engineer Construction*

Next, the model incorporated a design process for the complex system. One agent in an agent-based model represented one engineer. Each agent was responsible for one artifact in the system. Given the technical network of artifacts, this created an engineering organization following the mirroring hypothesis wherein engineers passed information via the technical network as frequently occurs in practice [77]. Although each agent modeled a human engineer, each agent used the technical objective function of its artifact as its utility function, so the objective functions will be spoken of as belonging to the agents. No cognitive factors affected agent decision-making.

Again, validated studies have shown that engineers sample their design space similar to optimization using simulated annealing [63]. During each turn of the model, the agent engineers used a set of constant input values $\mathbf{x_j}$ with which to optimize their objective functions. Agents searched the design space using a single iteration of the basin-hopping algorithm[1] [78] to reach a local optimum $y_i^* = f_i(x_i^*, \mathbf{x_j})$ with a random initial position in the domain of $x_i$, temperature of 1, the Limited-memory BFGS Bounded minimizer, step size of 10% of the domain, and the default tolerance of $1 * 10^{-5}$. The Sphere, Rosenbrock, and Styblinski-Tang functions were optimized using bounded Newton's method with the same tolerance given their few minima and smooth profiles to reduce computational cycles. In both cases, the engineer iteratively optimized their objective function with updated information from the other engineers.

## D. *Communication & Miscommunication Modeling*

Each turn of the model represented one design cycle in a system design process, also known as the Shewhart & Deming Cycle [79]. While the model schedule is described in Section III-E below, the material related to estimate communication will be defined here.

For purposes of model coordination, a system vector $\mathbf{S}$ stored the reported designs of all agents as a central repository. At the beginning of each design cycle, each agent received $\mathbf{S}$

[1]The Python programming language SciPy module deprecated simulated annealing in favor of the basin-hopping algorithm.

as a constant input before proceeding to optimize their variable $x_i$ using only the values from their networked neighbors $\mathbf{x_j}$. Then, each agent passed an "estimate" of their design $\widehat{x_i^*}$ back to the system vector for storage in $\mathbf{S}$ and a new design cycle would begin with the estimates as constants.

Miscommunication was modeled by varying the fraction of the organization using each estimate definition. Based on the definitions summarized in Section I, agents used one of two rules to communicate $x_i$ to the system for storage in $\mathbf{S}$:

**D1.** "Current" estimates, wherein the agent passed the current design $x_i$, or

**D2.** "Future" estimates, wherein the agent passed a future value $h_i$ equal to the median of a historical distribution of $i$ until $f_i(x_i) < f_i(h_i)$, at which point agent $i$ passed $x_i$ instead.

Practitioners have reported using historical information as projections of future outcomes [52] and using that historical information until prototype information is available [2], motivating the construction of **D2**.

Historical distributions of design outcomes were modeled by creating 101 system-level latin hypercube samples of the design space of $\mathbf{S}$. For each hypercube sample, all of the agents performed a single design cycle, saved their resulting optima $x_i^*$ in $\mathbf{S}$, and re-evaluated their objective function given the new single-iteration $\mathbf{S}$. This created a set of 101 randomly-generated systems and values for each $x_i$ with varied $x_j$'s and corresponding values of $y_i = f_i(x_i, \mathbf{x_j})$. Agents then chose the design $x_i = h_i$ corresponding to the median $m_i = y_i$ of the historical distribution of its artifact (and not the system as a whole) to use as its future or projected design.

Upon creation, each agent had a probability $p_e$ of being randomly assigned to use either the current method of estimation or the future method of estimation, where $p_e = 0$ represented all agents using the current method (**D1**) and $p_e = 1$ represented all future (**D2**). Hence, miscommunication of estimate definitions was predicted to occur when $0 < p_e < 1$, meaning engineers *disagreed* about the definition of an estimate to pass to the system. Values of $p_e = 0$ and $p_e = 1$ could produce different performance outcomes, but simulated agreement among the engineers.

