The Epistemology of Enterprises

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ABSTRACT

Enterprises are essential to the sustainment of our modern society. However, they rarely receive the level of attention and rigor that technical systems do. Treating enterprises as systems is a promising approach, but enterprises depend on a substantial social component. The inherent complexity of social systems introduces epistemic limitations that inhibit our ability to model social systems and predict their behavior. Consequently, traditional engineering approaches that rely on prediction and control can be ineffective or misleading when applied to enterprises. In this paper we explore the implications of these epistemic limitations on the engineering of enterprises. We conclude that it is necessary to apply dynamic strategies to mitigate these limitations and adapt enterprise modeling efforts accordingly. The goal with enterprises, in contrast to traditional technical systems, is to influence rather than control. We outline an interdisciplinary research agenda to progress toward this goal.

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1. INTRODUCTION

Enterprises are pervasive in modern society. Rouse [2005: 139] defines an enterprise as, “...a goal-directed organization of resources—human, information, financial, and physical—and activities, usually of significant operational scope, complication, risk, and duration. Enterprises can range from corporations, to supply chains, to markets, to governments, to economies.” In this paper, we consider an enterprise to be more than just an organization. An enterprise can consist of many independent organizations such as the U.S. health care system and/or substantial physical infrastructure such as the U.S. transportation system. It would be fair to assert that enterprises are how work gets done.

Despite their ubiquity, import, and goal-directed nature, it would be a stretch to suggest that more than a fraction have been engineered with the same level of discipline and rigor as a technical system such as an automobile, an airplane, or a command and control system. Rouse [2005] suggested that treating an enterprise as a system is a necessary first step toward a more methodical approach both to developing and to evolving enterprises.

At a high level, an enterprise is no different than a traditional engineered system. It is intended to provide some function or service. It accepts inputs and transforms them into the desired outputs but also creates waste products that must be disposed. Consequently, it would seem that by viewing an enterprise as a system, one can bring to bear the tools and methods developed to engineer systems. In principle, the application of these tools and methods should lead to more informed decisions by engineers, managers, and policymakers. Unfortunately, there is a critical feature of enterprise systems that impedes this approach: the hybrid nature of the enterprise.
Enterprise systems exist on the boundary where the technical meets the social, and they encompass both engineered and social components. In this paper, we will take a broad perspective of what constitutes an engineered system. An engineered system entails any purposefully designed structure whether tangible or intangible. Thus, an engineered system can include hardware and software as well as organizational structures, policies, and laws.

It is the social component that complicates the application of traditional engineering approaches. Historically, engineering processes and tools have not dealt with social phenomena in the same way that a social scientist would. Researchers in areas such as human factors and systems of systems often try to capture human phenomena in such a manner that they can be integrated into conventional engineering models. (This includes the authors’ own work.) For instance, the effect of conflicting stakeholder objectives might be captured via a Nash equilibrium. However, it is also known that the Nash equilibrium is not always the best predictor of human behavior [Aumann and Maschler, 1972]. On the surface, this would seem to be an issue of disciplinary stove piping: If one could find a way to bridge the gap between engineering and the social sciences, one should be able to adapt engineering processes and tools to accommodate social phenomena.

Unfortunately, the issue is more fundamental than overcoming interdisciplinary language barriers. It is epistemic. The complex nature of social systems limits our ability to measure them, model them, and predict their behavior. This limits the efficacy of engineering methods that rely on prediction and control. While researchers in the physical sciences may sometimes criticize the approaches employed by those in the social sciences, there is a reason why social scientists approach their subjects the way that they do. As we will explore in this paper, epistemological differences necessitate differing and sometimes incompatible modeling approaches. The implication is that efforts to leverage the increasing availability of large data sets and inexpensive computational power to impose a more engineering driven approach to evolving enterprises must explicitly recognize these limitations or else risk envisioning and developing fragile enterprises.

The intent of this paper is to consolidate and synthesize concepts from several different domains into a coherent understanding of these epistemic limitations. That understanding, in turn, serves as a guide for subsequent research on how to model and influence enterprise systems. We are arguing for a point of view rather than a methodological prescription. In short, we will assert that an enterprise system is the internal or external imposition of engineered systems on a social system to control or influence its behavior. However, the inherent complexity of social systems results in epistemic limitations on measurement, modeling, and prediction with regard to enterprise systems. Consequently, in many cases it is preferable to attempt to influence rather than control enterprise systems.

The remainder of this paper is organized as follows. In Section 2, we will discuss the concept of the enterprise as a system. Next, in Section 3 we will discuss the complexity of social systems and its consequences for enterprises. Then in Section 4 we will consider how these consequences manifest themselves in enterprise systems through a series of examples. Based on the conclusions we draw from the examples, Section 5 describes the strategy and modeling issues that arise. In Section 6, we lay out a research agenda to develop methods and approaches to improve the engineering of enterprises. Section 7 concludes the paper.

