Networked Miscommunication: The Relationship Between Communication Networks, Misunderstandings, and Organizational Performance

by

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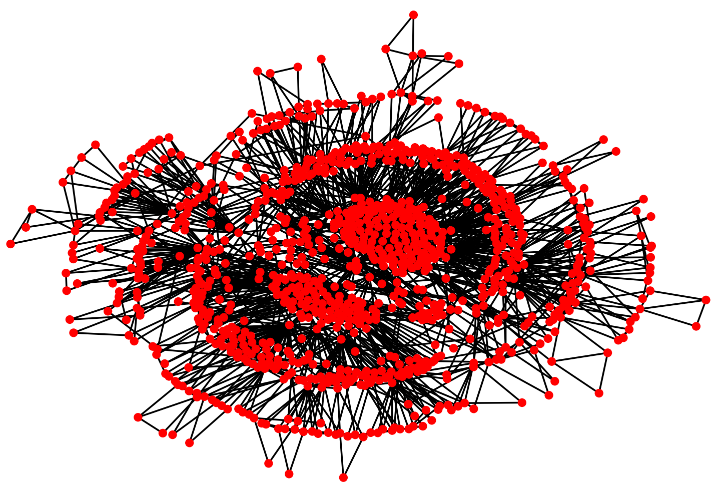

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ABSTRACT

In this dissertation, I introduce and define the concept of *networked miscommunication* — unintentional, aggregated effects of communication practices throughout an organization — and demonstrate its deleterious impacts on organizational performance through case studies and models. While "miscommunication" features prominently in accounts of high-profile complex system accidents, researchers have yet to demonstrate how communicative misunderstandings degrade organizational performance more generally.

I show that while miscommunication costs can result from misunderstandings distributed throughout an organization's communication networks, they also arise whenever a networked communicative interaction falls short of a desired organizational outcome. In my framework, miscommunication is not merely mistakes; practitioners can also be strategically ambiguous. Competitive environments make strategic ambiguity more likely than do cooperative organizational cultures. I therefore hypothesize that fostering cooperation over competition can improve organizational performance while also increasing equity.

I begin by exploring the responsibilities organizations bear as they develop, operate, and manage the complex systems that pervade modern society — whether those systems involve manufacturing, healthcare, or finance. Complex systems contain large collections of highly interacting, tightly coupled elements, making them susceptible to "normal accidents" such as Three Mile Island (Perrow, 1981, 2011). Organizations that suppress dissent, as was the case with the *Challenger* Space Shuttle disaster, will be more prone to these accidents (Vaughan, 1997). More recently, the 2018 Hawaii Ballistic Missile False Alarm highlights how misunderstandings in organizational communication networks affect complex system performance and hence organizational performance. This last type of failure is the primary focus of this dissertation.

After a review of the literature on communication and miscommunication, I dually define *miscommunication*: pragmatically as communication problems that negatively affect goal attainment, and integratively as misunderstandings that prevent participants from balancing their values. I then define networked miscommunication and present three studies that I use to identify a surprising and impactful type of unintentional communicative misunderstandings concerning the meaning of the term "estimates." I demonstrate how heterogeneous meanings of the word estimate both do and don't affect organizational performance.

My first study reveals that expert practicing engineers use cognitive heuristics and strategic

ambiguity to shape estimates of their designs. I then demonstrate how these behaviors increase system uncertainty via an Agent-Based Model and Monte Carlo simulation (Meluso & Austin-Breneman, 2018). To understand the strategic uses of estimates, I study a Fortune 500 company and find widespread variation among practicing engineers about what an "estimate" means independent of their division, title, and phase of product development. While some practitioners define estimates as approximations of current designs, others define them as approximations of future designs, points in a project which could be years apart. Importantly, engineers inadvertently aggregate estimates of different types into single values that inform programmatic decision-making, thereby constituting networked miscommunication (Meluso et al., 2020).

The third study, however, reveals a nuanced picture in which varied estimate definitions conditionally degrade organizational performance. In particular, future estimates degrade complex system performance relative to current estimates, constituting networked miscommunication despite a lack of misunderstandings. I also find that some misunderstandings can protect an organization from performance degradation. In organizations with equal use of current and future estimates, current estimates buffer systems against degradation caused by future estimates, indicating that performance degradation depends on communication network structure (Meluso et al., 2019). Collectively, these studies demonstrate the potential of networked miscommunication to affect organizational performance.

CHAPTER 1

Introduction

Virtually all people participate in organizations. At their core, organizations are "social structures created by individuals to support the collaborative pursuit of specified goals" (Scott & Davis, 2007, p.11). Organizations' goals are varied and diverse: from helping their constituent individuals advance their careers, build relationships, and provide stability, to collective ambitions to design goods, sell services, and fill vital societal needs (Scott & Davis, 2007).

The efforts of organizations to achieve their goals often require them to develop, operate, and interact with *complex systems*. Unlike "simple" systems, where the parts that make up a system interact in visible and predictable ways, the many parts of complex systems are intricately linked and can affect one another in ways that are harder to identify (Perrow, 2011; Clearfield & Tilcsik, 2018). "Even seemingly unrelated parts might be connected indirectly, and some subsystems are linked to many parts of the system" (Clearfield & Tilcsik, 2018, p.23) meaning that changes in one part of a system may easily affect other distant parts. Examples of complex systems include ecosystems, cities, markets, social networks, power grids, transportation networks, and healthcare systems among many others (Minai et al., 2006; Mitchell, 2009; Martin et al., 2016; Hofman et al., 2017; Clearfield & Tilcsik, 2018).[1]

Complex systems provide a context within which organizations can achieve elaborate goals. Doing so requires harnessing resources produced by the system. For example, shipping and air transport allow commerce to efficiently transit the globe; social media quickly connects marketers to consumers; and electricity powers practically everything, from finance to healthcare. As such, it is little surprise that the performance of organizations frequently relies on the performance of complex systems, for better and worse. We do not have to look far to find instances where the struggles of organizations to meet both their own goals and those of stakeholders are tied to complex system performance.

[1] Organizations both contain social networks internally and embed themselves in greater interorganizational networks (Scott & Davis, 2007), meaning they too are complex systems. For now, I will limit the conversation to complex systems with which organizations interact, though we will see in Chapter 5 that organizations often mirror the structure of the artifacts they create.

1.1 Tales of Performance Degradation

Three Mile Island. Famous stories of complex system failures now abound. One of the earliest is the Three Mile Island accident. On March 28, 1979, a nuclear reactor partially melted down at a plant on Three Mile Island near Harrisburg, Pennsylvania (US Nuclear Regulatory Commission, 2014). The United States Nuclear Regulatory Commission (USNRC) reported that a series of small failures, some even unrelated to the nuclear portion of the plant, others involving "misleading information" from instruments, led one of the cores to overheat.

This kind of cascade of failures in a tightly-coupled system is what became known as a "normal accident" (Perrow, 2011). A combination of "personnel error, design deficiencies, and component failures" left their marks on the Federal government and the nuclear industry. Although there were no resulting fatalities, the Three Mile Island accident in 1979 cost more than $1 billion in cleanup costs and increased public fear and distrust of nuclear energy (The Associated Press, 1993; US Nuclear Regulatory Commission, 2014).

The *Challenger* Space Shuttle Disaster. Seven years after Three Mile Island, on January 28, 1986, an even greater catastrophe occurred when the Space Shuttle *Challenger* exploded during launch, killing all seven astronauts on board. Countless studies have discussed the incident including a Presidential Commission (Rogers et al., 1986) and a seminal organizational sociology text (Vaughan, 1997). Causes that contributed to the failure included a "faulty design unacceptably sensitive to a number of factors" (Rogers et al., 1986, p.73), a flawed decision-making process (Rogers et al., 1986, p.83), and a "silent safety program" (Rogers et al., 1986, p.153), and "pressures on the system" going even as high as the White House itself (Rogers et al., 1986, p.165).

But Vaughan (1997) gets to the heart of the matter. She notes that "harmful outcomes can occur in organizations constructed to prevent them, as NASA was, and can occur when people follow all the rules, as NASA teleconference participants did" (p.xv). As much as the technology, she attributes the accident to the "production of culture" (p.394) from the White House on down, throughout NASA management, manifesting in a "culture of production" (p.396) and "structural secrecy" (p.397). These three factors "explain the normalization of deviance" (p.62) which allowed managers and engineers to ignore problems for years preceding the launch, ultimately ending in the failure of a complex system, and heartbreaking loss.[2]

The 2018 Hawaii Ballistic Missile False Alarm. On January 13, 2018, in the midst of heightened tensions between the United States and North Korea, the Hawaii Emergency Management Agency (HI-EMA) conducted an internal exercise of the ballistic missile defense emergency alert

[2]Perrow (2011) later attributes the poor decision and safety management to managerial exercising of power rather than a culture of deviance, but again, there are many studies on and interpretations of this event.

systems. According to a report from the Federal Communication Commission's (FCC) Public Safety and Homeland Security Bureau (Public Safety and Homeland Security Bureau, 2018, p.3), the drill went badly awry. At 8:07 am Hawaii Standard Time, emergency alert systems throughout Hawaii issued the following message:

> "BALLISTIC MISSILE THREAT INBOUND TO HAWAII. SEEK IMMEDIATE SHELTER. THIS IS NOT A DRILL."

While some residents noted that the corresponding sirens did not go off and questioned the alert, many residents feared for their lives. The situation was particularly stressful for deaf residents. The report describes how the Board of Directors of the National Association of the Deaf were meeting in Honolulu at the time. They sought immediate shelter, as directed, in a windowless storage room for more than 20 minutes until one member saw a corrective message on Twitter. At 8:42 am, after 38 minutes, HI-EMA received permission from the Federal Emergency Management Agency (FEMA) to issue a corrective message issuing the "all clear".

This incident, which led to at least one heart attack (Consillio, 2018) and subsequently to changes in the FCC emergency alert systems (Carman, 2018), highlights the important role that organizational communication plays in complex systems, such as emergency management systems. According to the FCC, the two leading causes of the false alert were "misunderstandings" (Public Safety and Homeland Security Bureau, 2018, p.14). The first instance involves the warning officer who triggered the alarm. He claims he didn't hear the "Exercise, Exercise, Exercise" statements that preceded and followed the simulation; however, it was also true that the supervisor issued an unusual line during the simulation that "this is not a drill." As a result, the warning officer attested that he "was 100 percent sure that it was the right decision [to issue the alert], that it was real." The FCC notes that "this fundamental misunderstanding played a critical role in the initiation of the false alert" (p.14).

But that was not the only "human error." The FCC reported that "a misunderstanding between the midnight shift supervisor and day shift supervisor also led to the drill being run without sufficient supervision" (p.14). The midnight shift supervisor "specifically decided to [conduct a] drill at shift change, reasoning that it would be most difficult for warning officers to properly respond to a call...announcing an incoming ballistic missile during a shift change." The midnight supervisor was all too correct. The midnight supervisor did not give the day shift supervisor either clear notice or enough time to prepare, meaning:

> "The day shift supervisor did not understand that the midnight shift supervisor intended to conduct a drill with the day shift officers during the shift change... As a result, the day shift supervisor was not in the watch center to supervise the drill. Other emergency management agencies the [Public Safety and Homeland Security] Bureau

> interviewed stressed the importance of proper drill supervision, and stated that conducting a drill without proper supervision would not be tolerated" (Public Safety and Homeland Security Bureau, 2018, p.14-15).

As we will see in Chapter 2, "misunderstandings" comrpise the basic building blocks of *miscommunication*. But for now, just observe that two relatively small instances of misunderstanding within an organization led to outsized effects in the performance of a complex system — in this case, the emergency warning system issued a false alert — thereby affecting the organization's abilities to achieve its goals of "promoting the safety of life and property through communications" and "provid[ing] an effective and reliable national emergency alert and warning system" (p.6). The point is that even when they are careful, organizations eventually — and inevitably — underperform stakeholder expectations. The next section explores *why*.

1.2 Mechanisms of Performance Degradation

In all three of these cases, complex systems performance threatened people's lives — and in one case took them — thereby yielding degraded organizational performance. Why do these kinds of accidents happen? And how? To answer these questions, we first need to answer (a) what is organizational performance? and (b) how does performance degrade?

Organizational performance, or organizational effectiveness, is often loosely defined in the literature, if defined at all (Snow & Hrebiniak, 1980). In part, this is because it isn't clear that we can define an organization as having a single goal across all of its participants (March & Sutton, 1997). Analysts select from a multitude of performance measures "ranging from productivity and profits to growth, turnover, stability and cohesion" depending on their context and conceptualization of organizations (Scott & Davis, 2007, p.326). Consequently, I define organizational performance with respect to each organization's goals throughout this dissertation such as minimizing mass (Chapter 3) or reaching the most optimal design (Chapters 4 & 5).

The organization and management science literatures often refer to *performance degradation* in somewhat technical terms, describing the conditions under which some organizational decision leads to reduced performance compared to an alternative choice. Carley & Lin (1997) use the term to refer to how particular organization designs improve or degrade the ability of an organization to identify an aircraft in a radar detection task given information distortion. Martin et al. (2016) describe degradation as decreased ability to predict the size of an information cascade on Twitter. And authors throughout the Rouse & Boff (2005) volume *Organizational Simulation* refer to degraded measures of performance (Klein et al., 2005; Levis, 2005). Given the availability and prescience of technical metrics, I similarly examine performance degradation in these terms.

Having defined organizational performance and performance degradation, we can turn to the question of what causes accidents like these to happen. Since the 1970s, scholarship has sought to identify the mechanisms which cause organizational inabilities to meet their stated goals and expectations (Scott & Davis, 2007). Pertaining to complex systems, several such theories arose from organizational sociology. In his study of Three Mile Island, Charles Perrow (1981, 2011) coined the term *normal accident*, identifying that the multitude and tight coupling of interactions in complex systems eventually yield cascading failures — not necessarily frequently, but inevitably, thereby making them normal. Diane Vaughan (1997) identified another source: the *normalization of deviance* wherein normative cultures of production and secrecy drive an organization to hide indications of failure.

In the organizational communication literature, Eisenberg & Phillips (1991) pose another source of performance degradation when managing complex systems (albeit indirectly). They recount a number of examples of *miscommunication* in organizations, instances where the result of a communicative interaction yield a problematic result for one or more organizational participants.[3] Other organizational scholarship — such as that from organizational communication on strategic ambiguity (Eisenberg, 1984), from management science on information distortion (Carley & Lin, 1997), and from organizational psychology on representational gaps (Cronin & Weingart, 2007) — corroborate the theory that miscommunication likely affects organizational performance. More recent evidence affirms that representational gaps indeed yield degraded performance and demonstrates that frame-of-reference training[4] has positive effects on performance (Firth et al., 2014).

Another vein of research with promise for complex system management is the relationship between communication networks and organizational performance. Sparrowe et al. (2001) found that both the the existence of positive and negative ties were linked to individual and group performance. Cummings & Cross (2003) established a negative performance relationship resulting from structural holes, core-periphery, and hierarchical group structures of communication. Recent works by Barkoczi & Galesic (2016) revealed that different learning styles perform better with different network densities, resolving some of the outstanding debate over efficient versus inefficient network structures. Especially relevant is work by Gokpinar et al. (2010) which found that organizational communication structures and product architecture both affect the number of complex system failures.

[3]I will provide more nuanced treatment of their argument shortly (Chapter 2), but the essence is nevertheless that that miscommunication can lead to organizational performance degradation by a number of paths.

[4]Frame-of-reference training is a form of organization intervention from the performance appraisal literature which seeks to reduce representational gaps by giving individuals from different units a shared standard with which they can make more accurate and reliable judgments (Firth et al., 2014).

1.3 Contribution

This dissertation draws from the bodies of knowledge on communication networks and miscommunication to identify a novel source of organizational performance degradation and address a gap in the research — *networked miscommunication* — which may affect complex system performance and therefore organizational performance. I do so over the course of three studies wherein I identify a surprising and impactful instance of miscommunication in practice despite the technical (and therefore presumably more quantitatively defined) nature of the work, establish the pervasiveness of that instance of miscommunication throughout an organization, and demonstrate the potential of that miscommunication to affect complex system (and hence organizational) performance.

I begin by providing background on the different analytical perspectives through which scholars study communication and miscommunication (Chapter 2). My first study identified the existence of ambiguity about the definition of the term "estimate" in engineering practice, showing that practitioners use cognitive heuristics and strategic ambiguity to create estimates of their designs which increase system uncertainty (Chapter 3) and so use estimates in multiple ways. My next study at a Fortune 500 firm found widespread variation among practicing engineers about the definition of "an estimate," independent of their division, title, and phase of product development (Chapter 4). Engineers inadvertently aggregated estimates of different kinds into single values that informed decision-making, thereby constituting networked miscommunication. My third study showed that miscommunication of estimates can degrade the performance of the complex systems created by organizations (Chapter 5). To do this, I simulated the performance of an organization as it develops a complex system using a novel agent-based modeling technique. Incorporating miscommunication into the development process clearly showed the even small, everyday instances of miscommunication can affect performance. I then discuss how these findings advance the state of knowledge, their limitations, and implications for further research into complex systems, organizational communication, and organizational culture (Chapter 6) before summarizing the work (Chapter 7).

CHAPTER 2

Background

Miscommunication and communication networks share the obvious ancestor of communication. But studies of communication have taken many forms over time, and the definition of communications highly depends on the discipline of inquiry, ranging from linear models of transmission-and-receipt to nuanced negotiation of meaning by two or more parties. For that reason, the following sections will begin by situating the meanings and applications of each of the foundational concepts of communication before proceeding on to miscommunication.

2.1 Communication

Two schools of thought have developed to explain communication, broadly referred to as the *objectivist* approach and the *interpretivist* approach (Montgomery & Duck, 1993; Leeds-Hurwitz, 1995b). Perhaps unsurprisingly, the objectivist approach embraces largely quantitative and graphical methods of analyzing communication derived from mathematical origins while the interpretivist approach embraces qualitative understandings from linguistics and sociology. The following sections describe each in turn.

2.1.1 The Objectivist Approach

Objectivist models of communication — broadly speaking, quantitative in origin and method — often trace the footsteps of Shannon's seminal text, *The Mathematical Theory of Communication* (Shannon, 1948). Shannon's method treats communication as a linear process with a transmitting party, a transmitted signal, and a receiving party. This conception of communication as information passed from party to party has become known as the "process" model of communication, or the "information transfer approach" in the organizational communication literature (Eisenberg et al., 2017). Out of the process model grew the idea of communication as networks (Stewart et al., 2003; Thompson, 2011). "*Communication networks* are the patterns of contact that are created by the flow of messages among communicators through time and space," and so *communication* is defined as the transmission and exchange of messages which may include data, information, knowledge, symbols, or "any other symbolic forms that can move from one point in a network to another" (Monge et al., 2003). Even given their simple forms, network models of communication display powerful results by demonstrating social theories of self-interest, collective action, exchange theory, dependency theory, and homophily among others (Monge et al., 2003; Newman, 2018).

Network models consist of "edges" or "ties," the connections between individuals or between teams through which information is exchanged (Brass, 1984; Balkundi & Harrison, 2006). Ties can further be divided into instrumental, expressive, and technical ties. Instrumental ties involve "work role performance and involve the exchange of job-related resources, including information, expertise, professional advice, political access, and material resources" (Ibarra, 1993). Expressive ties are affective in nature and provide social support for career advancement, personal values, and friendship (Balkundi & Harrison, 2006; Ibarra, 1993). Technical ties are synonymous with physical and functional interfaces in complex system design (Sosa et al., 2003). Collectively, they create networks of components that share interfaces to function as wholes (Sosa et al., 2007), also called product architectures (Ulrich, 1995), complex products (Sosa et al., 2003, 2015), and complex systems (Sosa et al., 2003). And while such technical interfaces may *seem* absent of communication, the very definition of interfaces necessitates communication for most engineering projects (Eckert et al., 2005). Consequently, tie categorizations are not mutually exclusive and frequently overlap, even creating one another (Balkundi & Harrison, 2006; Borgatti & Foster, 2003).