### *E. Model Schedule*

Each execution of the model first initialized a new system following the method outlined in Section III-A. After generating the system, historical distributions and medians were created following the method described in Section III-D. Then, the model performed design cycles—iterating through all of the agents in each cycle—until either the system design converged or the model performed 100 design cycles.

Determining system convergence first required a metric of system performance, defined simply as a sum of the reported objective evaluations of all of the agents during the current design cycle:

$$F(t, \mathbf{x}(t)) = \sum_{i=1}^{n} f_i(t, x_i(t)) \tag{5}$$

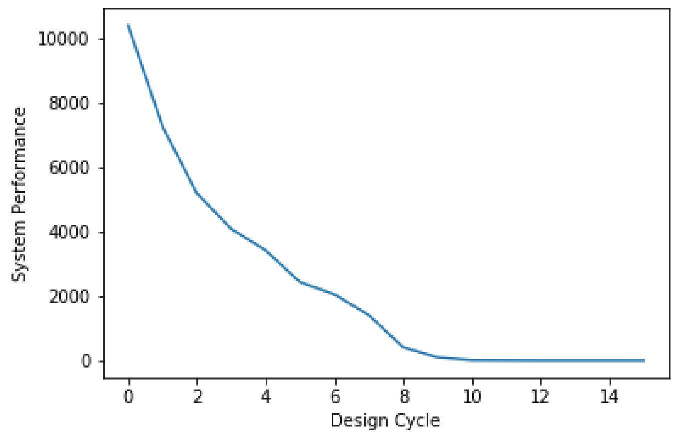



Fig. 4: Example of model design convergence for a network of $n = 1000$ agents using the Ackley function and $p_e = 0$. Shown as a function of the design cycle, smaller values of system performance represent better performance.

Although the $n$ objective functions $f_i$ have different magnitudes depending on the degree $k_i$ of each artifact $i$, the system performance was assumed to have a greater dependence on components which are more highly connected so simply adding their contributions exemplifies this behavior. System convergence was then defined as:

$$|F(t, \mathbf{x}(t)) - F(t-3, \mathbf{x}(t-3))| < \varepsilon \tag{6}$$

where $\varepsilon = 1.00$. If the number of design cycles was less than three the difference was calculated from the first to last points.

This completes the construction of CESIUM with simulated miscommunication. The model assessment criteria are discussed in the following section.

### *F. Model Assessment, Verification, & Validation*

The quality of the system can be assessed by measuring the number of design cycles it takes for the system design to converge and the resulting system objective function evaluation, values which largely depend on the selected objective functions and optimization algorithms.

As mentioned in the background on agent-based modeling, one can verify ABM units and structures. As CESIUM generates agents, offline unit testing was performed on the generation and execution of the model schedule for the agent generation module prior to simulation. Likewise, offline structure verification was performed to confirm CESIUM's ability to generate and design systems. The system test module verified the scale-free system structure resulting from generation, as evidenced by the graphics in Figure 1, and design convergence, shown in Figure 4. Validation was performed during the analysis (Section V).

### *G. Monte Carlo Simulation*

The Monte Carlo simulation explored how varying the fraction of the organization that used each estimate definition and the objective functions affected performance. To that end, the simulation varied probability $p_e$, from which an agent was assigned to use either the current or future estimation method, from 0 to 1 yielding $p_e \in \{0, 0.1, 0.2, \ldots, 0.9, 1.0\}$. For example, when $p_e = 0.3$, each agent had a 30% chance of being created with the current definition for its estimates and a 70% chance of being created with the historical definition for its estimates. Likewise, the simulation varied the objective function that all agents used during a given iteration of CESIUM across the four objectives defined in Section III-B. The simulation included 200 executions of each probability-and-objective combination to significantly surpass the Lee et al. threshold [59]. As specified in Section III-A, the Holme-Kim network generation algorithm's parameters remained constant across all runs of the simulation.

Given the 4 objective functions, 11 probabilities, and 200 executions per combination, CESIUM ran $4 * 11 * 200 = 8800$ times. Hence, the Monte Carlo generated 8800 unique and representative complex systems to test the effects of design process miscommunication on complex system performance.