2. ENTERPRISES AS SYSTEMS

2.1. Defining Enterprise Systems

Any attempt to discuss a general problem in the systems field inevitably runs into the ambiguous and overlapping categories of system classification. For instance, consideration of the term enterprise system suggests related categories such as systems of systems and socio-technical systems (Lock [2012]). Rightly or wrongly these terms are sometimes used interchangeably or in an overlapping way. Obviously, this terminological dilemma will not be solved in this paper. Instead, we will define what we mean by enterprise system in the context of this paper as well as its relationship to systems, systems of systems, and socio-technical systems acknowledging that others may differ with our definitions. Regardless, this will be sufficient to frame the subsequent discussion.

Figure 1 notionally depicts our definitions of enterprise system, system of systems, and socio-technical system for this paper. From our perspective, modern technological systems rarely exist in isolation. They are simultaneously embedded in one or more systems of systems, socio-technical systems, and enterprise systems. It is simply a function of how we draw the boundary. Thus, differentiation of these terms is largely one of emphasis. In Figure 1, we consider a system of systems to be one or more interacting technological systems that are managed and/or operated by independent organizations. (This would be consistent with Maier’s [1998] definition of a system of systems and Rhodes et al.’s [2009] assertion that systems of systems are developed and operated by enterprises.) The emphasis of work in systems of systems engineering is how to overcome the interoperability challenges among technological systems that result from this independence. Examples would include Darabi and Mansouri [2013] who consider the balance between autonomy and belonging as well

Figure 1. Notional view of enterprise systems relative to socio-technical systems and systems of systems.
as Dickerson [2013] who applies a model-driven framework to identify overlaps and inconsistencies among constituent systems.

We consider a socio-technical system to be the interaction between a technological system and social/organizational system. This is often framed as the joint optimization of the social and the technical systems [Ackoff and Emery, 1972; Trist, 1981]. The emphasis is on the interaction between the humans and the technology. Particularly relevant to the analysis presented in this paper is De Bruijn and Herder’s [2009] discussion of the importance of simultaneously considering a socio-technical system from both a hard system perspective and an actor perspective. In, particular they argue that the two views can never be fully integrated, but are both important.

Finally, we consider an enterprise system to be a collection of interacting organizations that construct and/or operate one or more technological systems to achieve a goal. We might consider an enterprise system to be a system of socio-technical systems. Here the emphasis is on the interaction among organizations and their use of technological systems to achieve some goal. A typical example of an enterprise system would be the U.S. healthcare system. It is comprised of a large number of interacting organizations and social systems that are attempting to use technology to deliver health care to the U.S. population. The interested reader is directed to Rouse [2015] for in depth discussion of the history and evolution of each of these categories of systems.

There are at least two broad perspectives with which one can view enterprises as systems. Architecting of enterprises is the perspective that is closest to traditional systems engineering. This view focuses on analysis and design of functions, structures, and processes that enable an enterprise to deliver its products and services. Also of concern are modeling, simulation and visualization of the complex systems and networks associated with the architectural view [Gharajedaghi, 2007; Giachetti, 2010].

The other perspective, more social in nature, focuses on the management of enterprises [Rouse, 2005, 2006]. Here the concern is with understanding value from the perspectives of markets and competitors, developing value propositions and effect are definitively linked.

Regardless of which perspective we take, the objective seems to be to determine how participants in an enterprise can go about engineering it in such a manner that they obtain the outcomes that they desire. Engineering an enterprise could involve altering organizational structures, technological systems, policies and laws, processes and procedures, etc. Note that we are using “engineering” as a verb to mean “design,” rather than just the activities of professional engineers.

The purpose of this paper is to consider the implications of attempting to engineer an enterprise as a system in the same way that we would engineer an aircraft as a system. We are not arguing that this is or should be done. Rather we want to consider how this approach does or does not work as we transition from a pure technological system to an enterprise system and then consider the implications for engineering an enterprise to achieve desirable outcomes. What we will subsequently argue is that as we transition from the pure technological system, we face increasing epistemic uncertainty that erodes the effectiveness of traditional engineering approaches due to the complexity of social systems. Aspects of this erosion are already observed in systems of systems and socio-technical systems, but here we want to push the boundary significantly and consider the effects.

2.2. Traditional Engineering vs. Engineering Enterprises

In order to establish context, we will begin with a brief examination of traditional engineering systems and then consider how they are impacted by adding a social layer to these systems. Traditional engineering is purposeful. A system is engineered to provide desired functions or services. The system takes in resources and energy and produces a desired output, but it also produces waste that must be disposed. For it to be useful, a system should reliably provide these functions or services. Ideally, for a given set of inputs and states, the system should always produce the intended outputs with acceptable levels of waste.

This is not to suggest that real engineered systems are 100% reliable or that there is no ability to trade reliability for cost or performance. Rather the point here is that for most engineered systems, there is some minimum level of reliability required for the system to be useful in the area of application. For example, not many would be willing to purchase a car where occasionally turning the steering wheel to the right caused the car to go left. Framing it from Poli’s [2013] perspective, engineered systems tend to be complicated, not complex. Cause and effect are definitively linked.