Network theory brings with it a suite of metrics for characterizing and understanding a network's structure, positioning, and evolution (Newman, 2018). One of the most often cited is centrality, the extent to which an actor occupies a central position in a network by having many ties with other actors (Kilduff & Brass, 2010). The simplest form, called either degree centrality or in-degree centrality, is merely the number of ties linked to a given node (Newman, 2018; Wasserman & Faust, 1994). Alternatives include eigenvector centrality, Katz centrality, and PageRank to emphasize relative importance in a network, directed ties, or both (Newman, 2018).

Several communication-relevant, network-derived insights from sociology and management include tie content (Balkundi & Harrison, 2006), structural holes (Burt, 1992), and brokerage (Stovel et al., 2011). Balkundi and Harrison demonstrated through a meta-analytic literature review and regression analysis that the in-degree centrality of instrumental and expressive ties both affect (a) team performance, "how well the team meets (or exceeds) expectations about its assigned charge at work," and (b) team viability, "a group's potential to retain its members—a condition necessary for proper group functioning over time" (Balkundi & Harrison, 2006). While expressive tie centrality has a comparable effect on team performance to instrumental centrality, expressive centrality has a stronger relationship with team viability than instrumental centrality (Balkundi & Harrison, 2006). Whether within or between teams, the strength of expressive ties has the potential to either facilitate or constrain the flow of resources within an organization (Brass, 1984; Balkundi & Harrison, 2006).

Burt's (1992; 2015) concept of structural holes arises from disparate social capital among individuals. People access information and resources commensurate to the size of the network they have access to but at the opportunity cost of sustaining each relationship. A structural hole is the *absence* of a tie between individuals who would otherwise benefit from interacting (Burt, 1992) and can be indirectly measured by using the redundancy or local clustering metrics (Newman, 2018). For those individuals to connect, they may need to go through a third "bridging" individual, resulting in increased likelihood of novel information for those who newly connect to the bridging individual (Burt, 2015), and increased strategic positions of power (Newman, 2018) or increased vulnerability (Stovel et al., 2011) for bridging individuals, a striking contrast (Stovel & Shaw, 2012).

Such intermediaries who facilitate "trade over gaps in social structure...of valued resources that would otherwise be substantially more difficult" are referred to as brokers in social, economic, or political networks (Stovel et al., 2011). Middlemen brokers often find themselves in tension with their connections as Stovel et al. describe:

> "Demand for brokerage is high when the flow of trustworthy information is low. At the same time, by definition, side parties are highly dependent on the broker, who in the short run, offers the only feasible path to a completed transaction. The dual demands of dependency and low information make side parties uncertain about the appropriate terms of the deal and undermine their confidence in the broker who advocates the transaction. Furthermore, because brokers almost always have more information than either of the side parties, they may be able to benefit more than they would in a competitive market, where the price of the transaction would be driven down by other potential intermediaries. Brokers' ability to exploit their favorable position for private benefit, now and in the future, exacerbates side actors' distaste for interacting with brokers" (Stovel et al., 2011).

Pertaining to complex systems, systems engineers and their processes often take on positions as brokers because they serve as "the bridges between project management and the technical team" (Kapurch, 2007). Practitioners recount similar experiences wherein systems engineers play crucial yet contested roles (Meluso et al., 2016) attempting to broker both information and trust in design processes.

Clearly, objectivist approaches provide valuable insights into organizational communication. And, while certainly desirable for mathematical modeling due to their quantitative nature, objectivist approaches are often critiqued not as being ‘wrong’ so much as “not [going] far enough” (Thompson, 2011). They necessarily simplify the multiple processes involved in each communicative interaction including individuals’ differing constructions and deconstructions of meaning, contextual determinants, and interactive asynchronicity (Thompson, 2011; Eckert et al., 2005). The dispute is not over whether process or structure are involved, but the extent to which objectivist models of communication incorporate (or neglect) the myriad processes described by the interpretivist approach.

2.1.2 The Intepretivist Approach

Interpretivism founds itself on what Denis McQuail (1984) describes as “a real complexity which defies covering by any single formula; a complexity stemming from several sources beside the mere quantity of elements and stages involved.” McQuail’s dismissive tone toward “formulas” and “quantities” in this quote, ironically a bit reductive itself, nevertheless emphasizes the complexity he espouses. In his own words, McQuail proposes a broad definition of communication by listing fundamental determinants of communication including symbols, understanding, interaction, process, commonality, channel, time, and intention among others (McQuail, 1984). Other scholars add terms like semiotics, social, construction of reality, creation of meaning, identity, culture, and context, often using slightly different language from one another while retaining the same intention (Thompson, 2011; Eckert et al., 2005; Leeds-Hurwitz, 1995a).

Enumerating these unifying terms simultaneously confuses and clarifies the issue of distilling a single definition; yet, it gives meaning to the shorter definitions such as that given by Fiske: in the interpretivist frame, *communication* is “social interaction through messages” (Fiske, 1990). This bears explaining, though, as it encapsulates the terms laid out in the previous paragraph. Thompson (2011) describes them as follows: The term ‘social’ implies the existence of communication in a context and with unique participants who—sending ‘messages,’ whether actively or passively, intentionally or otherwise—affect the success of the information exchange, or ‘interaction’. Taking communication as social means describing “events occurring between people in the process of interacting rather than reporting how events are perceived through a single person’s understanding,” capturing the mutual nature of communication as creating social meaning by and for both parties (‘interacting’) iteratively rather than purely linearly (Leeds-Hurwitz, 1995a). Said another way, communication is determined by the identities of the participants, the context of the interaction, the genre (or medium) of exchange, and the actions of exchange themselves (Thompson, 2011; Leeds-Hurwitz, 1995a).

Scholars in organizational communication share a similar definition oriented toward their discipline. Eisenberg et al. (2017, p.4) define organizational communication as "the interaction required to direct a group toward a shared goal". All the same elements exist: sociality, interaction, and messaging (via interaction and direction), while adding the goal orientation of organizations as defined in Chapter 1. Within this definition, scholars apply several frames for understanding organizational communication. The first is the information transfer approach mentioned in Section 2.1.1. The others examine communication as a transactional process, as strategic control, and as a balance of creativity and constraint (Eisenberg et al., 2017).[1]

Even in light of the macro vs micro emphases of the objectivist and interpretivist definitions of communication, respectively, notice the remarkable similarities. Both involve participants, exchange, and messages—albeit by varying definitions of each. So while the former simplifies transmission to illuminate the existence and patterns of communication, the latter emphasizes qualities of communication at the cost of scale. Need this be the case? Bavelas cautions:

> "These differences are socially constructed, and to the extent that we insist on maintaining them, we will severely limit the number of approaches we can invent to explore our common interests. A highly restricted choice of methods inevitably stunts the growth of theory as well. On the other hand, if we reject polarization, we may discover new, previously unexplored combinations of both approaches" (Bavelas, 1995).

2.2 Miscommunication

What makes communication into *mis*communication? Just as a vernacular definition of communication yields an incomplete understanding compared to the definitions presented in Sections 2.1.1 and 2.1.2, so too would treating miscommunication as "bad" or "failed" communication, though that is certainly how dictionaries portray it. In the opening chapter of their volume *"Miscommunication" and Problematic Talk*, Coupland et al. (1991b) cite studies showing that "clear, concise, honest communication is frequently the *cause* [sic] of difficulties as it is the solution to them. 'Miscommunication' is therefore not to be characterized simply as a deviation from some underspecified ideal"; that language use and communication are "even intrinsically flawed, partial, and problematic. To this extent, communication is itself miscommunicative".

The term miscommunication has multiple definitions depending on the disciplinary perspectives and objectives of the author. Generally we think of *miscommunication* as occurring whenever

[1]Deetz (2001) broadens the definition of organizational communication to include several possibilities: (a) the specialty of communication departments within organizations and communication associations, (b) communication as a phenomenon that exists within organizations, and (c) communication as a distinct discipline for describing organizations in the same way that psychology, sociology, economics, and other disciplines describe organizations. While a valid point, the focus on this dissertation is on communication within organizations as organizational communication.

the content or message of an interaction has not been adequately conveyed from one person to another (Holmes & Stubbe, 2015), or there is some "communicative 'deficiency' or 'problem' " in an interaction (Coupland et al., 1991b). More specifically, I refer to Tzanne's (2000) terminology and linguistic perspective:

> "The terminological position I follow is a rather simple one, in that it makes use of only two basic terms, 'miscommunication', which refers to the phenomenon as a whole, and 'misunderstanding(s),' which refers to individual occurrences of miscommunication in an exchange. The latter term may be modified as, for example 'possible misunderstandings'...or 'intentional misunderstandings'... A misunderstanding is defined as a mismatch between the speaker's intended meaning and the hearer's understanding of this meaning in the particular context of interaction" (Tzanne, 2000, p.33-34).

Tzanne's framing of miscommunication instances as one or more misunderstandings provides a valuable foundation given the plethora of synonymous language used to describe the phenomena. Table 2.1 shows the relationships between the terminology adapted from Tzanne (2000, p.37). While I will leave the exhaustive definitions of each term to Tzanne as they are fairly intuitive and less pertinent to organizational communication, Table 2.1 adds the language from organizational communication related to miscommunication (Eisenberg & Phillips, 1991; Eisenberg et al., 2017) and misinformation (Del Vicario et al., 2016) given the current interest in the subject.

Following Tzanne's definition, the table shows that miscommunication is an unintentional divergence of understandings between participants. People often use terms like misinterpretation, communication breakdown, and communication failure synonymously with miscommunication by this definition. It comes as no surprise that elements such as context (Tzanne, 2000), expectations (Mortensen, 1997), power (Holmes & Stubbe, 2015), deception (Anolli et al., 2002), negotiation (Bjørndahl et al., 2015), intent (Ladegaard, 2009), culture (Stubbe, 2000), etc. affect miscommunication as they too affect communication. A nearly endless list of factors may contribute to a lack of "mutual understanding" (Bjørndahl et al., 2015; Weizman, 1999) or "mutual knowledge" (Bazzanella & Damiano, 1999; Weigand, 1999) which constitute miscommunication in more ways than shall be recounted here. Regardless, miscommunication is a natural and expected element of the communicative process which may or may not resolve depending on the contexts, actions, identities, and genres involved.

As we move from the linguistic framing into the organizational framing, the definitions become more diverse. Eisenberg & Phillips's earliest work explicitly defining miscommunication (1991) defines it according to four separate traditions: for one or more parties to not be understood; achieve their respective communicative goals; be authentic, honest, and disclosive; or establish an open dialogue. I will highlight the pragmatic definition for its later value in assessing organizational performance: simply "failed goal attainment" (p.249). They side ultimately land on a

<table>
<tr><th rowspan="2"></th><th rowspan="2">Lack of Reception</th><th colspan="2">Divergent Understandings</th><th colspan="2">Shared Understandings</th></tr>
<tr><th>Unintentional</th><th>Intentional</th><th>Substantiated</th><th>Unsubstantiated</th></tr>
<tr><td>Message Perception</td><td>nonperception</td><td>misperception</td><td></td><td rowspan="4">effective communication</td><td rowspan="4">misinformation</td></tr>
<tr><td rowspan="2">Message Comprehension</td><td rowspan="2">noncomprehension</td><td colspan="2">misunderstanding</td></tr>
<tr><td>miscommunication
misinterpretation
communication breakdown
communication failure
(non-strategic) ambiguity</td><td>strategic ambiguity</td></tr>
<tr><td>Perception or Comprehension</td><td></td><td>mishearing</td><td></td></tr>
</table>

Table 2.1: Terminology of miscommunication. Adapted from Tzanne (2000). The modified version expressed herein incorporates the terminology from organizational communication (Eisenberg et al., 2017) and misinformation (Del Vicario et al., 2016).

more unifying, nuanced definition. First, *effective communication* is "discourse that promotes a balance between agency and constraint". In this frame, miscommunication is "the failure, in social interaction, to balance individual creative agency against the coordination and control that makes organizing possible" (Eisenberg & Phillips, 1991, p.246). And so we have two extrema: failed goal attainment on the one side and failed balance on the other.

Several decades later, Eisenberg et al. (2017, p.32) appear to shy away from these early definitions, only defining miscommunication in the information transfer approach as "when no message is received or when the message that is received is not what the sender intended." This is an understandable stance in light of the prior definition of effective communication which leaves anything else as suboptimal or "ineffective" communication. They attribute miscommunication in this vein to any of several causes:

Information overload: when the recipient of a message becomes overwhelmed by the amount of information they must process, whether by receiving too large a quantity (amount), receiving it too quickly (rate), or having insufficient resources to process the information (complexity) (Farace et al., 1977 via Eisenberg et al., 2017).

Information distortion: the effect of noise on a recipient's ability to process a message which could be semantic (the message has different meanings for different participants, roughly synonymous with miscommunication), physical (an external signal distorts the signal as it travels through some medium), or contextual (different experiences shape the way different participants construct meaning, again synonymous with miscommunication).

Ambiguity: when multiple possible interpretations of a message cloud the sender's intended meaning (Eisenberg et al., 2017) and leading to unintentional miscomprehension.

A variant of ambiguity is *strategic ambiguity*, wherein one of the participants intends to send ambiguous messages such that other participants may interpret the message in alternative ways, thereby promoting unified diversity, facilitating organizational change, and preserving existing positions. As strategic ambiguity is intended, it inhabits the intentional divergent understandings column in Table 2.1.

Another related concept from organizational psychology, representational gaps, is often discussed in concert with miscommunication though I will differentiate the two. A *representational gap* occurs when members of a team hold different mental models from one another about their team's goal. Representational gaps can arise from people starting with different knowledge bases, which they employ when assessing a problem, or from different values through which they determine what is beneficial or desirable. These differing conceptualizations of a problem can therefore lead to divergent understandings between team members (Cronin & Weingart, 2007) and could hence cause miscommunication. Hypothetically, it is conceivable that someone could intentionally create a representational gap via strategic ambiguity just as they could unintentionally do so through miscommunication. Similarly, a representational gaps could arise *due to* misunderstandings. I have not found literary evidence supporting either of these hypotheses to date and so they likely merit further study.

With the exception of the information transfer terms, the language in Table 2.1 is situated in the interpretivist approach. The objectivist approach addresses miscommunication via the information transfer tradition language of Eisenberg et al. (2017). For example, Shannon (1948) treats miscommunication as finding "the ways of transmitting information which are optimal in combatting noise" (p.407). He treats messages as statistical sequences with some probability of noise distorting each portion of a message. The mathematical solutions, of course, are to resend the message enough times that you can determine with a high degree of confidence that the original message has been transmitted via "an efficient code, allowing complete correction of errors and transmitting at [a known rate]" (Shannon, 1948, p.418). However, objectivist approaches to date have yet to scale up to larger communication networks.

2.3 Communication & Miscommunication in Engineering Design

Also of relevenance given the context of the upcoming studies is communication in engineering design. Engineering design research focuses on four topics related to communication: (a) the effects of networked communication on performance, (b) qualitative studies of how communication and miscommunication contribute to design practice, and (c) how communication affects complex system design.

Recently, engineering design has emphasized the effects of networked communication on team and system performance. Such network models squarely—and productively—fall into the objectivist paradigm of communication. They identify an increased frequency of unidentified interfaces (which are essentially structural holes) at system boundaries (Sosa et al., 2004); curvilinear relationships between genres of communication and a variety of performance objectives (Kennedy et al., 2011); the importance of managing subsystems with high centrality (Sosa et al., 2011); the evolution of information flows in complex engineered systems throughout the development process (Parraguez et al., 2015); the risk of coordination disruptions resulting from central third-party brokers (Sosa et al., 2015); the relationship between different interface distributions and the existence of design problems (Parraguez et al., 2016); the benefits of intentionally-designed communication structures in multi-team systems (Kennedy et al., 2017); and a method for predicting team performance from team attributes including (ethically-questionably) intellectual abilities and personality traits (Ball & Lewis, 2018).

Returning to the interpretivist frame, however, Sonnenwald (1996) identifies 13 "communication roles" in multidisciplinary design and how they collectively foster "integration, collaboration, and project completion" by "negotiating differences across organizational, task, discipline, and personal boundaries." Stempfle & Badke-Schaub (2002) observed team communication as a means to categorize thought into "the four basic cognitive operations of generation, exploration, comparison, and selection" before proposing a "two-process-theory of thinking in design teams." Eckert & Boujut (2003) present a volume on "design cooperation communication through physical or virtual objects" toward how to achieve "more effective representations of design ideas, that serve as more effective objects for mediating design communication." Eckert et al.'s (2005) chapter *Communication in Design* summarizes a combination of objectivist and interpretivist approaches to communication through a lens of cognition: as information, interaction, and situation. They proceed to enumerate many of the ways in which collaborative design involves communication including design handover, joint designing, idea generation, interface negotiation, conflict resolution, and decision making, among others. Eckert et al. (2013) identify "three layers of structure in design communication, each of which can be more or less formal: the design process, the interaction between participants, and the representations of design information". Furthermore, they note that "mismatches in the understanding of [communicative] formality can lead to misunderstandings, in particular across expertise boundaries. Finally, Butt et al. (2016) demonstrate how more effective communication increases stakeholder participation in design changes, "whereas lacking communication routines" is associated with task-oriented work and less stakeholder involvement.

Finally—and most relevant—engineers have studied complex system design communication via field studies (den Otter & Emmitt, 2008; Laufer et al., 2008), historical project data regression analysis (Robinson, 2010; Liu & Cross, 2016), and controlled laboratory experiments (Austin-Breneman et al., 2012), particularly highlighting elements such as the relationship between communication frequency and team performance (Patrashkova-Volzdoska et al., 2003). Den Otter & Emmitt (2008) used case studied to determine that participants viewed dialogue more favorably than meetings or electronic communication and that dialogue tended to be more time-efficient. Laufer et al. (2008) observed and calculated the significant portion of the day that construction managers spend verbally communicating (80%) with a strong preference for informal communication (a further subdivision of 88% of the 80%). Using a novel method of hourly surveys of design engineers, Robinson (2010) determined that 55.75% of their working time was spent acquiring and providing knowledge. Liu & Cross (2016) used regression analysis and structural equation modeling to find effectiveness, efficiency, and innovation as "primary dimensions of technical performance". Each metric was predicted with explanatory variables including management support, cooperation, communication, knowledge, and team harmony. In a study of graduate student complex system design teams, Austin-Breneman et al. (2012) found that students tended to conceptualize their subsystems separately and use trial-and-error methods instead of gradient information to optimize the performance of a system. And Patrashkova-Volzdoska et al. (2003) found curvilinear relationships for email and face-to-face communication indicating optimal performance in teams with moderate amounts of each variety rather than high or low levels of interaction via those genres.

Collectively, objectivist engineering design tends to focus on binary states of communication or networks of communicative interactions. Interpretivist approaches tend to capture preferences for face-to-face communication, performance generated by moderate or increased quantities of communication, and in rare cases the qualities of communication which benefit design. In only two cases do scholars reference concepts resembling miscommunication: Eckert et al. (2005) suggest causes and ways of resolving "communication breakdown" or "communication problems" and provide largely anecdotal methods for overcoming "not understanding the big picture", "missing information provision", "information distortion", and "interpretation of representation." Then in *Articulating (mis)understanding across design discipline interfaces at a design team meeting*, Luck (2013) examines social interaction from the perspective of natural language processing to identify ambiguity and uncertainty as different forms of misunderstanding interwoven throughout the conversation in a design meeting. She also noted the existence of "repair" processes to bridge misunderstandings, similarly identified in communication literature (Coupland et al., 1991b).