### *H. Responses to Critiques*

In light of the standard critiques of ABMs noted in Section II-B2, the authors took particular care to address each concern when constructing this model. To ensure the system was large enough, the ABM included 1000 engineers (agents) per simulation to represent a large engineering organization. To ensure sufficient complexity, the model created the system using a Holme-Kim preferential attachment network generation algorithm [41]. System interfaces matched a scale-free degree distribution, a demonstrated configuration for the degree of complex systems ranging from aircraft engines [22] to the entirety of the open internet [33]. Certainly, generating a single scale-free network does not confirm representativeness. Therefore, because every engineering system is unique, 8800 unique complex systems were generated and designed via Monte Carlo simulation to sample the effects of the specified behaviors across a significant number of complex systems.

## IV. Results

Before examining the effects of miscommunication where $0 < p_e < 1$, consider the difference between the cases in which all agents used the same definition of an estimate, that is current estimates with $p_e = 0$ and future estimates with $p_e = 1$. Two-hundred trials were run for each estimate definition and for each of the four objective functions. Throughout this section, *lower values* of both system performance and number of design cycles indicated that the system performed better by that metric.

As shown by the descriptive statistics in Table I, the Sphere and Styblinski-Tang objective functions quickly converged to the global optimum. The current estimate definition took 2 design cycles to reach the global optimum and waited the requisite 3 cycles to verify convergence for a total of 5. The future estimate definition converged after a single iteration, likely because the historical distributions already included 101 single-optimization trials meaning the first design cycle then met the termination criteria. System performance did not vary with estimate definition for these functions.

The Rosenbrock and Ackley functions produced more significant results. For the Rosenbrock, future estimates completed an average of 0.53 cycles sooner than current estimates (Figure 5a) with no performance difference. For the Ackley, future estimates completed an average of 0.35 cycles sooner than current estimates, but current estimates significantly outperformed future estimates performance by an average of 14.12 (Figure 5b). Shapiro-Wilk tests of the cycle and performance results for these functions reveal that none of the populations are normally distributed and so Mann-Whitney-Wilcoxon U tests were performed to examine the difference between the medians of the samples rather than the means (Table II). The Mann-Whitney-Wilcoxon tests found small but statistically-significant differences between the medians of the estimate definitions for the Rosenbrock cycle counts ($p < 0.0001$), the Ackley cycle counts ($p = 0.0224$), and the Ackley objective evaluations ($p = 0.0140$), all of which corroborate the respective differences of the means.

To understand these effects better and explore the hypothesized domain of miscommunication, the intermediate probabilities were then explored. Upon further inspection of the Rosenbrock results, values of $p_e \in \{0.1, \ldots, 0.9\}$ all produced outcomes identical to the current estimate definition $p_e = 0$ outcomes, suggesting that the historical data only dominated when current values did not exist.

On the other hand, the Ackley function produced greater variation. Figure 6a shows the full set of 2200 Ackley function system performance outcomes as a function of $p_e$, and Figure 6b the 95% confidence intervals of the means of 200 trials for each value of $p_e$. As $p_e$ increased, performance began to degrade at $p_e = 0.6$ suggesting that for the Ackley function, there is some probability at which the the existence of the future definition of an estimate begins to increase the variance or uncertainty of the system performance until it reaches its worst performance at $p_e = 1$.

## V. Analysis

### *A. Simulation Requires Sufficiently-Complex Functions*

The simulation shows that for the Sphere and Styblinski-Tang functions, a basic Newton's method optimization converged the system to a solution in too few design cycles for those functions to produce substantive interaction between agents. Evidently, either objective functions must be difficult enough for the optimization algorithms that agent interaction occurs before the system converges to an optimal solution or slower optimization algorithms must be used. Real-world objective functions are likely more complex or could undergo a different parameterization. The Rosenbrock function (with a wide, shallow region surrounding the minimum) and the Ackley function (with many local minima) were difficult enough objectives that the trials' respective optimization algorithms did not converge immediately, thereby slowing convergence enough to allow the agents to exchange information and testing how estimate definitions affect system outcomes.