2.4 Research Gap

Consequent to the background from these varying traditions, I consolidate and define relevant terms in Figure 2.1. I've chosen to define two separate definitions of miscommunication, one pragmatic and one integrative, to acknowledge the multiple traditions and objectives of forming definitions. The pragmatic definition, while meaningful for evaluating organizational performance, contains less nuance and appreciation of multiple knowledge bases than the integrative definition. In contrast, the integrative definition fills a valuable role in combining the intents and expertises of linguists with those or organizational scholars in a unified form. Neither definition is purely "right," nor "wrong," simply different perspectives grounded in different objectives. In that light, I will ground miscommunication whenever possible in misunderstandings throughout the remainder of this dissertation while acknowledging that not all instances of miscommunication need strictly incorporate misunderstandings.

That said, I will now return to what miscommunication might constitute in networks. If misunderstandings in an organization's communication network were to hinder organizational perfor-

Complex System: A large collection of elements with significant interaction and tight coupling between those elements.

Miscommunication (pragmatic): When communicative interaction results in a 'deficiency' or 'problem' that hinders at least one of the engaged parties' abilities to fulfill their individual or collective goals.

Miscommunication (integrative): One or more instances of misunderstanding that prevent the participants from balancing their individual and collective values.

Networked Miscommunication: An unintentional, aggregated effect of communication throughout an organization's communication networks that hinders organizational goal attainment.

Figure 2.1: Terminology definitions.

mance, those misunderstandings would constitute miscommunication with respect to the organization's goals and potentially with respect to the goals of individual members within the organization. Therefore, we can define *networked miscommunication* as an unintentional, aggregated effect of communication throughout an organization's communication networks that hinders organizational goal attainment. This definition leans more on the pragmatic definition of miscommunication for the functional reason that assessing the integrative definition in aggregate would prove quite challenging if not impossible.

Figure 2.2 shows one avenue by which networked miscommunication may occur. Just as the inevitability of failures (Perrow, 2011) and suppression of organizational dissent (Vaughan, 1997) can affect complex system performance, so too may certain quantities and types of misunderstandings in an organization's communication network. Hence, the networked misunderstandings would affect organizational performance and constitute networked miscommunication.

Researchers have extensively studied how both communication network structure and content affect organizational performance (Balkundi & Harrison, 2006). Similarly, scholarship has addressed how small information distortions affect organizational performance (Carley & Lin, 1997) and related concepts like representational gaps affect organizational performance (Firth et al., 2014). However, the topic of how misunderstandings distributed throughout a communication network affect organizational performance has not received sufficient treatment. The following chapters of this dissertation address this research gap by demonstrating that misunderstandings in an organization's communication network can affect organizational performance by affecting complex system performance.

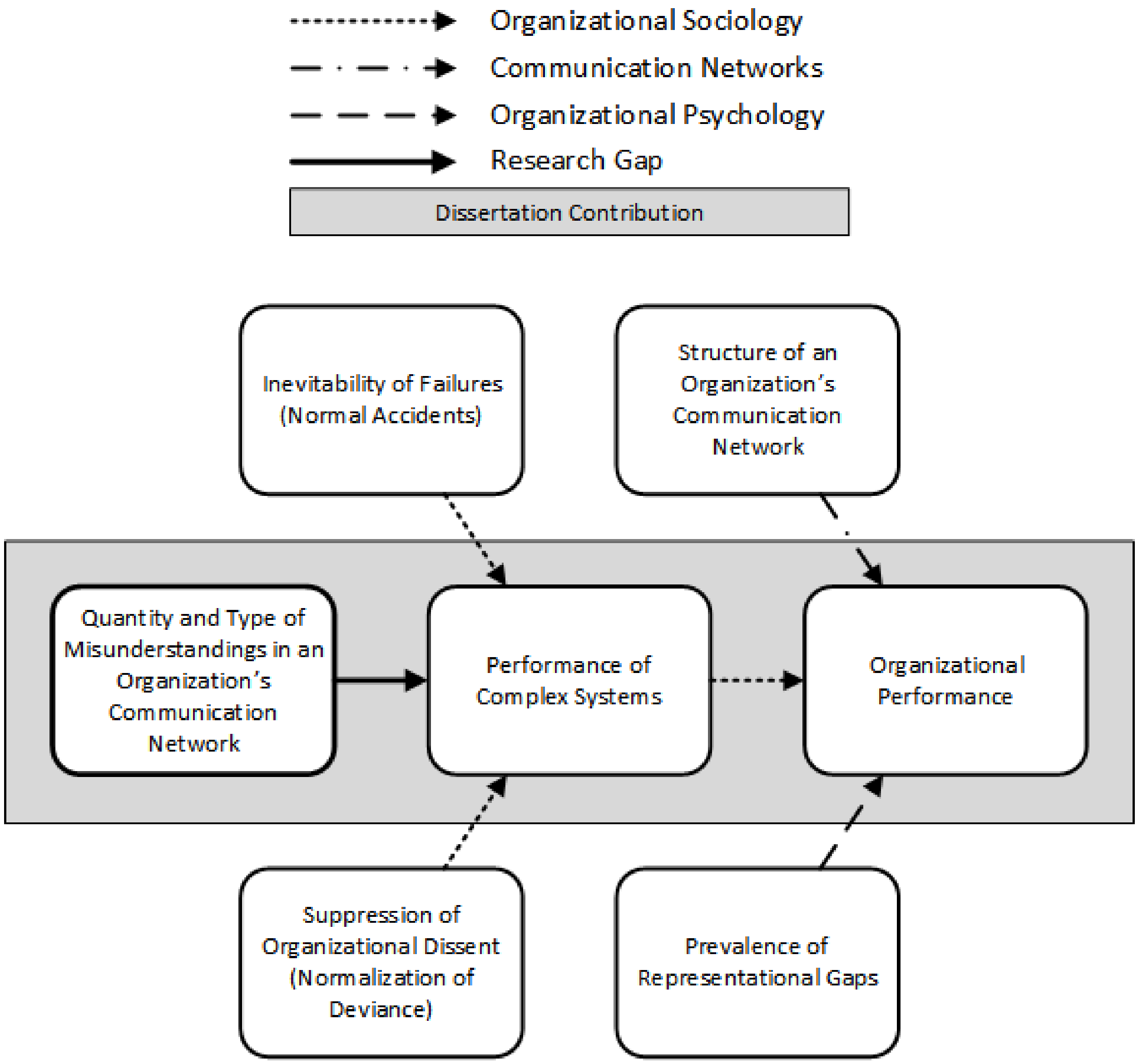


Figure 2.2: Factor Diagram & Research Gap. Relevant factors which affect organizational performance according to the organizational sociology, networks, and organizational psychology literatures. This dissertation demonstrates that misunderstandings throughout an organization's communication network can affect organizational performance and therefore constitutes networked miscommunication. Several relevant terms are defined in Figure 2.1.

CHAPTER 3

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

This chapter was coauthored with Jesse Austin-Breneman and published in the Journal of Mechanical Design under the same title in 2018 (Meluso & Austin-Breneman, 2018).

3.1 Abstract

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.

3.2 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) (Bloebaum & McGowan, 2012; McGowan et al., 2013; McGowan, 2014). Design teams necessarily work in parallel when designing LaCES, including during the early stages of design which shape the full life of a system (Yassine & Braha, 2003; Eppinger, 1991). Early in the design process, systems architects characterize the design of a system or subsystem based on very little information (Ye et al., 2015). 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 (de Weck & Eckert, 2007). The estimated values of design parameters affect both the evolution of a design and the eventual performance of the final system design (Crossland et al., 2003).

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 (Dubos et al., 2010). 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 (Ryan & Townsend, 1997). In 1994, a Pegasus XL failed in part due to uncertainty in mass properties (Chang, 1996). The challenge becomes reducing uncertainty to ensure that the system's measured performance meets specified requirements, despite the cost and difficulty.

To reduce parameter uncertainties, systems engineers methodically advance the design of a system using analytical tools (Kapurch, 2007; Cardin et al., 2007). Techniques like the "Systems V" promote defining requirements, breaking a system down into subsystems, and then integrating them back into a final system (Forsberg & Mooz, 1994; Office of the Deputy Under Secretary of Defense for Acquisition and Technology Systems and Software Engineering, 2008; Clark, 2009). More recently, design researchers have begun using economic methods to develop alternative frameworks such as Value-Driven Design (VDD) (Collopy & Hollingsworth, 2011; Collopy et al., 2012; Mullan et al., 2012; Bertoni et al., 2016).

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 (Kahneman et al., 1982; Slovic et al., 2002). 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 (Kahneman & Tversky, 2001). 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 (Wertz et al., 2011).

3.3 Related Work

3.3.1 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 (Kapurch, 2007). 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 (Forsberg & Mooz, 1994; Office of the Deputy Under Secretary of Defense for Acquisition and Technology Systems and Software Engineering, 2008; Clark, 2009). 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 (Kapurch, 2007).

Systems have grown larger and more complex over time, giving rise to the name LaCES (Office of the Deputy Under Secretary of Defense for Acquisition and Technology Systems and Software Engineering, 2008; Bloebaum & McGowan, 2012; McGowan et al., 2013; McGowan, 2014). At the highest level, design management methods become more sophisticated and flexible to accommodate the large number of design changes (Cardin et al., 2007). Nevertheless, traditional systems engineering methods may not design and manage LaCES effectively (Collopy, 2012). Time and cost overruns are common yet canceling programs may similarly not be an option (Bloebaum & McGowan, 2012).

Recently, an alternative suite of tools for managing LaCES has emerged including Value-Driven Design and Decision Analysis (Kim et al., 2003; Collopy & Hollingsworth, 2011; Collopy, 2012; Collopy et al., 2012). These and similar frameworks use economic theories to optimize the systems engineering process by passing objective functions to subsystems instead of requirements (Collopy & Hollingsworth, 2011). Systems engineering research is in the process of stretching further into this domain (Tibor et al., 2014; Kannan et al., 2015; Kwasa et al., 2015; Bhatia et al., 2016; Kannan et al., 2016; Subramanian et al., 2016).

3.3.2 Uncertainty in system engineering

Mitigating risk in complex system design through the management of uncertainty is a key task in systems engineering (Herrmann, 2015). Uncertainty is defined as 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" (Austin-Breneman et al., 2015). Margins are frequently added to estimated values in complex system design to account for future design changes as a risk management strategy (Takamatsu et al., 1970), and can be the product of heuristics and intuition (Austin-Breneman et al., 2015) or formally calculated as a replacement for heuristics (Thunnissen, 2004). A variety of formal strategies are used to implement and manage margins throughout complex system design (Takamatsu et al., 1970; Thunnissen, 2004; Gu et al., 2000; Helton, 2011; Sentz & Ferson, 2011).

3.3.3 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 (Anderson & Barrios, 1961; Wallsten, 1981, 1983). 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 (Slovic & Lichtenstein, 1971; Kahneman et al., 1982). 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 (Finucane et al., 2000; Slovic et al., 2002). 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 (Slovic et al., 2002). This study uses these concepts to inform the qualitative interview analysis.

3.3.4 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 (Macy & Willer, 2002; Macal & North, 2009). Implementation of an ABM varies depending on the application, but one method of note is heterogeneous simulated annealing teams (HSAT) agent-based modeling (McComb et al., 2016). An HSAT ABM is a multiagent simulated annealing algorithm which uses Cauchy and Triki adaptive schedules (McComb et al., 2016; Triki et al., 2005). This study uses an HSAT ABM to model engineers' estimation strategies.

3.3.5 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.

3.4 Phase 1: Practitioner Interviews

3.4.1 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. As denoted in literature on qualitative research (Patton, 2014), this interview data demonstrates the existence of behaviors in the the systems engineer population. The sample size and methodology used are not capable of measuring—nor intended to measure—to what extent the described behaviors exist in the engineering population at large. The data resulted in criteria for designing the model described in Phase 2.

3.4.2 Results

The majority of the practitioners emphasized that expertise and historical data are critical on new programs. One stated that engineers "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. Still, according to a second, "Those estimates just come from seat-of-the-pants experience, having built something somewhat comparable in the past. We'll truly start at that crude of a level." Typically "what you'll find at the center of all this is a spreadsheet with the actual masses of components that they've used and flown in the past," mentioned a third. In one column "you'll see actuals. Then really an estimate—a whack at what the new items look like."

So experts form initial estimates from historical data plus "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." Several practitioners 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. Memorably, one practitioner described bad systems engineers as having 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 [mission] 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, several practitioners recounted that systems engineers and managers "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."

3.4.3 Qualitative Analysis

First, note that historical information anchors new design estimates, as with the anchoring heuristic discussed in Section 3.3.3. 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 (Austin-Breneman et al., 2015).

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. For example, a systems engineer may continue to push subsystems to reduce mass after initial estimates if reducing mass to allow for additional payload mass is necessary to fulfill the scientific mission.

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

This qualitative analysis and therefore the following ABM are limited by several factors. First, only expert practitioners were interviewed. This may introduce a bias into the reported differences in behaviors of systems and subsystem engineers. However, all seven interviewees spent significant portions of their careers working at the subsystem level which may mitigate this concern. Second, the sample size is small and therefore it is likely that there are many additional, perhaps even competing, strategies for managing uncertainty in subsystems which were not identified. This does not negate the results found here, but suggests that further work is necessary to capture the entire spectrum of strategies used. Finally, interview data does not capture the proportion of systems engineers which use these strategies. Therefore, results do not generalize to the population of systems engineers, but rather indicate the impact of using these strategies.

3.5 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 (Wertz et al., 2011). The simplified system was made up of eight agents, shown in Figure 3.1 along with the agent interactions. Seven subsystem agents and one system-level agent, defined in Table 3.1, exchanged information during each iteration of the model, called “design cycles” to match the industry practice of applying the Shewhart and Deming Cycles (Anderson & Rungtusanatham, 1994). 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.

3.5.1 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 with mean μ_{h_i} and variance ${\sigma_{h_i}}^2$—for comparable subsystem final masses from spacecraft of the same class. Subsystems calculate 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 calculates (or recalculates) its sample mean estimate $\overline{m_i}$ and sample variance estimate $\overline{\sigma_i}^2$:

$$\overline{m_i}(m_{i1}, m_{i2}, ..., m_{iq_i}) = \frac{1}{q_i}\sum_{j=1}^{q_i} m_{ij} \tag{3.1}$$

$$\overline{\sigma_i}^2 = {\sigma_{h_i}}^2 / q_i \tag{3.2}$$

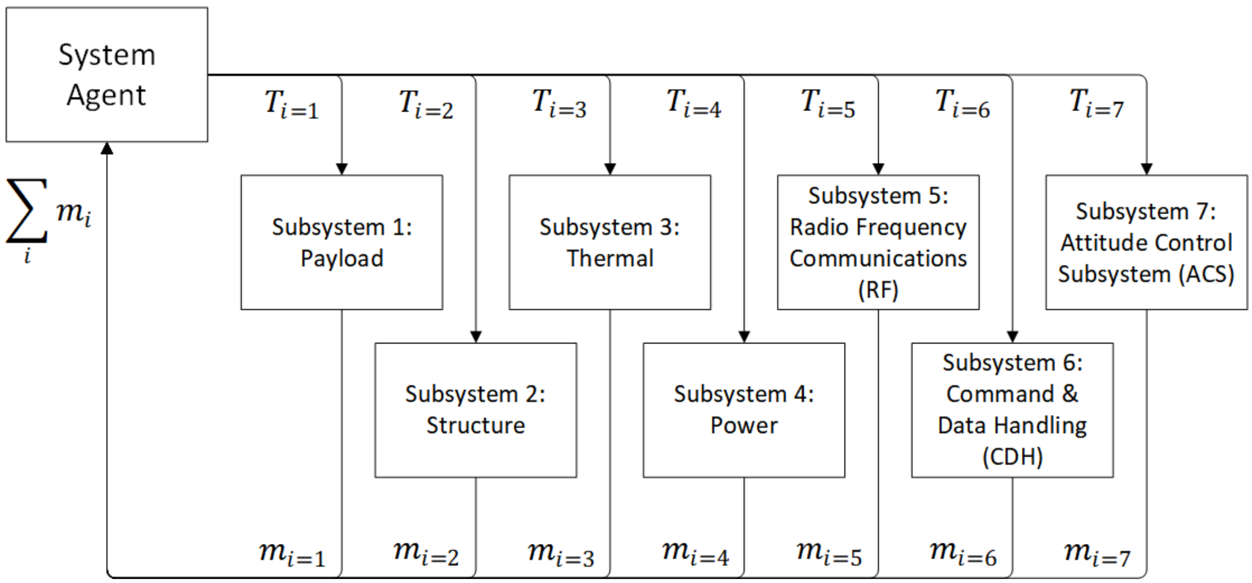


Figure 3.1: Spacecraft development Agent-Based Model information flow diagram. The information flow chart for the Agent Based Model. Arrows indicate the direction and content of information exchanged between the agents during each design cycle

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 3.1: Spacecraft subsystem nomenclature and parameter values. 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 Wertz et al. (2011).

where $m_{i1}, m_{i2}, ..., m_{iq_i}$ are mass samples and q_i the total number of samples taken for the i^{th} subsystem. Equation 3.2 satisfies C.2. Each draw of a sample represents the subsystem expending resources as a real team would expend labor or capital to refine a mass estimate. The model assumes the distribution of mass on the current design task is the same as the historical distribution. Therefore, given infinite samples the subsystem mass estimate should regress to the historical mean.

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 3.1). 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 (Azzalini, 1985):

$$u_i(\delta_i, \alpha_i) = A_i * 2\psi_i(\delta_i)\Psi_i(\delta_i, \alpha_i) \tag{3.3}$$

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

$$\psi_i(\delta_i|{\sigma_{h_i}}^2) = \frac{1}{\sqrt{2\pi{\sigma_{h_i}}^2}} e^{-\frac{{\delta_i}^2}{2{\sigma_{h_i}}^2}} \tag{3.4}$$

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:

$$\Psi_i(\delta_i, \alpha_i) = \frac{1}{2}\Big[1 + erf\frac{\alpha_i\delta_i}{\sqrt{2}}\Big] \tag{3.5}$$

and A_i is a normalizing constant:

$$A_i = \frac{1}{max(2\psi_i(\delta_i)\Psi_i(\delta_i, \alpha_i))} \tag{3.6}$$

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 subsystem skew parameter 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 estimates slightly larger than the historical mean as "good," while estimates which are either below the mean or too far above the mean are "bad" and therefore require action. Consistent with the above cited literature, the adjustable skew normal distribution was chosen for this study to enable modeling the agents as favoring values around the historical mean. It is important to note that although the agents may favor values different from the historical mean, the underlying distribution from which the samples are drawn is the historical distribution.

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:

$$T_i = T_i + \frac{T_i - 1}{T_\xi} u_\xi * H(T_\xi - u_\xi) \tag{3.7}$$

where $H(x)$ is the Heaviside function. Equation 3.7 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 $\overline{\sigma_\xi} = \epsilon\sigma_{h_\xi}$ on the nth design cycle, where parameter ϵ dictates the fraction of the historical standard deviation within which the sample standard deviation must converge.

3.5.2 Simulation Parameters

Each of the eight agents forms a historical normal distribution based on the values provided in Table 3.1. 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 (Wertz et al., 2011). 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 (Wertz et al., 2011). 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 convergence parameter $\epsilon = 0.2$. The Monte Carlo executed the ABM 1000 times for each combination of skew parameters 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.

3.5.3 Results

Figures 3.2 and 3.3 show an example model run in which subsystem skew parameter $\alpha_i = 0.01$, system skew parameter $\alpha_\xi = -0.005$, and the convergence paramter $\epsilon = 0.20$. In this case, the subsystem favors values larger the historical average and the system favors values which are less than the historical average. Figure 3.2 shows the mass estimates mapped onto each agent's utility function. Figure 3.3 plots each agent's estimate uncertainty against the number of design cycles.

The control case in which $\alpha_i = 0$, $\alpha_\xi = 0$, and $\epsilon = 0.20$ 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 (represented by a system skew parameter $\alpha_\xi = -0.005$) to incentivize the subsystems to decrease their masses. On the other hand, subsystems favor masses which are high with respect to the mean (represented by a subsystem skew parameter $\alpha_i = 0.01$) to minimize resource expenditure, and increase bargaining power (Austin-Breneman et al., 2015).