Both the Rosenbrock and Ackley tests show that the "current" and "future" definitions of an estimate produced

| Function | Est. Def. | Trials | Cycles | | | Performance | | |
|---|---|---|---|---|---|---|---|---|
| | | | Mean | St. Dev. | St. Err. | Mean | St. Dev. | St. Err. |
| Sphere | Current | 200 | 5.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Future | 200 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Styblinski-Tang | Current | 200 | 5.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Future | 200 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Rosenbrock | Current | 200 | 5.00 | 0.00 | 0.00 | 15837.29 | 0.00 | 0.00 |
| | Future | 200 | 4.47 | 0.50 | 0.04 | 15837.29 | 0.00 | 0.00 |
| Ackley | Current | 200 | 15.81 | 1.68 | 0.12 | 0.16 | 1.74 | 0.12 |
| | Future | 200 | 15.46 | 1.84 | 0.13 | 14.28 | 42.63 | 3.01 |

TABLE I: Descriptive statistics resulting from the Monte Carlo simulation of the Agent-Based Model. Shown are the results with all agents using the current estimate definition ($p_e = 0$) and the historical-median-as-future definition ($p_e = 1$).

| Function | Metric | Sides | U | p | Med. Diff. | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|---|
| Rosenbrock | Cycles | 2-sided | 30700 | 2.2e-16 | 0.999948 | 5.03177e-5 | 0.999930 |
| | Performance | 1-sided | 20650 | 0.2868 | 5.63887e-11 | -5.82077e-11 | — |
| Ackley | Cycles | 2-sided | 22590 | 0.0224 | 2.28188e-5 | 1.15252e-5 | 0.999963 |
| | Performance | 1-sided | 17459 | 0.0140 | -8.71753e-5 | — | -5.94237e-5 |

TABLE II: Mann-Whitney-Wilcoxon U tests for the Rosenbrock and Ackley functions, both cycles and performance. Each line compares the difference of the current and future estimate definition medians. Performance U statistics were 1-sided due to lowerer bounding of the objective functions at 15837.29 for the Rosenbrock and 0 for the Ackley, while the cycles were unbounded and therefore used 2-sided calculations.

significantly different performance outcomes from one another. The Rosenbrock result is less convincing: only the 100% or "pure" use case of future estimates improved the mean number of design cycles to design convergence. While the actual source of the Rosenbrock difference is unknown, it is likely attributable to either the objective function or convergence rules. Future estimates may have outperformed current estimates because the median of the initial sampling used for future estimates generally fell in the large central valley characteristic of the Rosenbrock function. The system evaluations resulting from even a single iteration of the model may then have been sufficiently close to the criteria of the rules governing convergence that the rules themselves may have contributed to the difference. However, the mean cycles to convergence under the Ackley were much larger and therefore less likely to have been affected by the model rules.

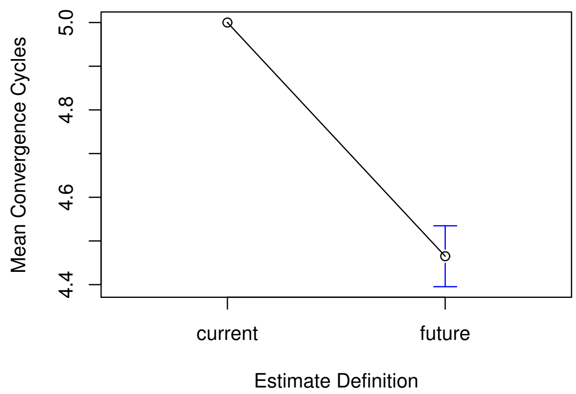
### B. Ackley Function Revealed Variation