Figure 3.4 shows the 1000-trial distributions for both the unbiased and the biased cases. Table 3.2 contains the mean and variance for the final state of each agent including distance from historical mean δ, variance of the estimate $\overline{\sigma}$, 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 skew parameters α_i and α_ξ. Figure 3.5 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.

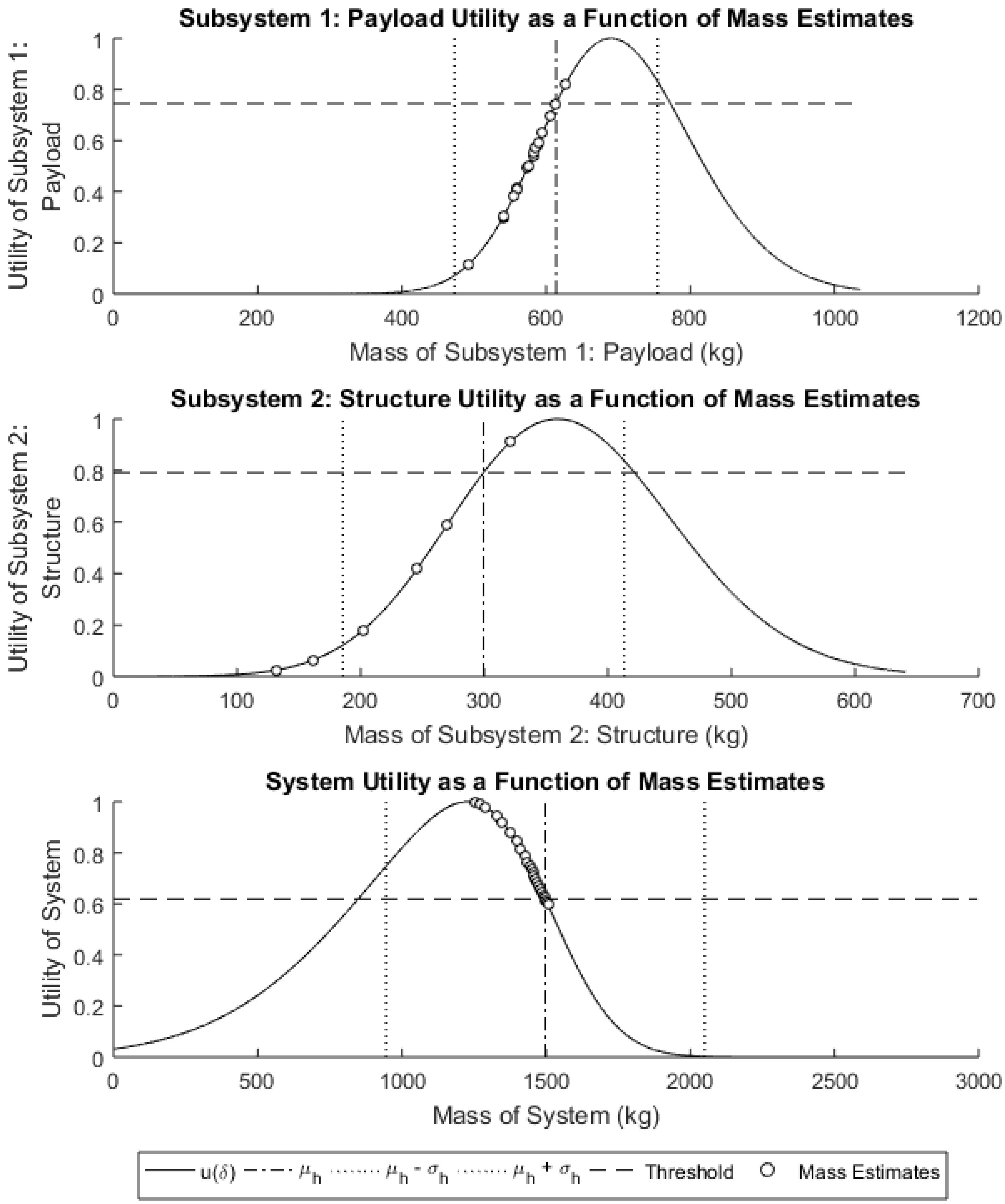


Figure 3.2: Subsystem and system estimate utilities. Graphs showing the mass estimates for each agent and their respective utilities. Note differences in the number of estimates and the skew of the utility functions for the subsystems and system.

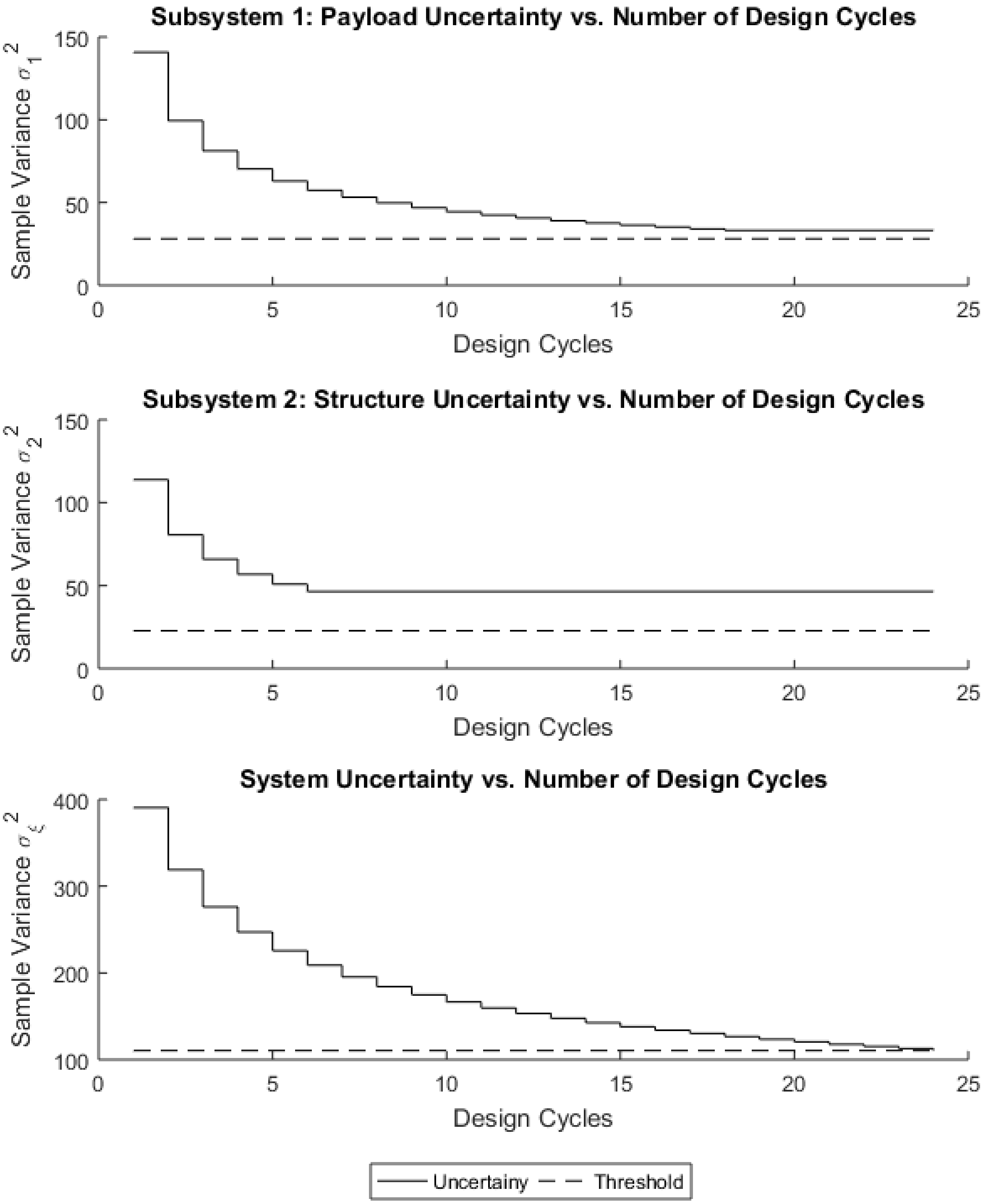


Figure 3.3: Subsystem and system estimate uncertainties. Each agent's uncertainty as a function of number of design cycles. Subsystem 2 does not converge to the prescribed uncertainty threshold due to bias.

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
$\epsilon = 0.25$	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
$\epsilon = 0.25$	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 3.2: Spacecraft subsystem and system results. The mean and variance for each agent in the 7-subsystem Monte Carlo simulation in both the unbiased and biased cases.

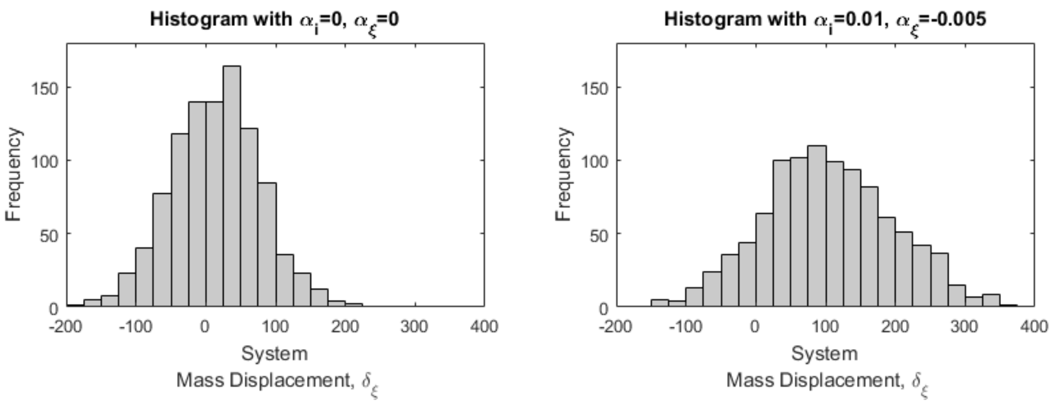


Figure 3.4: Monte Carlo simulation mass displacement histograms. Histograms of the 1000 trials for each of the unbiased and biased cases, respectively.

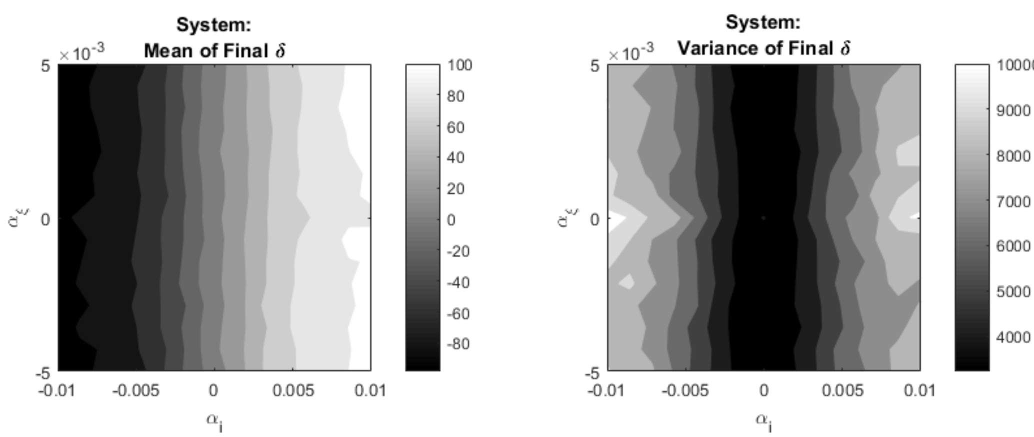


Figure 3.5: Monte Carlo simulation mass displacement mean and variance. Plots of the mean and variance for the system performance δ_ξ as a function of subsystem skew parameter α_i and system skew parameter α_ξ.

3.6 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 3.3 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 3.4 and Table 3.2. 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 3.5 indicates that as modeled, the mean and variance of the distance from the historical mean δ_ξ primarily depend on subsystem biases and minimally on system biases which supports the practitioners' intuition that subsystem bias negatively affects system performance. This 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. It should be noted that this counter-intuitive result is only applicable to system design teams which behave in the manner described in the model. There are a wide range of possible requirements negotiating and communication strategies that would not produce these results. Additionally, there are other factors which could interact with the described behavior to produce different results. However, the model does reflect strategies reported in the practitioner interviews. To improve system performance in complex system design teams which behave in this manner, 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.

3.7 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.

3.8 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 (Glaser & Strauss, 1967; Corbin & Strauss, 2008). A larger sample of the systems engineering population which included subsystem engineers could be surveyed to measure the extent of the described behaviors and identify new strategies. 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. For example, a game-theoretic model could examine differences in how subsystem agents respond to assigned mass targets. 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.

CHAPTER 4

Estimate Uncertainty: Miscommunication About Definitions of Engineering Terminology

This chapter was coauthored with Jesse Austin-Breneman and Jose Uribe. It was published under the same title in the Journal of Mechanical Design in 2019 (Meluso et al., 2020).

4.1 Abstract

Communication has been shown to affect the design of large-scale complex engineered systems. Drawing from engineering design, communication, and management literature, this work defines miscommunication as when communication results in a “deficiency” or “problem” that hinders parties from fulfilling their values. This article details a consequential example of miscommunication at a Fortune 500 engineering firm with the potential to affect system performance. In Phase 1, interviews with engineering practitioners (n=*82*) identified disagreement about what constitutes a parameter “estimate” in the design process. Phase 2 surveyed engineering practitioners (n=*128*) about whether estimates communicated for system-level tracking approximate “current” design statuses or “future” design projections. The survey found that both definitions existed throughout the organization and did not correlate with subsystem, position, or design phase. Engineers inadvertently aggregated both current and future estimates into single system-level parameters that informed decision-making, thereby constituting widespread or systemic miscommunication. Thus, even technical concepts may be susceptible to miscommunication and could affect system performance.

4.2 Introduction

As society’s technological capabilities grow, so too does the prevalence of complex systems. Large-scale complex engineered systems (LaCES, or just complex systems) are engineering projects with significant cost and risk, extensive design cycles, protracted operational timelines, a significant degree of complexity, and dispersed supporting organizations (Bloebaum & McGowan, 2012) which include everything from civil (e.g. water, power, transportation) to commercial (e.g. e-commerce, financial, healthcare) to defense infrastructures (e.g. cyber, aircraft, spacecraft) (Bloebaum & McGowan, 2012; McGowan et al., 2013; McGowan, 2014). Designing, coordinating, implementing, and operating such complex and increasingly-ubiquitous systems often requires organizations to employ and integrate numerous design methods including multidisciplinary design optimization (Tedford & Martins, 2010; Simpson & Martins, 2011), concurrent engineering (Eppinger, 1991; Yassine & Braha, 2003), and systems engineering (Forsberg & Mooz, 1994; Clark, 2009; Keating et al., 2003).

Consequently, communication plays a critical role in engineering design processes (Eckert et al., 2005; Maier et al., 2009; Eckert et al., 2013; Luck, 2013). But just as "good" communication produces beneficial results, "bad" communication, "misunderstandings" between people, too little communication, and too much communication can have serious consequences. In 1999, the Mars Climate Observer infamously failed to orbit Mars because one ground software file "failed to use metric units" instead of imperial units in part due to "inadequate communications between project elements" during the design process (Board, 1999; Sauser et al., 2009). In 2003, the Columbia Accident Investigation Board assigned partial responsibility for the Space Shuttle Columbia disaster to multiple engineering communication issues including "organizational barriers that prevented effective communication of critical safety information and stifled professional differences of opinion" (Gehman Jr et al., 2003; Guthrie & Shayo, 2005). In fact, in a review of 50 space system failures, J. Newman emphasizes that "communication failure" is one of the most prominent causes of complex system failure because "the vast majority of mishaps involved...misunderstanding or incomplete understanding of ambiguity" including design fundamentals such as "inadequate design margins, unknown synergistic effects, [and] invalid assumptions" (Newman, 2001).

These reports paint a daunting picture. The reader can likely recall one or more instances in their own work where "communication failure" created obstacles if not threatened the success of their work altogether. Scholars and practitioners alike refer to such instances of communication-that-causes-problematic-outcomes as "miscommunication" (Coupland et al., 1991b; Eisenberg & Phillips, 1991; Tzanne, 2000). *Miscommunication* happens 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 (Coupland et al., 1991b; Holmes & Stubbe, 2015). Communication scholars note the potential of miscommunication to impact organizational outcomes (Eisenberg & Phillips, 1991) as the aforementioned federal disaster reports and studies corroborate.

Despite evidence to the contrary, it is easy to dismiss instances of miscommunication as exceptions rather than commonplace in engineering communication. But is miscommunication the exception? Or is miscommunication prevalent? By definition, miscommunication is communication. Management studies have shown that organizational communication affects team performance (Maier et al., 2012; Liu & Cross, 2016). Engineering design research into communication describes how "communication breakdowns" occur in engineering design (Eckert et al., 2001, 2005; Maier et al., 2008) and how network topologies affect performance (Sosa et al., 2004, 2011; Parraguez et al., 2015). Collectively these studies suggest that widespread or *systemic* miscommunication throughout an engineering organization likely affects system performance. Then how widespread or systemic is miscommunication in engineering design organizations?

To answer this question, the authors examined a recently-identified case of a commonly-used engineering term with demonstrated ambiguity. Several recent studies have called into question the ubiquity of the definition of "parameter estimates" in engineering practice. Ye et al. (2015) show that expert uncertainty estimates added negligible value compared to an architecture design tool. Austin-Breneman et al. (2015) identified and simulated biased estimate passing through interviews with practitioners suggesting estimate ambiguity. Further investigation by Meluso & Austin-Breneman (2018) into estimation strategies concurred that practitioners bias estimates as a "negotiation and resource conservation strategy" which may increase system uncertainty. The ambiguity noted by these studies, coupled with pilot interviews for this paper, highlight the lack of understanding surrounding how practitioners define the term "estimate" in complex system design.

Estimates play a particularly important role in complex system design. Organizations frequently combine estimates from hundreds or even thousands of people and use those combined estimates to make strategic decisions about how programs and entire companies should proceed. Consequently, any uncertainty in the definition of an estimate — let alone the values of the estimates themselves — could have significant repercussions for organizational performance. To that end, this article addresses the following research questions:

(1) How do engineering practitioners define "an estimate" in complex system design?

(2) How do estimate definitions vary throughout an engineering organization?

(3) How does communicating varied estimate definitions yield miscommunication?

This study consisted of two phases. Phase 1 interviewed engineering practitioners ($n = 82$) about their design estimation practices to identify the existence of multiple definitions of what constitutes "an estimate". Phase 2 surveyed engineering practitioners about which definition they used when communicating with others in the organization. The data will show that what constitutes "an estimate" varied independent of subsystem, position, and design phase. Hence, differing definitions of a fundamental engineering concept created a high probability of systemic miscommunication indicating the potential of miscommunication to affect complex system performance.

4.3 Background

In order to understand miscommunication, one must first define communication. Both terms largely depend on the discipline of inquiry, so the following sections integrate multiple definitions into terminology applicable to engineering and management.

This section summarizes the approaches through which scholars study communication by drawing from communication studies, sociolinguistics, management, and engineering design. It then reviews the literature on and defines miscommunication before continuing with a brief recitation of parameter estimation and uncertainty definitions. Finally, it states the research gap and describes the organizational context in which the study took place.

4.3.1 Communication

Over time, two approaches have developed for studying communication. Quantitative models of communication (also called the Objectivist Approach (Montgomery & Duck, 1993; Leeds-Hurwitz, 1995b)) trace the footsteps of Shannon's seminal text, *The Mathematical Theory of Communication*, which treats communication as a process with a transmitting party, a transmitted signal, and a receiving party. This conception of communication as information passed from party to party has become known as the "process" model of communication. Out of the process model grew the idea of communication as networks (Stewart et al., 2003; Thompson, 2011). "*Communication networks* are the patterns of contact that are created by the flow of messages among communicators through time and space," and so *communication* is defined as the transmission and exchange of messages which may include data, information, knowledge, symbols, or "any other symbolic forms that can move from one point in a network to another" (Monge et al., 2003). Even given their simple forms, network models of communication display powerful results by demonstrating social theories of self-interest, collective action, exchange theory, dependency theory, and homophily among others (Monge et al., 2003; Newman, 2018).

Qualitative researchers (or the Interpretivist Approach (McQuail, 1984)) critique quantitative models for oversimplifying the multiple processes involved in each communicative interaction including differences of meaning, context, and interactive asynchronicity (Thompson, 2011; Eckert et al., 2005). Here, *communication* is more broadly defined as "social interaction through messages" (Fiske, 1990) to incorporate the *identities* of the participants, the *context* of the interaction, the *genre* (or medium) of exchange, and the *actions* intended by exchange (Thompson, 2011; Leeds-Hurwitz, 1995a).

Note that quantitative models simplify transmission to illuminate the existence and patterns of communication, while qualitative models unsurprisingly emphasize qualities of communication to understand how it occurs. Need this be the case? Bavelas suggests that this difference presents an opportunity to "discover new, previously unexplored combinations of both approaches" (Bavelas, 1995) which this article capitalizes on through its mixed methods approach.

4.3.2 Communication in Engineering Design

Engineering design research focuses on three topics related to communication: (a) qualitative models of how communication contributes to design practice, (b) quantitative models of the effects of individuals' cognition on system performance, and (c) quantitative models of the effects of networked communication on system performance.

Eckert's framework aptly summarizes the focus of qualitative studies by differentiating "three layers of structure in design communication [including] the design process, interaction between participants, and representations of design information" (Eckert et al., 2013). Design process studies find that communication through virtual and physical objects facilitates "cooperation" and "mediation" of designs (Eckert & Boujut, 2003). Interaction research notes the "integration, collaboration, and project completion" (Sonnenwald, 1996) faculties of communication including activities such as design handover, joint designing, idea generation, interface negotiation, conflict resolution, and decision making, among others (Eckert et al., 2005). And design representation studies find that communication aids "cognitive operations of generation, exploration, comparison, and selection" (Stempfle & Badke-Schaub, 2002) or information, interaction, and situation (Eckert et al., 2005).

Next, engineering cognition is studied through multi-agent systems (MASs) and agent-based models (ABMs). While the distinction between MASs and ABMs is slight, MASs tend to create small groups of highly interdependent decision-makers (usually less than 10) and optimize system performance given the agents' cognition rules (Zhong et al., 2012; McComb et al., 2015, 2016, 2017). ABMs, on the other hand, typically involve larger numbers of highly-autonomous agents (usually more than 10, often more than 100) with external influences (Bonabeau, 2002; Panchal, 2009; Crowder et al., 2012; Martínez-Miranda & Pavón, 2012; Darabi & Mansouri, 2017; Soyez et al., 2017). As LaCES are "made up of many smaller engineered systems [that are] designed, developed, and operated by another large 'system' of dispersed, loosely connected people" (Bloebaum & McGowan, 2012), ABMs are more common in complex system modeling.

Finally, engineers have studied complex system design communication via field studies (den Otter & Emmitt, 2008; Laufer et al., 2008), historical project data regression analysis (Robinson, 2010; Liu & Cross, 2016), and controlled laboratory experiments (Austin-Breneman et al., 2012). Several studies explore the relationships between network properties like modularity (Sosa et al., 2004), centrality(Sosa et al., 2004, 2011; Parraguez et al., 2016), brokership (Sosa et al., 2015), and system design outcomes. Other investigations include curvilinear relationships between genres of communication and performance objectives (Patrashkova-Volzdoska et al., 2003; Kennedy et al., 2011), how information flows and structures affect team performance (Parraguez et al., 2015; Kennedy et al., 2017), and methods of evaluating communication quality (Maier et al., 2006, 2009, 2012).

4.3.3 Miscommunication

What makes communication into *mis*communication? It takes many forms, and not always intuitively: "Clear, concise, honest communication is frequently the *cause* of difficulties as it is the solution to them. 'Miscommunication' is therefore not… [simply] a deviation from some underspecified ideal" (Coupland et al., 1991a, emphasis in original). *Miscommunication* is better defined as when communication results in a "deficiency" or "problem" that hinders one or more of the engaged parties' abilities to fulfill their individual or collective values (Coupland et al., 1991b; Holmes & Stubbe, 2015). What constitutes a "deficiency" or "problem" is a matter of individual participant expectations (Mortensen, 1997). Context (Tzanne, 2000), action (Anolli et al., 2002; Holmes & Stubbe, 2015), identity (Stubbe, 2000), and genre (Eisenberg & Phillips, 1991) shape miscommunication as they shape communication.

The quantitatively-oriented literature does not appear to define miscommunication, although similar ideas exist in perception of network structure (Krackhardt, 1987) and forming networks from participant "interpretations of one or more significant communication messages, events, or artifacts" (Monge et al., 2003).

Engineering design examines similar concepts without explicitly defining miscommunication. Eckert, Maier, and McMahon suggest causes and ways of resolving "communication breakdown" or "communication problems" and provide methods for overcoming "information distortion", "not understanding the big picture", "missing information provision", and "interpretation of representation" (Eckert et al., 2005). Luck uses natural language processing to identify ambiguity and uncertainty in social interaction as different forms of "misunderstanding" (Luck, 2013). She also noted the existence of "repair" processes to bridge misunderstandings (Luck, 2013), previously identified in sociolingustics (Coupland et al., 1991b). Though valuable, both leave systemic implications to the reader.

Noteworthy in the current climate: miscommunication is not misinformation.

4.3.4 Parameter Estimation & Uncertainty

Engineering estimates are critical for managing uncertainty when designing complex systems (Crossland et al., 2003) and facilitating "mutually consistent solutions" across interfaces (Eckert et al., 2005). Despite its foundational nature, precise definitions of "an estimate" are difficult to find in engineering texts (Beck & Arnold, 1977; Allen, 2006; Morrison, 2009; Devore, 2011). Those that address it refer the reader to texts on statistics (Beck & Arnold, 1977) or require the reader to infer its meaning from context by giving imprecise definitions such as "a single number that is our 'best' guess"(Devore, 2011). As mentioned in Section 4.2, several recent studies also support that how engineers estimate design parameters in practice differs from the textbook definitions (Crossland et al., 2003; Austin-Breneman et al., 2015; Ye et al., 2015; Meluso & Austin-Breneman, 2018).

Uncertainty, on the other hand, receives significant attention. Engineers calculate uncertainty via the standard statistical concepts of confidence or uncertainty intervals (Abernethy et al., 1985; Devore, 2011), the Method of Imprecision (Antonsson & Otto, 1995), design margins (Eckert et al., 2014; Austin-Breneman et al., 2015), and cognitive heuristics of uncertainty (Kahneman et al., 1982; Crossland et al., 2003; Austin-Breneman et al., 2015; Meluso & Austin-Breneman, 2018). Classifications exist to assist engineers in selecting uncertainty estimation methods (de Weck & Eckert, 2007). Ironically, some estimate uncertainty may arise from ambiguity in the qualitative definition of "an estimate" rather than the quantitative bounds.

4.3.5 Research Gaps

Organizational communication affects team and system performance. While anecdotal evidence documents instances of miscommunication in engineering design, a gap exists in the knowledge of how pervasive miscommunication is in engineering practice. The literature suggests that widespread miscommunication in engineering organizations would likely affect the performance of the systems that engineering organizations create.

Significant ambiguity also exists as to what "an estimate" is in engineering practice. While statistics provides definitions, engineering literature rarely does so and studies of industry definitions yield varying definitions. Therefore, a gap exists in understanding how practitioners define what constitutes "an estimate".

4.3.6 Study Context

To incrementally address the research gaps, the authors conducted a study at a Fortune 500 engineering firm that develops complex systems. The sponsoring division of the firm asked the researchers to investigate the estimation methods of engineers in their organization to help improve the quality of the system-level estimates that program management used to affect project outcomes. Systems engineers aggregated estimates from the artifacts that compose the system to form a system-level estimate.[1] This process of integrating artifact estimates played a crucial role in turning communication into miscommunication as the following sections reveal.

4.4 Phase 1: Practitioner Interviews

The first phase of the study sought to answer how engineers define "an estimate" in complex system design. Semi-structured interviews were conducted with engineering practitioners in the setting described in Section 4.3.6.

4.4.1 Interview Methodology

Over the past decade, interviewing has significantly increased in popularity in engineering design research (Srivastava & Shu, 2013; Austin-Breneman et al., 2015; Gericke et al., 2016; Kim et al., 2016; Withanage et al., 2016; Eng et al., 2017; Bao et al., 2018; Sinha et al., 2018; Sinitskaya et al., 2019; Yuan et al., 2018). Interviewing is a powerful tool that "gives us access to the observations of others" (Weiss, 1994) to reveal what, how, and why things happen (Gerber & Linda, 2010). Semi-structured interviews begin with a set of predetermined questions, but allow the researcher to deviate from the questions to inquire further about participant statements or implications (Weiss, 1994; Gubrium & Holstein, 2001; Seale et al., 2004; Morse, 2012).

Two interviewers conducted 97 semi-structured interviews about estimation methods and definitions through an initial pilot study ($n = 13$) and the primary study ($n = 82$). The pilot interviews informed the design of questions for the primary study, resulting in 19 open-ended questions with both planned and organic follow-up questions. The researchers designed the questions to elicit responses about the participants' knowledge and experiences of estimation methods and definitions. For example:

- "Walk me through the process you used to come up with your first estimate for one of your artifacts."
- "What prompted you to update this estimate? Where did the information get updated?"
- "Through our interviews, we're finding that people define 'an estimate' in different ways. How would you define an estimate?"

[1]Some terms have been changed to generic terms such as "artifacts" and "parameters" for confidentiality of both the company and participants. The term "artifacts" serves as an umbrella term for any type of designed system element including physical parts, software, processes, information, etc. "Parameters" could be any property of an artifact such as physical, electrical, financial, data, time, etc.

Following well-established methods, each interview began with the participant's background to build rapport. The interviewer then asked each participant to describe how they estimate parameters using an example from their work. To avoid biasing the participants into using a specific definition of an estimate, the interviewer left explicit questions about how the participant defines an estimate until the final moments of the interview.

Most interviews lasted from 45 to 75 minutes and covered the majority of the defined questions, time being a significant limiting factor given the initial 60-minute time slots for the interviews. Many participants graciously and willingly spoke for an additional 15-30 minutes as they recounted their perspectives. The interviews included individuals across 10 subsystems, 3 positions, and 2 design phases.

Audio from the interviews was recorded and transcribed. The software NVivo was used to analyze and categorize interview responses as recounted in the following sections.

4.4.2 Interview Results

Most participants used "estimates" as requisites of their work and spoke of providing one another with estimates of their designs. However, there was no consensus about what the term "estimate" meant, even within subsystems, positions, and design phases.

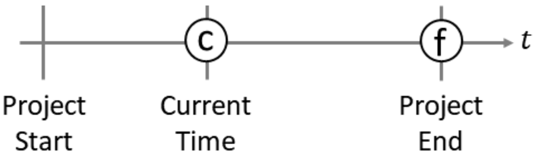
To illustrate this, consider the ways engineers spoke about estimating parameters of their artifacts. Engineers spoke of numerous sources of their estimates including fundamental physical properties, information from managers and systems architects, and past experience. One engineer said: "I take my [basic physical properties], I try to approximate for better or worse, and then I just calculate the [properties] of my [artifact] by hand," what some call back-of-the-envelope calculations. Another engineer described a similar process but with the caveat that "we look [at] the previous [design] and we estimate. Then we say 'this previous design was X-by-Y-by-Z dimensions, and now I'm gonna be A-by-B-by-C'. I can just do a ratio, a quick estimate, and it's fairly accurate." While also an estimate-by-hand of sorts, instead of basic physical properties, the basis of this method was a previous artifact. Many engineers referred to this process as "benchmarking," using historical information or reference systems to predict an outcome. But the engineer also mentioned that the estimate is "fairly accurate." Against what are they comparing their estimates to gauge the accuracy? Quotes like these indicated that some deeper point of reference was likely being used to define an estimate.

Engineers also spoke of managerial sources and methods of their estimates. "Typically, the project management will take a previous system, take some percentage off [a parameter,] and say 'That's your estimate, go meet that. This is what we want'." Another mentioned that "from my system architects, I get a diagram, a very very coarse diagram that tells me this is what we're going to have...I do some really coarse estimating just based on material properties." Note that these quotes make reference to a future time by stating "go meet that" and "this is what we're going to have," implying action toward an objective which program management says is "what [they] want." Others frequently used similar language referencing points in the future, such as "It's not actual, so you're taking either your best guess, or using what information you have to come up with a number, right? A 'ballpark' number." The engineer contrasts "actual" prototype or completed artifact descriptors with preliminary or calculated "ballpark" artifact descriptors. A different engineer provided a more explicit example by describing that "An estimate to me is when we use best last data to guess, it's kind of an educated guess on what the [value] is gonna be." Hence, some engineers appeared to be defining their estimates as predictions of *future* values of a parameter.

However, the accounts of others contradicted the "future" definition. "So they're asking me for an estimate, but they're not *really* asking me for an estimate. They're asking me 'What do you currently have released?' They call it an estimate, but I don't view it as that. We end up coming back and taking what we got. We may look at it and go, 'Okay, but I don't have [most of my artifact] done yet', so you might [guess] that number. But the rest of it's gonna be what you've already released." [participant emphasis]

In this excerpt, the participant articulates the tension inherent to a manager or systems engineer's request for an "estimate" based on the definition of the term. The clause "but they're not *really* asking me for an estimate" reveals the participant's belief that more than one definition exists. "We end up coming back and taking what we got" suggests that an estimate *doesn't* refer to a future point in time. This engineer believes that, when a manager or a systems engineer asks for an estimate, they are actually asking "What do you currently have released?" and providing that information instead. Indeed, several participants concisely described their estimates as a "snapshot in time". Yet another noted that "it's based on what we know at this point in time, based on the information that we've been given...My estimate for the [parameter] today is...based off my understanding of information that's available today. I don't know what it will be later. If nothing changes then my number stays the same, if something changes then my number will have to change." This was a common refrain among many engineers. How can I know what the value *will* be when I don't know what changes to expect? As a result, these engineers simply provide *current* values of a parameter.

Is an estimate a representation of the current design status? Or is an estimate a prediction of the future, final design status? The answer is likely both, at different times, in different contexts, and for different reasons. Regardless of which definition is formally "correct" according to the management (the future definition), engineers widely exchanged information based on one definition, the other, and sometimes both.



Category	Est. Types & Relationship
C1	c
C2	f
C3	c = f
C4	c & f

Figure 4.1: Estimate definition categories. A timeline and table showing the four categories of estimate definitions, how each is situated in the project timeline, and relationships between estimates within each category. **C1** involves only a current estimate; **C2** only a future estimate; in **C3**, the current estimate is the same as the future estimate; and **C4**, separate current and future estimates both exist.

The researchers investigated this hypothesis throughout the primary interviews by asking: "When you provided an estimate for your artifact, did that estimate represent a calculation of the current value or a prediction of the production value of the parameter?" The question captures the interactive nature of communication through the word "provided" while categorizing responses and was placed at the end of the each interview so as not to bias the responses.

4.4.3 Interview Analysis

The participants' responses reflected even further complexity, falling into four categories (also in Figure 4.1):

C1. An estimate describes the **current** state of design.

> "It's a calculation of the design as it is—we have a [model] in the CAD software...The software calculates what the [parameter value] is."

C2. An estimate describes production intent, or predicts a **future** state of design.

> "Estimates are during sourcing...Here's a good example: This was the first use of this size box and we had no experience with this type of architecture. So there was

		Interview Responses			Survey Responses		
		Num. Resp.	Estimate Type		Num. Resp.	Estimate Type	
			Current	Future		Current	Future
Subsystem	1	8	5	4	19	7	5
	2	2	0	2	8	1	3
	3	5	4	2	10	7	1
	4	2	0	1	4	2	1
	5	10	5	8	8	5	2
	6	17	9	10	6	2	3
	7	2	1	2	23	10	8
	8	26	17	12	18	6	7
	9	9	6	4	16	9	2
	10	1	0	0	29	15	8
Position	Resp. Eng.	46	27	26	88	44	32
	Eng. Mgm.	31	18	16	10	6	4
	Sys. Eng.	3	1	2	23	14	4
Phase	R & D	32	20	16	49	24	13
	Prod. Dev.	71	41	38	116	55	38
Total		82	47 (57.3%)	45 (54.9%)	128	64 (50.0%)	40 (31.3%)

Table 4.1: Estimate definition interview and survey responses. Interview and survey response totals. Some interview participants responded that they use both types of estimates or worked multiple stages of design and so were included in both categories. The survey allowed individuals to select the type of value which they communicated “for system-level tracking”, but selection of both current and future estimates was not an option. Some interview and survey participants chose not to respond to questions about their subsystem, stage of the design process, or their definition of an estimate. Consequently, the numbers shown may not add up to the number of individuals in a given subsystem, stage, or in total.

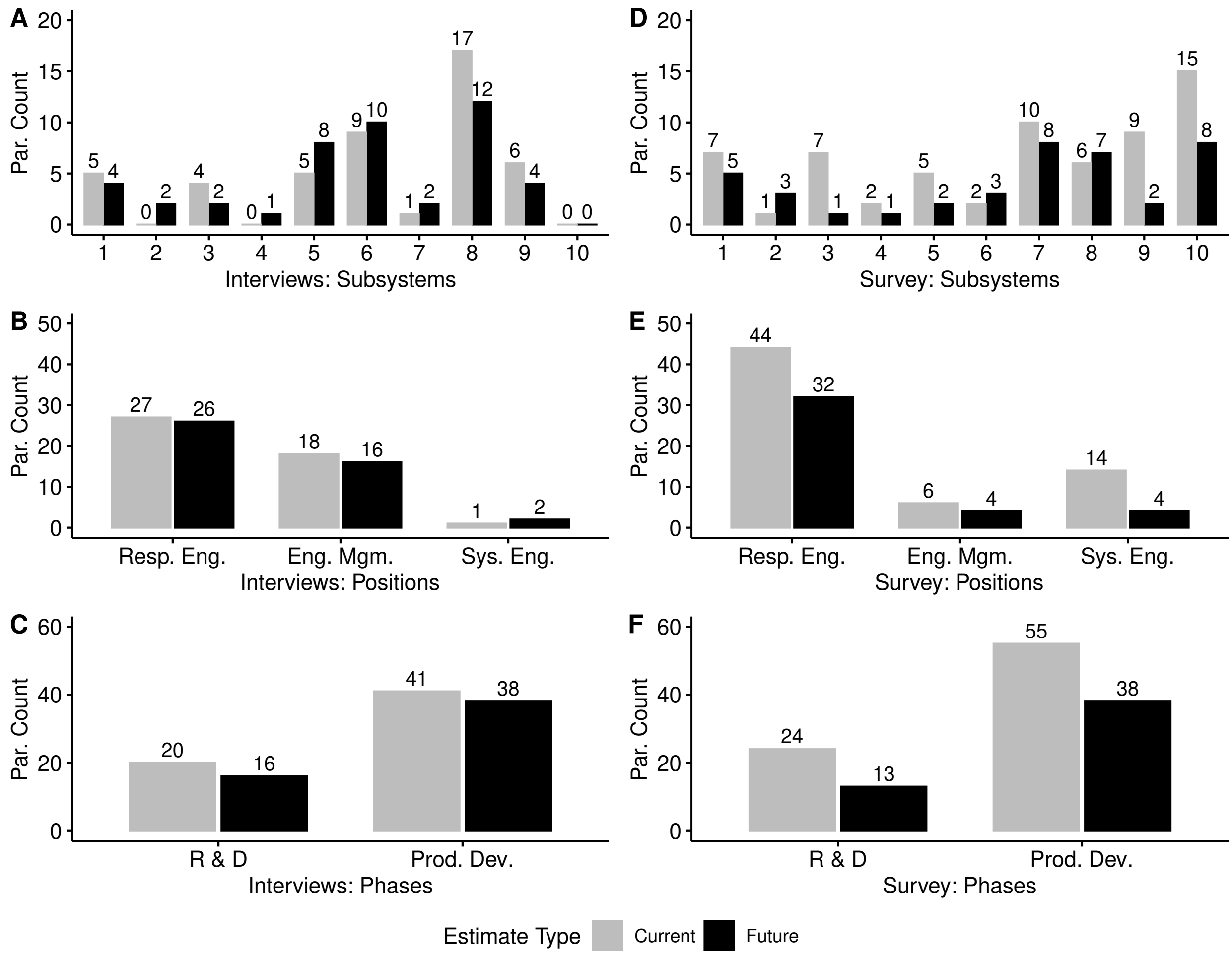


Figure 4.2: Interview and survey estimate definition responses by subsystem, position, and phase. Bar graphs of the results documented in Table 4.1 for the interviews (A-C) and the survey (D-F). Bars represent the number of participants from each group who responded that they use each estimate type. As in Table 4.1, the bars for each group may not sum to the number of participants in the group. Note that some participants in nearly every group expressed that they use each estimate definition demonstrating substantial variation in estimate definitions.

quite a bit of liberty and [we had] a pretty good idea of what it would [measure]. But going forward, [the estimate] is still that [same value]. This being the new system, the estimate is probably a little wider as far as how close we think we're gonna get."