The Ackley performance variation reveals two noteworthy outcomes. First, current estimates yielded better system outcomes than future estimates with statistical significance, although the mechanism causing the degraded performance of future estimates is unclear. Recall that agents using future estimates did not change the values they communicated to the system until their current design surpassed the historical median. If most of the $j$ agents in the system decided their future estimates were "good enough" so as not to change them, then the $\mathbf{x_j}$ values feeding into the objective function $f_i$ of agent $i$ would have made $x_i$ less likely to change. The process would then replicate with agents depending on $x_i$. If insufficient change occurred within a few turns, it may have caused some systems to converge before reaching a global system optimum which may also account for the difference between the future and current cycle counts. One would expect a negative correlation between performance and number of design cycles in such a case; a Pearson's correlation for the Ackley function with $p_e = 1$ indeed finds a correlation of 0.127 with statistical significance ($p = 0.037$) suggesting some small contribution.

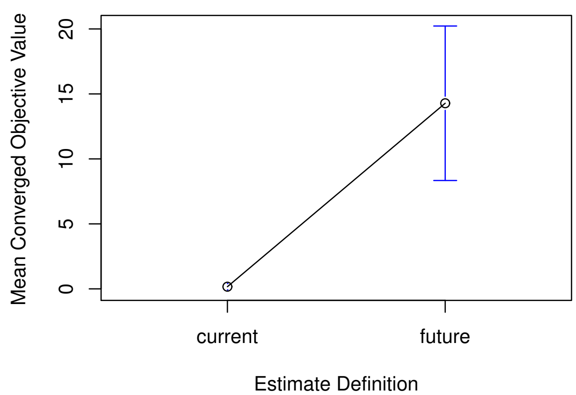
Also note that mean system performance varied across the intermediate range of $p_e$ in which some population of agents used each definition, thereby simulating miscommunication. The most convincing case that miscommunication affects system performance *would* have been degraded performance for $0 < p_e < 1$ compared to $p_e = 0$ and $p_e = 1$. Arguably, this was not the case. However, performance was consistently better for values of $p_e < 0.6$ until the mean system performance began to degrade with $p_e \geq 0.6$—wherein more than half of the population used future estimates—before reaching its worst performance at $p_e = 1$. The variation reveals a strong dependence on not only the choice of estimate definition, but also on the fraction of the population which uses each definition.

### C. Hypothetical Examples: Variation in Practice

Consider a hypothetical situation in which an organization sought to improve the performance of their systems and knew multiple definitions of an estimate existed in their organization. The organization's ability to improve system performance would depend on the initial value of $p_e$ and the definition that the organization sought to establish as the "correct" definition, either the current or future definition. If $p_e \in (0, 0.5]$, disseminating to engineers that estimates should be current values (and reducing $p_e$) would have little effect on system performance. Conversely, establishing future estimates as correct (and increasing $p_e$) would only worsen system performance—both in magnitude and uncertainty—if the ending state had $p_e \in [0.6, 1)$. So system performance

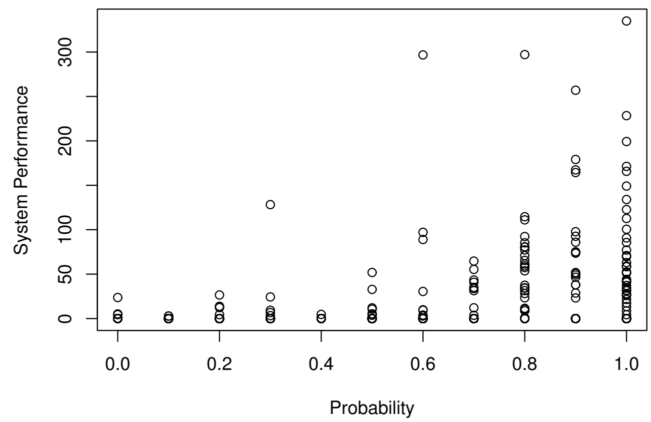



(a) Rosenbrock function cycles

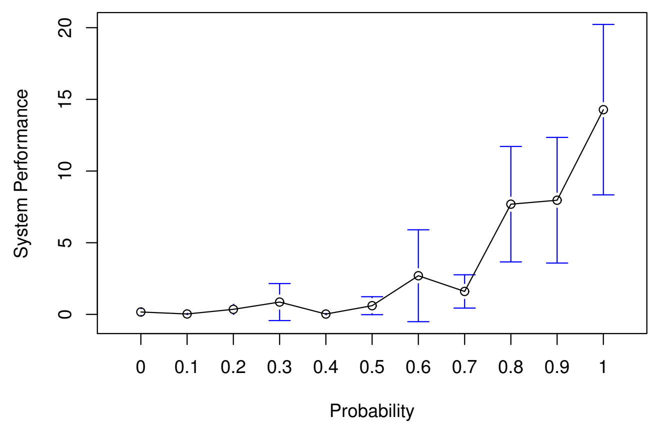



(b) Ackley function performance

Fig. 5: Means 95% confidence intervals for the different estimate definitions of the respective functions. The current definitions do not show error bars due to their small scale.




(a) Ackley Performance Scatterplot




(b) Ackley Performance Means & 95% Confidence Intervals

Fig. 6: Ackley function performances as a function of the probability $p_e$ of an agent using the current or future estimates. Purely current estimates are represented by $p_e = 0.0$ while purely future estimates are represented by $p_e = 1.0$.

would be fairly robust to changes on the domain $p_e \in (0, 0.5]$. This also means that variation in estimate definitions are *not* problematic for system performance on this domain and would not constitute systemic miscommunication.

On the other hand, consider $p_e \in [0.6, 1)$. Increasing $p_e$ would reduce the *average* performance both in magnitude and uncertainty. Conversely, decreasing $p_e$ would increase the average performance with potential uncertainty reduction. Hence, this domain is not robust to changes in $p_e$. Whether due to the reduced performance or the uncertainty associated with changes from an initial $p_e$, estimate definition variation on this domain *does* cause problems for system performance and is therefore miscommunication, although improvements may also occur. An organization could not reasonably predict the quality of the system estimate they can expect to produce without fully surveying their organization's estimate definitions. Further testing would be necessary, though, to examine how changing definition use in the population would affect system performance as each instance of the model assumed one objective function for all agents and one value of $p_e$.

### D. Model Validation

The final analysis step is validation. Face validation requires the mechanisms and properties of the model to represent the real world, while empirical validation requires the data generated by the model to similarly correspond to real-world patterns [60]. Despite the causal uncertainties of the results, the model provides face validation and avenues for empirical validation. Each aspect of the model thoroughly grounds itself in literary evidence and so satisfies face validation at both the unit and structural levels. The model produced results consistent with expert experiences and hypotheses [31] along with implicitly validating the claim that using multiple definitions of "an estimate" may cause miscommunication.

Empirical validation, the more challenging of the two, necessitates pattern matching with real systems and often involves parametric tuning. To date, it is not possible to comparably sample thousands of complex systems for information on their estimate definitions and consecutive system performances; although, case studies could confirm the mechanisms and possibly singular results corresponding to the results described herein. For example, the slow innovation produced by emphasis on "heritage" designs in aerospace and defense contexts may corroborate the results.

## VI. Discussion

CESIUM provides insights into estimate definitions, the effects of miscommunication on complex system performance, and finally complex system modeling.

The study found a statistically-significant difference in performance between 100% use of "current" and "future" design estimates suggesting that current estimates may yield better system outcomes than future estimates albeit at a small cost to project schedule. The difference between the current and future estimate definition cases highlights how future estimates, closely tied to static historical data, may reduce an organization's ability to converge to an optimal solution. Placing past results as component performance targets may impede system innovation more than communicating the state of one's design. Importantly, these findings are not to say that *component-level* innovation becomes more likely owing to the process of communicating one's current design status instead of a future projection. The old cliché maintains that the whole is more than the sum of its parts, and indeed, the simulation's outcomes contend that a complex system's ability to innovate is more than the sum of artifact innovations, precisely the goal of design optimization [62].