C3. An estimate describing the current design *is the same as* production intent.

> "An estimate is whatever is close as I can get to what I think it's going to end up being when it's a real [artifact]. So right now, my estimate is what's actually in [the computer model], because I'm assuming that's *the most accurate I can be to what it will end up being* [emphasis added]. But if you came and told me that you had to [make a change]...you'd have to do some math, or something. There's no [model] yet, so I'd have to work with somebody to get a number to estimate it."

C4. Separate estimates exist for both the current design *and* production intent.

> "[My estimate] is my living judgment, and then the actual estimate that we give [the systems engineers] is based on [a computer model]. We don't ballpark it...Once we start hitting prototypes, we'll start bringing in [measured values], and that [measurement] gets reflected in the tracking system...We will start looking at the system and say, 'Okay, so our ballpark number is good.' And if my [model] number is higher, I know it's going to be that number. So, we'll [take] that [value]."

In the quotes, examples **C1** and **C2** refer to a single point, either the current design or the final design respectively. Participants using **C1** typically expressed uncertainty about the future and so only provided the current state of design, whereas those using **C2** expressed uncertainty about the changes they would experience throughout the development process but confidence in the properties of a design they usually ended up with. Examples **C3** and **C4** indicate that some individuals track both current and future values as estimates. Some engineers use one shared value to satisfy both current value requests and future value requests (example **C3**). Others recognize that their current value is unlikely to stay the same and so they develop a separate, predicted value (example **C4**). But in all cases, the two points of reference were the current and final designs.

To confirm the existence of estimate definition variation, the number of interview responses associated with each of these two categories—*current* and *future* estimates—were coded and tabulated as shown in Table 4.1 and Figure 4.2. If an individual used both current and future estimates, whether as **C3** or **C4**, the participant was counted in both estimate categories. While participants were largely self-consistent in their definition use, both the interviewing and coding processes methodically identified those inconsistencies and resolved them through follow-up questions and/or grounded theory analysis (Corbin & Strauss, 2008) so as to code the responses appropriately. Responses were tabulated by different subsystems represented in the company's organizational structure, by three different types of positions (responsible engineers, engineering managers, and systems engineers), and by the different phases of the design process in which the individuals participated (research & development and product development). Participants only chose one subsystem but could choose both phases or neither phase of the design process.

Of the 82 interview participants, 47 (57.3%) used current estimates and 45 (54.9%) used future estimates in their work. Figures 4.2A-4.2C show that variation existed across nearly all subsystems, positions, and design phases, although many subsystems and one position were not sufficiently represented in the interviews. Nevertheless, the existing variation indicates varied definitions of "an estimate" throughout much of the organization. Phase 2 further examines this variation and examines its relationship to miscommunication.

Other factors may also affect estimate definition. Many participants knew of the existence of more than one definition of an estimate as evidenced by their use of separate numbers for current and future. When participants gave information to other engineers, they chose a value to pass corresponding to a definition. This introduces further complexity: Do engineers choose which estimate to pass? How? And when?

In **C2**, the participant mentioned "having no experience with this type of architecture". It's possible that variables beyond the subsystem, position, and design phase demographics may contribute to estimate definition, such as an employee's experience. Experience may be multiply defined depending on the context as experience with a particular artifact, system architecture, or career experience. Similarly, the objective or purpose of the estimate may influence definition choice. While some engineers needed to provide estimates for "sourcing", others' estimates were "living judgments" of design status. The recipient of an estimate may also affect estimate definition, whether a systems engineer, a manager, or a fellow responsible engineer. Estimate definition selection probably depends on the actions being performed through "estimating", the contexts in which engineers are estimating, the identities of the individuals and teams involved, and the medium through which the information is being communicated—whether via a formal requirement, just a friendly face-to-face update, or anything in between.

4.5 Phase 2: Practitioner Surveys

The second phase addresses how estimate definitions varied throughout the organization with statistical analysis of survey responses. Next, it demonstrates how such variation in fact constitutes miscommunication with problematic results for the system. A survey of practicing engineers in the same organization corroborated the variation in definition use as described in the following sections.

4.5.1 Survey Methodology

While “in-depth interviews yield descriptions of experiences, processes, and events” (Weiss, 2004), surveys are effective tools which “report the distribution of people’s actions or opinions in tables and statistics” (Schuman, 2002). After identifying the estimate definitions and existence of variation from the interviews, a survey of practitioners ($n = 128$) confirmed the definition variation across the greater organization.

Along with questions on other practices about estimation methods, the engineers were asked to respond to the following question: “The estimate I provide for system-level tracking (a) reflects the current state of design, or (b) reflects expected production intent.” Of course, the interviews demonstrated that some engineers generate both types of estimates. The phrase “provide for system-level tracking” asks the individuals to respond with the type of information that they communicate to others working on the system so as to differentiate from any internal estimates the individual may keep separate from the distributed value. Thus, the question identified any variation in the values *formally communicated* by the participants to others in the organization for system-level tracking.

4.5.2 Survey Results

Table 4.1 also records the number of individuals who reported using either “current” or “future” estimates during the surveys. As with the interviews, responses are tabulated by subsystem, position, and design phase. Unlike during the interviews, survey participants were only allowed to specify one type of estimate that they provide for system-level tracking—either current or future estimates.

Participant responses varied significantly, with 64 of 128 (50.0%) participants reporting that they communicate estimates defined with respect to their current design and 40 (31.3%) with respect to their future design. Variation existed within every subsystem, position, and phase. Fisher’s exact tests (Agresti, 1992) of count data with a confidence level of 0.95 examined whether the definitions correlated with particular subsystems, positions, or phases and found that results for subsystems ($p = 0.3704$), positions ($p = 0.3009$), and phases ($p = 0.3045$) were not statistically significant with respect to estimate type and are therefore independent of estimate type. As participants could select one or both design phases, the Fisher’s exact test was calculated using categories of R&D, Product Development, or both.

4.5.3 Survey Analysis

The survey results corroborate the interview findings that engineers throughout the organization *communicate* both “current” and “future” estimates for system-level tracking. Estimate definition communication varies independent of an engineer’s subsystem, position, and design phase meaning that virtually every subset of the organization communicates both types of estimates.

Recall that systems engineers aggregated these artifact estimates (Section 4.3.6) into a future estimate (Section 4.4.2) for program management. Rather than combining all future representations of the system’s artifacts, the survey results indicate that systems engineers inadvertently combined some mix of current and future estimates into a system-level “estimate”, which is likely composed of both definitions and unlikely to be a “future” estimate of the system.

This mixed system estimate yields numerous problems. First, program management did not ask for a system estimate mixing together the current evolving design and the final projected design. Program management was making decisions based on information representing something other than what they requested and cannot meet their stated goals accordingly. Next, mixing estimate types creates uncertainty in the system estimate because the estimate neither represents the current system nor the final system. While one may debate whether current or future estimates produce better system outcomes, an unknown mixture of the two does not accurately represent either type of estimate and therefore contains additional uncertainty on top of whatever existing uncertainty a current or future system estimate would hold. Furthermore, a study by Meluso et al. demonstrates that mixed estimate definitions may significantly degrade system performance (Meluso et al., 2019). Their study also shows that current estimates likely outperform future estimates suggesting that even requests for future estimates may constitute a “problem” if the organization seeks to optimize performance.

Communicating information that represents two definitions of an estimate for the purpose of integrating those estimates constitutes a problematic outcome and is therefore miscommunication. If engineers did not need to communicate their estimates but instead used the estimates purely for their own purposes, it would not be considered miscommunication. Likewise, if those estimates did not play a valuable role in the organization through aggregation, the communication would not be perceived as problematic. However, because the information serves a valuable purpose through its communication, this *estimate uncertainty* neatly matches the definition of miscommunication as multiple definitions of estimates result in a problem that hinder parties from fulfilling their values. Moreover, the miscommunication is also *systemic* because, far from existing in isolation, estimate definition uncertainty was widespread throughout the organization across all subsystems, positions, and design phases.

4.6 Discussion

In Section 4.4, the interviews found that participants defined estimates with respect to their current design, their future design, with current and future designs as one and the same, and with separate current and future estimates. These estimate definitions exposed that two temporal reference points govern estimate definitions: a "current" point in time and a "future" point in time. The survey presented in Section 4.5 found that estimates communicated for system-level tracking, either "current" or "future" estimates, varied independent of the participants' subsystem, position, and design phase. These results are noteworthy for several reasons:

Estimate definitions. The interviews of Phase 1 found that practicing engineers in this organization defined estimates not based on a textbook statistical definition of what constitutes an estimate but with respect to a point in time in the design process, likely as a function of numerous contextual variables. That is not a judgement on the value or rigor of the practices engineers use—indeed, some participants attributed great value to parameter estimation while others expressed apathy. It does, however, expose that sufficient uncertainty exists regarding the definition of an estimate to merit clarifying what one means by "an estimate" when either giving or receiving such parameter value approximations. Estimation remains a crucial tool for understanding the development of complex systems, and definition ambiguity may very well degrade the abilities of managers and engineers to accomplish their objectives if not addressed.

But as noted in the introduction, estimates are merely one case of ambiguity related to a commonly-used engineering term. Other examples of foundational engineering terms—and organizational language more broadly—may exist wherein "academic" definitions evolve to a state of ambiguity based on particular contexts; the identities of the parties involved in communicating about those concepts; the actions that individuals seek to perform through their communication; and the medium of communication. For example, "strategic ambiguity" about other "boundary objects" may similarly degrade the abilities of organizations to achieve their collective values, even as they benefit the individual (Eisenberg, 1984; Barley et al., 2012).

Miscommunication. The surveys of Phase 2 found widespread variation throughout the organization about what defines the estimates communicated for system-level tracking. The act of communicating and aggregating multiple definitions of estimates toward valuable system-level objectives thereby constitutes miscommunication. Miscommunication about theoretically simple engineering concepts—like what constitutes "an estimate"—may be more common than previously supposed.

The literature states that miscommunication is common and may affect organizational performance. This study extends the previous research by showing that, as in this firm, miscommunication may be widespread throughout organizations with potential implications for the products and systems created by an organization. While not evidence that serious and systemic miscommunication exists in *every* complex system design organization, other instances likely exist and by definition produce outcomes detrimental to project success.

Organizational contribution. Estimate definitions varied independent of subsystem, position, and design phase. According to organizational literature, such independence from organizational characteristics is unusual because knowledge (such as definitions of shared terminology) is embedded in organizational units (Dougherty, 1992; Kogut & Zander, 1992). Why, then, do estimate definitions vary *within* units and *not* vary dependent on subsystems, positions, or design phases?

Section 4.4.3 notes that other variables may affect estimate definition choices. Frequency of artifact design changes, particular projects, organizational directions, estimation methods, engineer experience, etc. may all contribute to estimate definition selection. While it is easy to suggest that communication factors like context and action likely affect the selection, more specific causality requires further study.

4.7 Conclusion

In practice, miscommunication takes many forms, ranging from imperceptible differences in understanding (e.g. when you understand *most* of what another person is saying, but not quite *all* of it), to substantive disagreements based on differences in workplace cultural norms (e.g. managing supplier or customer expectations), to the meaning of shared terminology as in this case ("You meant X? Oh, I thought you meant Y!") (Coupland et al., 1991b). The analysis herein suggests that miscommunication exists even about foundational engineering terminology like the meaning of "an estimate".

Phase 1 of this study interviewed engineering practitioners ($n = 82$) about how they estimate parameters of designed artifacts. Practitioner definitions of what constitutes an estimate referred to a point in time in the design process. Participants use "current" estimates that approximate the design as it is at that point in time and/or "future" estimates that predict the state of the design at some future point. In Phase 2, surveys of practitioners ($n = 128$) verified the interview findings. Communicated estimate definitions varied throughout the organization and within every subsystem, position, and design phase. Widespread definition variation indicates disagreement and therefore systemic miscommunication given the necessity of exchanging estimates in their work.

1. How do engineering practitioners define "an estimate" in complex system design?

Engineers define estimates as approximations of a design with respect to a point in time. While some used "current" estimates representing their design at that point in time, others used "future" estimates representing an outcome later in the design process.

2. How do estimate definitions vary throughout an engineering organization?

   Estimate definitions varied both within and independent of an engineer's subsystem, position, and design phase, suggesting some other variable causes estimate definition selection.

3. How does communicating varied estimate definitions yield miscommunication?

   Communicating parameter estimates that refer to different points in the design process increases estimate uncertainty because aggregating those estimates integrates designs which correspond to two different points in time.

In sum, engineering practitioners used multiple definitions of the term "an estimate" which yielded systemic miscommunication about designs. And while estimate miscommunication specifically may not be a problem in every engineering organization, most organizations *do* experience problems resulting from communication (Eisenberg & Phillips, 1991), precisely the definition of miscommunication. As demonstrated here, practicing engineers may even miscommunicate about engineering fundamentals which merits further study as it holds great potential to affect organization and system performance.

4.8 Future Work

More research is needed to understand how engineers estimate parameters in practice. While this study identified *that* estimate definitions vary in practice, further qualitative research could examine definitions in other industries, include larger sample sizes, training, geographical co-location, etc. to expose *how* decision-making leads engineers to those definitions and explain definition variation. Identifying other instances of systemic miscommunication in organizations may lead to further insights as to how and why miscommunication becomes systemic. Work should also go toward identifying ways of resolving such social systemic problems as their potential to impact organizational performance is clear. To that end, as in the Meluso et al. paper (Meluso et al., 2019), agent-based modeling appears a promising avenue for developing methods of mitigating existing problems and solving others before they arise.

CHAPTER 5

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

This chapter was coauthored with Jesse Austin-Breneman and Lynette Shaw. It was published under the same title in the IEEE Systems Journal in 2019 (Meluso et al., 2019).

5.1 Abstract

Communication in engineering organizations affects the performance of the complex 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, this work demonstrates that miscommunication may affect system performance.

5.2 Introduction

“Communication problems” are some of the most frequently-cited causes of engineered system failures (Newman, 2001; Meluso et al., 2020) across numerous disciplines. Aerospace highlights dozens of examples (Newman, 2001), the most prominent of which are the Space Shuttle Challenger (Rogers et al., 1986) and Columbia (Gehman Jr et al., 2003) disasters. Federal investigations of each incident similarly cite "organizational barriers that prevented effective communication of critical safety information and stifled professional differences of opinion" (Gehman Jr et al., 2003; Guthrie & Shayo, 2005). 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 (Berman & Fung, 2018). Forensic software engineering often attributes software shortcomings to poor communication (Johnson, 2002), totalling in the millions and perhaps billions of dollars in losses (Charette, 2005).

The previous examples all feature *complex* systems, a particularly fraught domain in engineering design (Collopy, 2015). *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" (de Weck et al., 2011). 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 (Bloebaum & McGowan, 2012; McGowan et al., 2013; McGowan, 2014). Significant cost and risk, extensive design cycles, protracted operational timelines, and dispersed supporting organizations fundamentally characterize complex systems (Bloebaum & McGowan, 2012). These complexities plus the growing demands on these systems pose substantial challenges to the designers of such systems (Bloebaum & McGowan, 2012).

Communication plays a pivotal role in addressing these challenges. 'Good' communication can improve engineering organization performance (Eckert et al., 2005; Maier et al., 2009, 2012; Eckert et al., 2013; Luck, 2013; Liu & Cross, 2016) and system performance (Sosa et al., 2004, 2011; Parraguez et al., 2015). Yet 'bad' communication, 'misunderstandings' between people, too little communication, and too much communication hold the potential to degrade performance (Meluso et al., 2020). Readers can likely recall instances in their own work where communication "failed" causing more problems than it resolved, as with "design churn" (Yassine et al., 2003). 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" (Meluso et al., 2020).[1] While scholars hypothesize that miscommunication *should* affect organizational outcomes (Eisenberg & Phillips, 1991), this connection remains to be tested. This paper seeks to establish that connection by demonstrating that miscommunication may reduce organizational performance during a complex system development process.

Demonstrating that any particular factor affects complex system performance is challenging, especially miscommunication. One option is for researchers to obtain large datasets of empirical

[1] Section 5.3.1 describes the nature of communication and miscommunication in further detail.

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. (2020) 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. (Beck & Arnold, 1977). 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 play a substantive role in determining system performance. When developing complex systems, program managers and system engineers frequently combine estimate from hundreds or even thousands of contributors. Consequently, any ambiguity in estimate definitions — let alone the values of the estimates themselves — could easily affect complex system performance (Meluso et al., 2020). Hence, highly-quantifiable concepts like 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.

5.3 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.

5.3.1 Communication & Miscommunication

Broadly defined, *communication* is "social interaction through messages" (Fiske, 1990). 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 (Shannon, 1948; Stewart et al., 2003; Thompson, 2011). Interpretive models examine linguistic and social meanings of communication through their contexts, actions, identities, and genres (or mediums) (Leeds-Hurwitz, 1995a; Thompson, 2011). Both have 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" (Meluso et al., 2020). "Deficiencies" and "problems" are matters of interpretation in singular instances (Mortensen, 1997); but at scale, their effects through "engagement" may harm the process of "fulfilling values" (Eisenberg & Phillips, 1991) which this article demonstrates.

As recounted in Section 5.2, significant anecdotal evidence exists to suggest that miscommunication affects complex system performance. While scholars posit that miscommunication likely affects performance (Eisenberg & Phillips, 1991), further evidence is necessary to demonstrate this connection. The model described herein adds treatment to that effect.

5.3.2 Complex System Modeling Methods

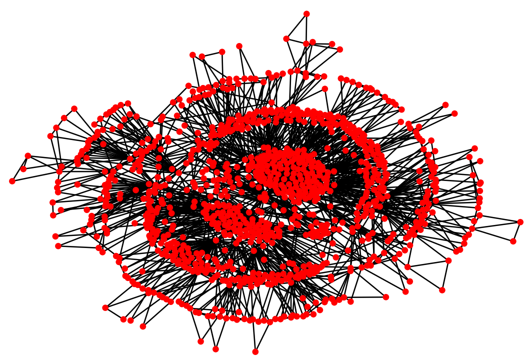
The systems literature defines an *artifact* as a piece of technology designed to serve a specific purpose (de Weck et al., 2011), an umbrella term for any technical product of human minds including physical parts, software, processes, information, etc. A *complex system* is "a system with components and interconnections, interactions, or interdependencies that are difficult to describe, understand, manage, design, or change" (de Weck et al., 2011). Methods for modeling complex systems include functional models, cellular automata models, game theory models, and dynamical systems models among others (Salvucci-Favier, 2016). Most relevant to this study are network, agent-based, and design optimization models.