Miscommunication was represented by fractional population use of the two estimate definitions in the simulation. The modeled cases involving disagreement between engineers over the definition of an estimate showed that system performance varies as the fraction of the population using each definition varies. While the greatest disagreement between agents about the definition of an estimate ($p_e = 0.5$) did not see the worst performance, the spectrum over which the population used varying degrees of each definition reveals the inherent uncertainty that arises from miscommunication. Ironically, estimate definitions may have no effect on, improve, or degrade performance based on the initial distribution of the definitions throughout the organization.

But the crux of the matter remains: for lack of a shared definition of what constitutes "an estimate", differing definitions may provide an impetus of performance uncertainty and variation, thereby constituting miscommunication. In fact, any such "communication problem" in organizational contexts—whether uncertainty, variation, etc.—is necessarily miscommunication as one would not otherwise identify the communication as "problematic" in the first place.

Furthermore, the simulation merely serves as a lower bound of the effects of miscommunication in engineering practice. The results demonstrate that even when engineers only exchange purely technical information with one another (like estimates), such interactions may contain substantial miscommunication and affect system performance. Involving managers, executives, customers, suppliers, multiple departments, and other organizational roles that contribute to the heterogeneity of real-world engineering organizations could very well yield greater performance loses than those captured here.

Finally, experimentation with the objective functions and optimization algorithms found that either the objective function must be sufficiently complex or the optimization algorithms must be sufficiently representative of human design space search processes, even with the existence of simple objective functions, to facilitate the study of communication phenomena. This poses a challenge for the design and implementation of validated complex system models in that it increases the difficulty of constructing representative complex system models with practical implications. Researchers likely need to devote resources to understanding what types of objective functions sufficiently represent artifacts, design processes, and their relationships in complex systems if models like CESIUM are to become functional for real-world applications.

## VII. Conclusion

Communication affects complex system performance and scholars have hypothesized the same for *mis*communication—when communication results in "problematic" outcomes. The authors' previous study found that even communication about technical concepts such as estimate definitions in complex system design may yield miscommunication [2]. This study sought to demonstrate that miscommunication indeed affects system performance. To do so, it described CESIUM, a generative network agent-based model of a complex system and the design process, and added miscommunication to the simulation.

Use of different definitions of what constitutes a "parameter estimate" appeared to affect complex system performance. Communicating representations of "current" designs outperformed communicating predictions of "future" designs. Varying the proportion of the population of engineers that used each definition also varied system performance albeit uncertainly, providing some validation that using multiple definitions of an estimate constitutes systemic miscommunication in complex system design processes.

Therefore, the simulation demonstrates that miscommunication about purely technical information may substantively affect complex system performance. The results serve as a lower bound on miscommunication's potential to affect performance as the simulation only addresses prescribed technical interactions in organizations of homogeneous populations, and provides ample opportunity for future work.

## VIII. Future Work

This study reveals numerous opportunities for future work in complex system modeling toward the development of complex system design theory. Section II-B1 notes that scholars disagree about the extent to which complex systems follow scale-free degree distributions which this study relies upon. Section III-C mentions that CESIUM does not include any cognitive factors in agent decision-making. And Section III-F defines but one measure of system performance, which is often much more complicated than a sum of parts.

Researchers should explore different network structures, objective functions, performance metrics, behavioral patterns, organization populations, etc. to better understand why complex system development organizations so often struggle to complete projects successfully [9]. For example, the Holme-Kim algorithm provides tunable clustering or modularity which may be useful for representing subsystems. Alternate system performance measures may better assess artifact interdependence, such as by normalizing individual artifact outcomes and weighting them according to their degree. Rather than creating homogeneous networks of artifact objective functions, a simulation could capture goal variation in organizations through heterogeneous systems of objectives randomly assigned from a probability mass function. As in practice, engineers could hold responsibility for more than one artifact, or multiple engineers could share responsibility for one artifact. Communication alone offers opportunities through the study of how the contexts, actions, identities, and genres of both individuals and teams shape the ways in which they interact with one another [2]. Finally, case studies could further validate the findings described herein. Perhaps some of these opportunities will prove fruitful toward the betterment of complex systems and society.

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