5.3.2.1 Network Models

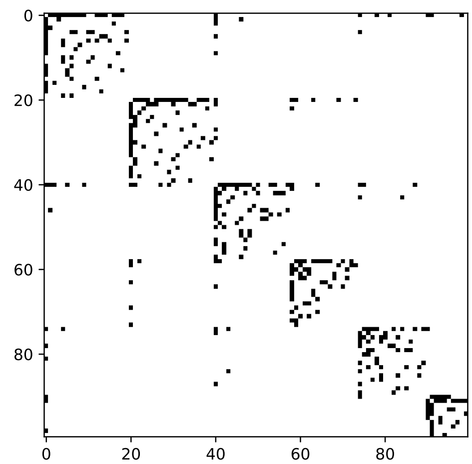
Network theory represents systems of people or artifacts as nodes and edges, as shown in Figure 5.1a. *Nodes*, points connected to one another in pairs, may represent people, subsystems, artifacts, etc. in a complex system. Connections or interactions between nodes are called *edges* or *ties* and can be represented by an adjacency matrix (Newman, 2018) as in Figure 5.1b. In complex system design, interactions are *interfaces* between artifacts from which one can form a Design Structure Matrix to represent a complex system (Sosa et al., 2011). 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) (Newman, 2018).

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* (Newman, 2018). 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 (Barabási et al., 1999; Albert & Barabási, 2002; Newman et al., 2003; Braha & Bar-Yam, 2004, 2007; Clauset et al., 2009; Sosa et al., 2011; Newman, 2018). 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 α is the exponent of the power law with typical values of $2 \leq \alpha \leq 3$ (Newman, 2018). The resulting function appears as a negatively-sloping line in a log-log plot as in Figure 5.1c. Braha & Bar-Yam (Braha & Bar-Yam, 2004, 2007) and Sosa et al. (Sosa et al., 2011) suggest that complex system degree distributions 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 (Clauset et al., 2009; Sosa et al., 2011); however, studies are sufficiently varied to suggest what may be a broader trend in complex system structures.

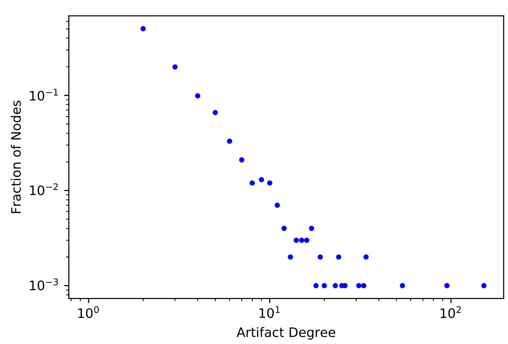
A less-popular subject in network theory with significant potential is that of generative network models that algorithmically construct networks out of basic rules (Newman, 2018). One of the most common network generation algorithms is called preferential attachment which builds a network by connecting new nodes to existing nodes with an attachment probability proportional to the degree of the existing node (Newman, 2018). Several such algorithms exist including those of Price (Price, 1976), Barabási & Albert (Barabási et al., 1999), and Holme & Kim (Holme & Kim,



(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 (Newman, 2018).

Figure 5.1: Undirected network representations. Visual representations of undirected networks generated with a Holme-Kim preferential attachment algorithm and a clustering probability of $c = 0.9$.

2002), all of which generate networks with scale-free degree distributions (Newman, 2018; Holme & Kim, 2002). Recent advances in peer-to-peer network studies allow generative algorithms to establish hard or soft cut-offs in the distribution (Guclu & Yuksel, 2007; Kumari et al., 2011). 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 $k_i \geq 2$ (Holme & Kim, 2002) by creating two edges from each new node, consistent with the minimum degree of networks identified by Sosa et al. (Sosa et al., 2011).

5.3.2.2 Agent-Based Modeling

Agent-based modeling is a widely-used, effective, and tested method for simulating communication in complex systems (Grimm et al., 2006, 2010; Bonabeau, 2002; Macal & North, 2010). 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 (Bonabeau, 2002). 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 (Macal & North, 2010). 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 (Macal, 2016).

Recent applications of ABMs include systems design (Panchal, 2009; Darabi & Mansouri, 2017; Soyez et al., 2017; Meluso & Austin-Breneman, 2018) and organization studies (Axelrod, 1997; Macy & Willer, 2002; Pitt et al., 2011; Anjos & Reagans, 2013). 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" (Salvucci-Favier, 2016). 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" (Bloebaum & McGowan, 2012), ABMs facilitate simulation of aggregated artifacts in ways that top-down models cannot (Macal, 2016).

ABMs are commonly critiqued for being too opaque or for being unrealistic "toy problems" (Garcia & Jager, 2011). Responses from tens of experts now provide rigorous protocols for describing and analyzing ABMs as a result (Grimm et al., 2006, 2010; Lorscheid et al., 2012; Lee et al., 2015). This study draws from Grimm et al.'s (Grimm et al., 2010) "ODD Protocol" (Overview, Design concepts, and Details) which clarifies model descriptions and the Lee et al. ABM analysis criteria (Lee et al., 2015) 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 (Wilensky & Rand, 2015).

5.3.2.3 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* (Papalambros & Wilde, 2017). They do this through *objective functions*, sets of evaluation criteria typically constructed as functions describing the relationships between independent variables (or *decision variables*) (Papalambros & Wilde, 2017). 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 (Martins & Lambe, 2013).

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 (McComb et al., 2015, 2016).

5.3.3 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” (Antony, 2014). Recently, significant effort has gone toward documenting state-of-the-art approaches to rigorously testing and analyzing ABMs (Eckhardt, 1987; Lee et al., 2015). Monte Carlo simulations are the quintessential method for testing ABMs and generating statistically significant outcome distributions of the assessment metrics (Bruch & Atwell, 2013; Lee et al., 2015). Indeed, numerous studies to date use Monte Carlo simulations to model design teams (Kennedy et al., 2011; Kwasa et al., 2015; Sosa et al., 2015; Ayala et al., 2017; McComb et al., 2017) including with ABMs (Sarioughin et al., 2001; Crowder et al., 2012; Meluso & Austin-Breneman, 2018).

Many of the standard techniques for systematically exploring design spaces still apply to agent-based modeling, including random, factorial, and latin hypercube sampling (Sacks et al., 1989; Lee et al., 2015); however, scholars urge caution owing to the substantially greater complexity of ABMs compared to other modeling methods (Sanchez & Lucas, 2002). For example, Lee et al. (Lee et al., 2015) 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.

5.4 Methodology

This section draws on Section 5.3 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.

5.4.1 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 5.1c for a network of $n = 1000$ artifacts. Each artifact is assumed to interface with at least two other artifacts (Sosa et al., 2011). 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 $c = 0.5$ (Holme & Kim, 2002). The result is a complex system of n interacting artifacts with no formal hierarchy.

5.4.2 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

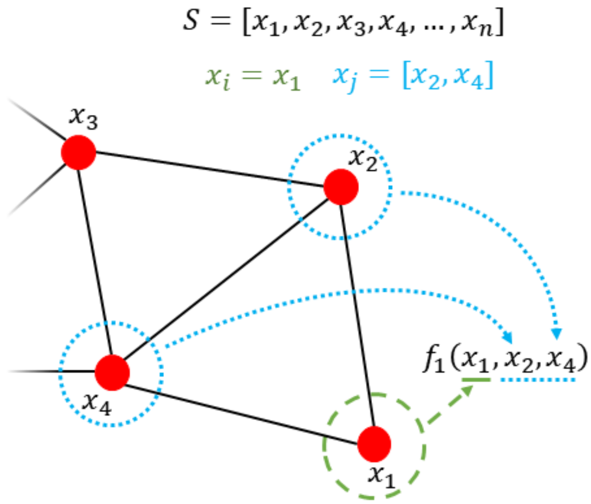


Figure 5.2: Complex system agent interaction. An example of agent interaction. In this case, the i^{th} agent is agent 1 with variable $x_i = x_1$. Agent 1 is neighbors with $j \in \{2, 4\}$ and so $x_j = [x_2, x_4]$. Therefore, agent 1's objective function is $f_1(x_1, x_2, x_4)$.

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 $\mathbf{x_j}$ 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 5.2 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:

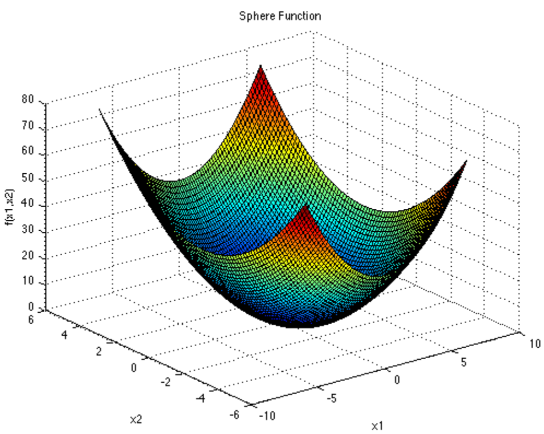
(a) The Sphere Function (Surjanovic & Bingham, 2013), an easily-converged function with a single minimum, on the recommended evaluation domain for all $x_m \in [-5.12, 5.12]$:

$$f_i(\mathbf{x}) = \sum_{m=1}^{k_i+1} x_m^2 \tag{5.1}$$

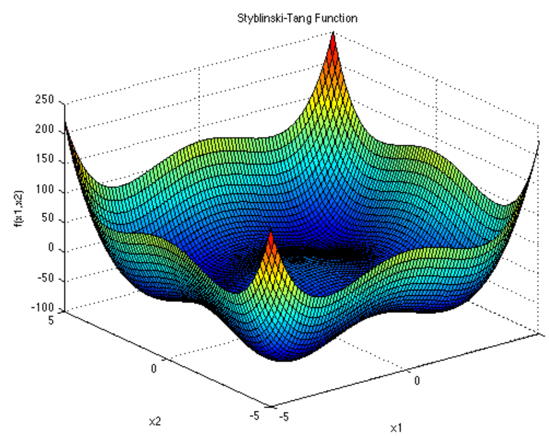
The optimum $\mathbf{x}^* = (0, \ldots, 0)$ minimizes f_i for the Sphere Function yielding $f_i(\mathbf{x}^*) = 0$.

(b) The Styblinski-Tang Function (Surjanovic & Bingham, 2013), an easily-converged function with multiple minima, on the recommended evaluation domain for all $x_m \in [-5.00, 5.00]$:

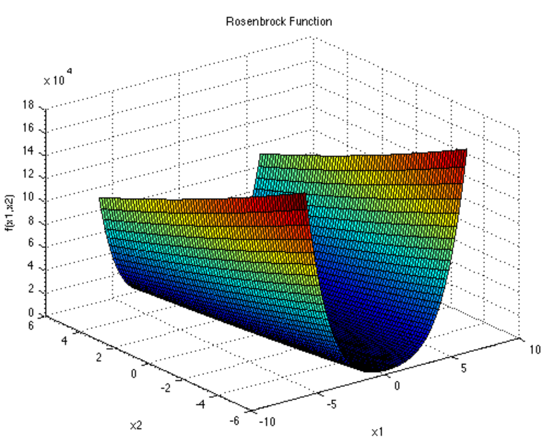
$$f_i(\mathbf{x}) = \frac{1}{2} \sum_{m=1}^{k_i+1} (x_m^4 - 16x_m^2 + 5x_m - 78.332332) \tag{5.2}$$



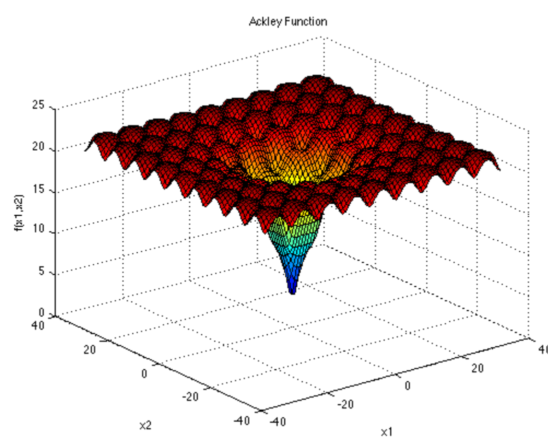
(a) Sphere Function



(b) Styblinski-Tang Function



(c) Rosenbrock Function



(d) Ackley Function

Figure 5.3: Selected objective functions. Graphical representations of the selected objective functions with two decision variables (Surjanovic & Bingham, 2013).

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

(c) The Rosenbrock Function (Surjanovic & Bingham, 2013), a more challenging function with a single minimum, on the recommended evaluation domain for all $x_m \in [-5.00, 10.00]$:

$$f_i(\mathbf{x}) = \sum_{m=1}^{k_i} \Big(100(x_{m+1} - x_m^2)^2 + (x_m - 1)^2\Big) \tag{5.3}$$

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

(d) The Ackley Function (Surjanovic & Bingham, 2013), 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 $c = 2\pi$:

$$\begin{aligned} f_i(\mathbf{x}) = & -a \exp\left(-b\sqrt{\frac{1}{k_i+1}\sum_{m=1}^{k_i+1} x_m^2}\right) + a \\ & - \exp\left(\frac{1}{k_i+1}\sum_{m=1}^{k_i+1} \cos(cx_m)\right) + \exp(1) \end{aligned} \tag{5.4}$$

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

Figure 5.3 shows these functions in two dimensions. Collectively, n coupled objective functions $\{f_1, \ldots, f_n\}$ compose the system being designed.

5.4.3 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 (Colfer & Baldwin, 2016). 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 (McComb et al., 2015). 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[2] (Wales & Doye, 1997) 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.

5.4.4 Communication & Miscommunication Modeling

Each turn of the model represented one design cycle in a system design process, also known as the Shewhart & Deming Cycle (Anderson & Rungtusanatham, 1994). While the model schedule is described in Section 5.4.5 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 $\mathbf{S}$ 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 5.2, 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 (Meluso & Austin-Breneman, 2018) and using that historical information until prototype information is available (Meluso et al., 2020), 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

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

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.

5.4.5 Model Schedule

Each execution of the model first initialized a new system following the method outlined in Section 5.4.1. After generating the system, historical distributions and medians were created following the method described in Section 5.4.4. 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:

$$F(t, \mathbf{x}(t)) = \sum_{i=1}^{n} f_i(t, x_i(t)) \tag{5.5}$$

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:

$$|F(t, \mathbf{x}(t)) - F(t-3, \mathbf{x}(t-3))| < \varepsilon \tag{5.6}$$

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.

5.4.6 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

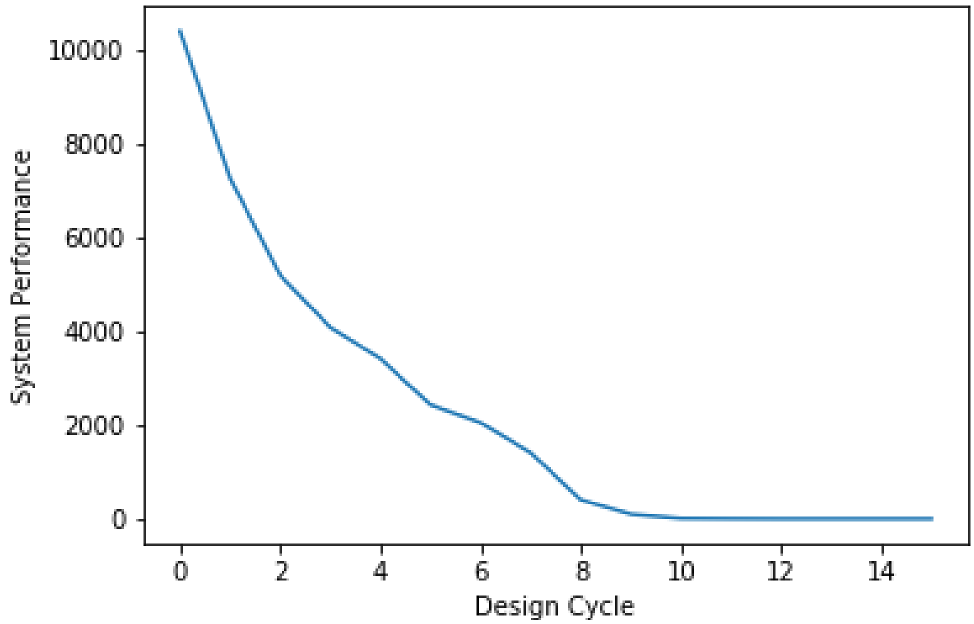


Figure 5.4: Complex system design convergence. Example of model design convergence for a network of $n = 1000$ agents using the Ackley function and $p_e = 0$. Shown as a function of the design cycle, smaller values of system performance represent better performance.

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 5.1, and design convergence, shown in Figure 5.4. Validation was performed during the analysis (Section 5.6).

5.4.7 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 5.4.2. The simulation included 200 executions of each probability-and-objective combination to significantly surpass the Lee et al. threshold (Lee et al., 2015). As specified in Section 5.4.1, 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.

5.4.8 Responses to Critiques

In light of standard critiques of ABMs noted in Section 5.3.2.2, 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 (Holme & Kim, 2002). System interfaces matched a scale-free degree distribution, a demonstrated configuration for the degree of complex systems ranging from aircraft engines (Sosa et al., 2011) to the entirety of the open internet (Newman, 2018). 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.

5.5 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 5.1, 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

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 5.1: Complex system Monte Carlo simulation descriptive statistics. 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 5.2: Objective function cycle and performance median comparisons. 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 lower 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.

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 5.5a) 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 5.5b). 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 5.2). 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 5.6a shows the full set of 2200 Ackley function system performance outcomes as a function of p_e, and Figure 5.6b 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 $p_e = 1$.

5.6 Analysis

5.6.1 Simulation Requires Sufficiently-Complex Functions

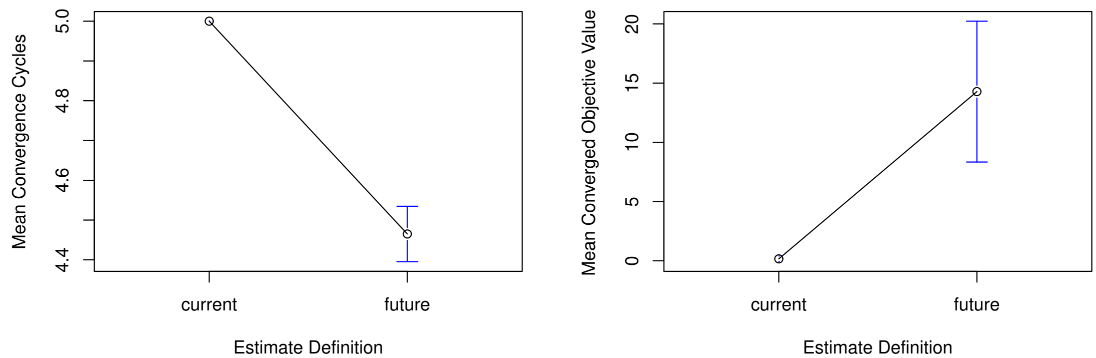
The simulation shows that for the Sphere and Styblinski-Tang functions, a basic Newton's method optimization converged the system to a solution in too few design cycles for those functions to produce substantive interaction between agents. Evidently, either objective functions must be difficult enough 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 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.

5.6.2 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



(a) Rosenbrock function cycles   **(b)** Ackley function performance

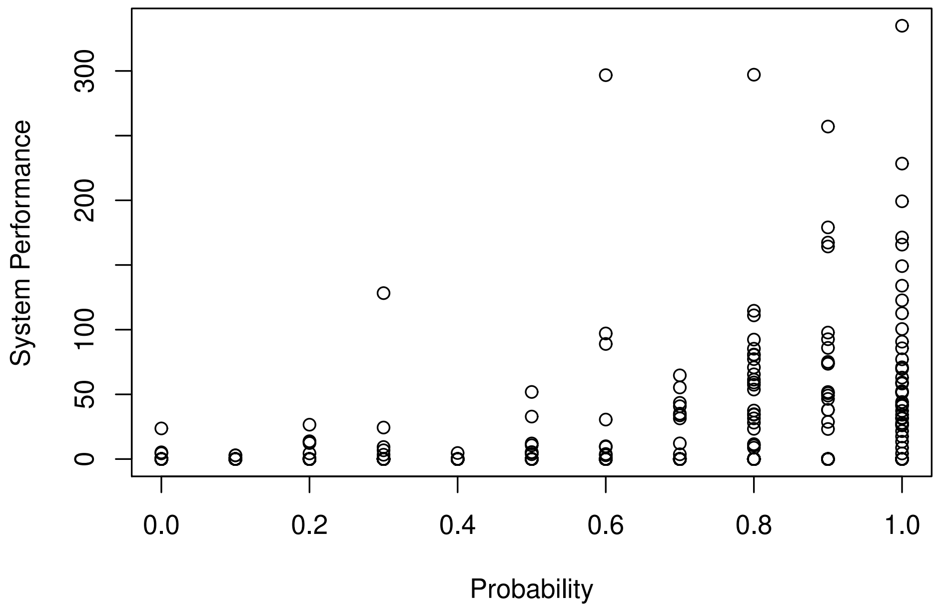
Figure 5.5: Estimate definition performance confidence intervals. Means 95% confidence intervals for the different estimate definitions of the respective functions. The current definitions do not show error bars due to their small scale.

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.

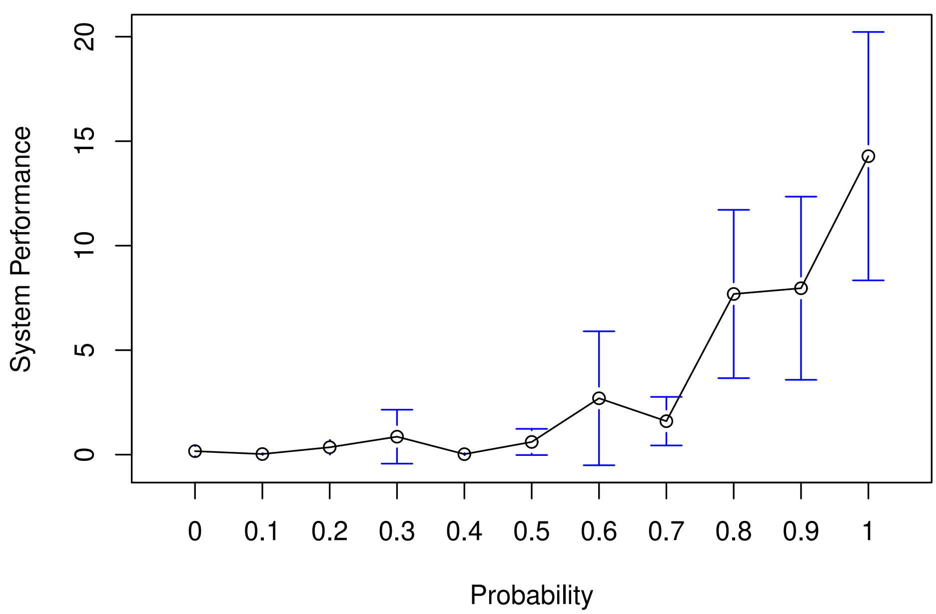
5.6.3 Hypothetical Examples: Variation in Practice

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 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.



(a) Ackley Performance Scatterplot



(b) Ackley Performance Means & 95% Confidence Intervals

Figure 5.6: Ackley function performance. 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 $p_e = 1.0$.

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.

5.6.4 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 (Wilensky & Rand, 2015). 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 (Eisenberg & Phillips, 1991) 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.

5.7 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 (Martins & Lambe, 2013).

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.

5.8 Conclusion

Communication in engineering organizations 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(Meluso et al., 2020). 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.

5.9 Future Work

This study reveals numerous opportunities for future work in complex system modeling toward the development of complex system design theory. Section 5.3.2.1 notes that scholars disagree about the extent to which complex systems follow scale-free degree distributions which this study relies upon. Section 5.4.3 mentions that CESIUM does not include any cognitive factors in agent decision-making. And Section 5.4.6 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 (Collopy, 2015). 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 (Meluso et al., 2020). 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.

CHAPTER 6

Discussion

The previous three chapters demonstrate the relationship between instrumental communication networks, misunderstandings in those networks, and organizational performance. This chapter summarizes the collective findings, describes the implications of my work, relates it to existing theory, and articulates the limitations.

6.1 Summary of Findings

Chapter 3 identified ambiguity about the definition of the term "estimate" in engineering practice. Engineers utilize estimates strategically to protect themselves and advance their interests. The chapter also demonstrated the ability of "gaming" behavior to degrade system performance and increase its uncertainty. Based on the uncertainty surrounding the definition of "an estimate," Chapter 4 explored how practitioners define the term, demonstrating that widespread variation existed in a Fortune 500 firm about the definition including within every organizational unit surveyed. Engineers inadvertently aggregated estimates of multiple types into single values that informed decision-making, thereby demonstrating that misunderstanding about estimate definitions throughout an organization's communication network constitutes networked miscommunication.

To further characterize the relationship between misunderstandings and organizational performance, Chapter 5 explored how variation in the definition of "an estimate" affected complex system performance, and hence organizational performance. Varying the fraction of the organization which used each definition of an estimate varied system performance and uncertainty. However, a nonlinear trend emerged in system performance degradation more attributable to estimate definition than frequency of misunderstandings throughout the organization. This counterintuitive finding yielded two conclusions: (1) that current estimates significantly outperform future estimates when aggregated in an instrumental communication network, and (2) that current estimates may provide a buffer against the degradatory effects of future estimates even when future estimates form the majority.

In this case, conclusion (1) bucks the interpretive definition of miscommunication and the idea that it must be misunderstandings that degrade organizational performance. Even when the organization communicates only future estimates, it degraded system performance. This still meets the pragmatic definition of miscommunication in that organizational performance degraded which is nevertheless a detrimental outcome for the organization given the problem framing. In contrast, while certain starting points for an organization may still degrade performance as an organization seeks to change the organizational use of definitions, conclusion (2) suggests that some terminological conceptualizations could mitigate aggregate misunderstandings. This too confirms that even in highly technical contexts — where one might expect the greatest certainty about communication due to the quantitative nature of the discipline — misunderstandings throughout an organization's communication network can affect complex system performance and thus meets the criteria of networked miscommunication.

6.2 Implications

6.2.1 Opportunities to Improve Communicative Effectiveness

While it may not surprise readers to learn that miscommunication affects performance, how it propagates through communication networks and the scale at which it does so may. Individual instances of misunderstandings between individuals may produce individually trivial changes for directly engaged participants. One might anticipate that the repercussions of the misunderstanding would then peter out as each participant communicates with their neighbors. Yet, in concert with a network of hundreds of other individuals, whose responsibilities depend on the aggregate results of hundreds of others, performance degradation can emerge in unexpected ways. For example, each agent i used either the current or future estimate definition. Each of their neighbors j would then receive estimates of varying types from their neighbors k which determines the magnitude of the changes to j's updated estimate, in turn affecting the magnitude of each k's updated estimate, and so on. If the majority of the organization defines estimates as future estimates, rather than petering out, the communication network may propagate the effects of misunderstandings via slow changes to the complex system's design and so yield performance degradation. Conversely, if even half of the organization were to use current estimates, it may incentivize agents of all estimate types to update in response to frequent updates, and in so doing coax the system toward optimal performance.

This is not just a challenge for those explicitly engaged in management. The emergence of performance degradation in a highly technical context, as with engineering estimates, broadens its applicability. Estimates *could* be mathematically calculated if an organization so chose (though we saw in Chapters 3 & 4 that this often isn't what happens in practice), bolstering the confidence of decisions made on those values. But how many other traditionally technical terms might also have ambiguous definitions? This is not to suggest that a specific term is ambiguous in every organizations, rather that *some* term may be ambiguous in *many* organizations, consequently leaving the potential to affect performance. Furthermore, if *technical* language can yield such sizable effects — and is already so definitionally ambiguous despite the ability to quantify the information — how much will non-technical concepts with more substantial definitional ambiguity affect organizational performance?

Consider a related case: what if slight misunderstandings took place not in estimates, but in communicating a more explicit goal such as requirements of a deliverable? It is quite conceivable that individuals would develop different mental models of those goals and pursue them accordingly, the namesake of representational gaps. In time, some of those objectives might undergo repair through further negotiation of meaning, but others would likely not, both frequent outcomes according to the sociolinguistic literature (Coupland et al., 1991b). Anyone who has ever produced something that didn't meet their employer's expectations by mistake can attest that such singular experiences are uncomfortable at best, and catastrophic at worst. Integrating these instances with one another throughout a larger instrumental or expressive network — some repaired, some merely identified, and still others undetected altogether — could prove substantial to an organization's performance.

As we see even from the case of estimates, though, evaluating particular terminological instances and predicting the significance of the consequences may prove challenging. Our understanding of misunderstandings may benefit from investigating the substantial nuance within tie content, in the meanings of language exchanged between communicative participants, how individuals construct these ideas from unique contextual, individual, purposive, and medial factors given that we now recognize some of how networked misunderstandings can affect organizational performance. For estimates, our ability to assess the repercussions for organizational performance depended on the quantifiable nature of the mathematical and heuristic definitions of estimates alike. But combining mixed methods (semi-structured interviews plus surveys) with agent-based modeling as done here could help resolve that issue.

Therefore, examining instances of miscommunication — or indeed, communication more generally — in sizable communication networks such as those that exist in organizations can teach us much about how any number of sociolinguistic conceptualizations may affect organizational performance. This includes unintentional and intentional misunderstandings from the category of divergent understandings, as well those from *shared* understandings including effective communication and misinformation. We may be able to start answering other questions as well: How can we avoid miscommunication? How can we mitigate miscommunication? How can we better incentivize effective communication? For example, that current estimates provided a buffer against some of the performance repercussions of future estimates indicates that it may be possible to improve organizational communication in strategic locations throughout a communication network without needing to change communicative practices everywhere throughout an organization. This would require developing an intervention to repair a particular instance of miscommunication in a network. So hopefully, Carley's new frontier of computational organization science (Carley, 2002a,b) is more within reach with the addition of these methods, at least with respect to organizational communication and performance.

6.2.2 Cooperative Cultures May Outperform Competitive Cultures

The studies in Chapters 3 & 4 also reveal some of the obstacles that competitive cultures appear to cause. Chapter 3 noted that some systems engineers try to engender good will and feelings of control in subsystem engineers by granting agency, but only once the system has established targets for the subsystem engineers that push them outside of their comfort zones. As the title of the chapter suggests, the subsystem engineers and systems engineers seemed to "game" one another to get the best outcome for their personal interests. Why? What caused this? Is it even surprising? Systems engineers believed that subsystem engineers wouldn't try any harder than they needed to to meet the requirements, or would try to "play the hero" if they did. So, the systems engineers chose to give subsystem engineers incentives via difficult requirements before relaxing those requirements if the subsystem engineer couldn't meet it.

This kind of gaming dynamic inspired a line of questioning about feedback during the interviews at the Fortune 500 firm under study in Chapter 4.[1] I was surprised to hear engineers tell stories of being stood up in front of boards of managers and scolded when they didn't meet their targets, being pushed and prodded until they met the goals of program managers. Several engineers described how they specifically set out to avoid those confrontations ("taking flak", "someone will be spanking them") and avoid stress ("leave me alone", "it creates more work for us") by initially providing conservative estimates ("some security", "a little extra") that they can improve later if they needed to. In contrast, others described that when managers openly ask what they can do to help ("we're willing to spend X dollars if you can do Y") that it substantially motivated engineers. One particularly salient example of the difference that organizational culture made for an employee who had changed organizations a few years prior:

> "But how [my last company] came to that point, or the conclusion and how they implemented that solution, but that's what was different. [At my last company] it's antagonistic, it's like, you know, blame the person... asking why the hell did he do

[1] These stories did not make it into the paper both topically and for reasons of space.

> that...crucify him, make a bloody glorious example of him, before we get, before we start spending energy on the issue itself, how are we going to resolve the issue, and then spending time further to implementing the issue. How do we implement it?... Do we use our best judgment or do we, you know, test and verify til kingdom come before we implement anything. Risk tolerance and everything kind of comes into play, but the energy required to solve a task [at my last company] was about three or four times more than the energy that I spend here, resolving that same issue or task. And it was very eye opening for me that, my god, the cultures of the companies makes a huge difference, my leadership makes a huge difference, does the leadership have confidence in me, do they give me not only the responsibility and the accountability, but do they give me the authority, to make certain decisions. All that stuff, all those dynamics make a huge impact on how things are done, and ultimately how much money you spend, behind doing all this stuff."

As this quote clearly demonstrates, trust empowered this employee while blame and distrust exhausted them.

But what's more, these quotes reveal a parallel between organizational cultures and the estimate definitions from Chapters 4 & 5. When engineers protected themselves from competitive organizational cultures, they employed strategically ambiguous estimates or artificially conservative estimates which the engineers only updated once they were confident, nearly identical to the specifications for future estimates in 5. Likewise, when engineers felt empowered to make their own decisions, they felt motivated to respond to organizational incentives, just as current estimates responded to changes in network neighbors.

To put it succinctly: future estimates resemble the behavior of employees in competitive organizational cultures while current estimates resemble the behavior of employees in more cooperative organizational cultures. The results of Chapter 5 take this one step further still. Current estimates (à la more cooperative cultures) significantly outperformed future estimates (á la more competitive cultures) which indeed suggests that more cooperative cultures may outperform more collaborative cultures.

While the hypothesis that more collaborative cultures will outperform more competitive cultures remains untested as of yet, it nevertheless provides an exciting possibility for both improving the performance of organizations and advancing more equitable organizational outcomes. Previous work within gender and women's studies on masculinity contest culture (MCC) suggests that competitive culture perpetuates barriers to the advancement of women in organizations (Berdahl et al., 2018). But what if such cultures also negatively affect organizational performance? If true, it would open the possibility that we could improve organizational performance by promoting more cooperative workplace cultures, and in so doing, simultaneously reduce the prevalence of

MCCs. The negotiatons literature certainly suggests that collaboration (a balance of competition and cooperation) gives participants more options for improved collective performance (Kopelman, 2014). Testing this hypothesis could therefore provide a powerful incentive toward both improved organizational performance and equity.

6.3 Relationship to Existing Theory

Collectively, these results are consistent with the examples from practice noted by Eisenberg & Phillips (1991) that miscommunication can affect outcomes, although my work suggests the effects are conditional on other factors such as which terminology the misunderstanding exists about and how widespread each possible comprehension is throughout the organization due to their distinct abilities to effect further choices as noted in Section 6.2.1.

Also, while this dissertation examines an adjacent concept, our results generally support the findings of Carley & Lin (1997) that information distortion conditionally affects organizational performance. Carley & Lin examined information distortion as inputs to organizational decision-making (which could, but does not necessarily, create misunderstandings), whereas here I studied divergent understandings of shared terminology within the organization (unintentional misunderstandings). Still, if we took an information distortion via an open systems perspective (Scott & Davis, 2007) wherein the misunderstanding takes place between an external communication participant and an internal participant, the effects would be the same.

Although the concept of representational gaps is specific to goal definition, the findings herein relate in that estimates informed organizational decision-making (Chapter 4), a form of goal. In that context, I corroborate the findings of Firth et al. (2014) related to performance degradation due to representational gaps because the Holme-Kim algorithm clustering mimics the creation of multi-team systems.

However, while the aforementioned Eisenberg & Phillips, Carley & Lin, and Firth et al. studies examine related concepts, this study scales up the study of miscommunication to organization communication networks. While these works are limited to teams of fewer than 20 people, this dissertation expands the treatment of miscommunication in organizations up from small organizations to a much larger scale at 1000 agents in an organizational communication network. In doing so, it makes a novel contribution to the literature.

6.4 Limitations

The results of this dissertation are limited first of all in that they address a particular case of miscommunication. While practitioners throughout industry utilize estimates, the studies described a limited set of experts from varying backgrounds (Chapter 3) and one firm that interacts with complex systems (Chapter 4). It is possible that these definitions do not extend to other firms or industries. There may be deeper rationales motivating practitioners to use each definition that could explain some of the variation which we did not have access to for reasons of time and contract.

The study in Chapter 5 is limited in that it examines a set of representative objective functions. It also assumes a scale-free degree distribution as the structure of both the complex system and the organizational communication. While there is some evidence to support the distribution hypothesis, the results do not apply to all organizations that develop complex systems nor to all organizations, but merely demonstrate that such repercussions for organizational performance are possible. In addition to exploring alternative objectives and network structures, directed communication networks would also merit further exploration to mitigate uncertainty as many instrumental ties are directed rather than bidirectional as assumed by the model.

CHAPTER 7

Conclusion

Many modern organizations develop, operate, and manage complex systems to achieve their goals. However, the nature of complex systems as collections of highly interacting, tightly coupled elements leaves them prone to normal accidents and susceptible to failures in organizations that suppress dissent. Such degradations in complex system performance often degrade organizational performance due to organizational reliance on complex systems for goal attainment. The literature has long shown that communication network structure can affect organizational performance and theorized that miscommunication does so as well.

My dissertation demonstrates that miscommunication — dually defined (1) pragmatically as communication problems that negatively affect goal attainment, and (2) integratively as misunderstandings that prevent participants from balancing their values — can affect complex system performance and, in so doing, affects organizational performance. I call this phenomenon in which the unintentional, aggregated effects of communication in networks leads to performance degradation *networked miscommunication*.

I demonstrated networked miscommunication over the course of three studies. The first study observed that practitioners utilize the word "estimate" to defend themselves and for strategic ambiguity, identifying that multiple definitions of the term likely existed. It also found that by strategically "gaming" one another, practitioners may negatively affect system performance and increase system uncertainty.

Building on the uncertainty surrounding the term "estimate" observed in the first study, the second study identified pervasive use of both "current" and "future" definitions of the term estimate throughout a Fortune 500 firm, including within every organizational unit surveyed. The firm informed strategic decision-making with system-level estimates formed by combining estimates communicated by individuals throughout the organization, regardless of their estimate definition, consequently yielding networked miscommunication.

The third study then simulated varied use of those two estimate definitions throughout an organization developing a complex system. I found that even without explicit misunderstandings, networked communication of future estimates degraded performance compared to that which current estimates could accomplish, yielding networked miscommunication again. However, current estimates could in effect buffer the system's performance against the performance degradation caused by future estimates, leaving hope that it may prove possible to mitigate the effects of networked miscommunication through some intervention.

Collectively, these studies demonstrate the potential of misunderstandings and communication networks themselves to degrade organizational performance with implications for both preventing communication degradation and improving organizational communication. If even technical terminology, which one might reasonably expect to be the most well defined, can contain misunderstandings that affect organizational performance, how many other cases of terminological misunderstandings may affect performance? The literature on miscommunication describes numerous ways that miscommunication occurs with varying degrees of reparability indicating that the topic certainly merits further study. It appears possible to mitigate some of the effects of networked miscommunication, though, as the introduction of current estimates to buffer against the performance losses of future estimates found in the third study.

The studies also imply potential organizational performance improvements via choices of organizational culture. Based on the qualitative data from the first two studies, practitioners tended to use future estimates for protection from more competitive environments while they used current estimates in more transparent and cooperative environments. The third study found that current estimates outperformed future estimates, leading to the hypothesis that more cooperative organizational cultures may outperform more competitive ones. While this hypothesis certainly requires further inquiry, if true, it could prove beneficial toward improving organizational performance and creating more equitable organizations.

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