How is this accomplished? Prediction and control are central. The engineer designs the structure of the system to achieve the desired input/output relationship. The only way he or she can do so is if he or she can predict the behavior of the system in its operational environment. Note that prediction does not necessarily mean predictive modeling. System testing and design heuristics based on past experience can also be used to achieve a level of confidence in system performance. The critical point is that the engineer intentionally restricts the degrees of freedom within the system so that its behavior does not spontaneously change during operation. To do otherwise would be self-defeating.

What happens when we transition from a pure technological system and introduce an organization? It turns out that reliability is desirable for organizations as well. Hannah and Freeman [1984] take an ecological view of organizations. In particular, they consider that demands for accountability and reliable output tend to favor the selection of organizations with a high degree of structural inertia (i.e., resistance to change). Thus, organizational change tends to occur due to the entry of new organizations into the ecosystem rather than existing organizations adapting. However, this is not universally true. It is a consequence of the environment. Depending on the nature of the operational environment, selection
pressures may not be strong enough to ensure that the only organizations with high inertia survive (e.g., highly turbulent environments). Consequently, we cannot view an organization as an isolated system; rather we need to consider the larger ecosystem in which it operates as the resulting evolutionary pressures are critical to understand.

When we expand the view beyond just a single organization to an ecosystem of organizations, understanding the behavior of social systems is critical because we can no longer ensure that there is a mechanism to enforce reliable behavior. A social system is almost the diametric opposite of an engineered system. It serves a multiplicity of purposes. It does not have any particular design. It does not have any particular outputs. The people within it can have an enormous number of different intentions and interactions, and the system can reconfigure itself. As a result, it has a large number of degrees of freedom, and its behavior can spontaneously change. In short, it is what many would call a complex system. Since a social system has no particular unified goal on its own, another way to look at an enterprise is to view it as the imposition of engineered systems (physical and organizational) onto a social system by one or more members of that social system to control or at least influence its behavior.

Williamson [1979] considers the impact of opportunism on contract structure and governance. When the nature of a transaction precludes an unambiguous contract, there is the potential for parties to the contract to opportunistically exploit the ambiguity for their own gain. Organizations emerge as governance structures to regulate opportunism that can occur during highly idiosyncratic transactions, particularly those involving highly specialized human and physical assets. Unfortunately, this regulatory mechanism necessarily means a loss in efficiency versus market governance. Interpreting Williamson’s result in our context implies that imposing an engineered structure on a social system to achieve a viable output seems to be a necessary evil. However, for enterprises we broaden this context beyond a single organizational structure, and this would suggest some loss of control. For example, the design of infrastructure systems such as transportation networks can influence the public’s behavior, but it cannot achieve outcomes reliably. A government may build a new highway to encourage growth in a particular corridor, but it cannot force people and businesses to relocate there. Other factors may overwhelm the apparent incentive.

The core issue is that, within an enterprise, the social system is far more adaptable than the engineered system. Ashby’s law of requisite variety is instructive here. In the engineered system, we intentionally limit the number of degrees of freedom to achieve predictable behavior, but then we use this engineered system as a control mechanism for a social system with an enormous number of degrees of freedom. However, the law of requisite variety tells us that a control mechanism must have at least as many degrees of freedom as the system it controls [Ashby 1956]. As a result of this misalignment, the social system can adapt to the engineered system in unexpected ways to which the engineered system is unable to respond. The solution that some attempt is to forcibly restrict the degrees of freedom available to the social system. This would seem to be the tact that autocratic governments take, but this risks alienating individuals and actually harming the overall capabilities of the enterprise.

The reason is that this same adaptability also lends resilience to the enterprise system. The social component can alter, expand, and update the engineered component in response to experienced or anticipated events. This also leads to the observation that enterprises must maintain and evolve themselves. We sometimes view the situation as an external entity such as a government or board of directors imposing controls on an enterprise, but really they are just as much a part of the enterprise. Returning to the health care example, the U.S. Government plays multiple roles including regulator (the Affordable Care Act), payer (Medicare/Medicaid), and provider (VA and military hospitals). While the government has a great deal of influence on the enterprise, it would be a stretch to say that it is an external entity. It is just as much a part of the enterprise as the private health care providers, insurance companies, medical professional organizations, and patients.

Thus, the challenge of engineering an enterprise is that it cannot be engineered, at least not in a conventional sense. For narrative purposes, we will consider the plight of a hypothetical enterprise engineer to highlight this, though we acknowledge no such actual person exists. Rather there is a collection of actors each of whom have limited influence and may or may not be cooperating.

A hypothetical enterprise engineer may try to design organizational structures, policies, and physical systems to steer the social system in a desired direction, but the social system can often change faster than these structures can be altered to compensate. This might be manageable if the enterprise engineer could predict the response of the social system to the interventions, but the complexity of the social system limits his or her ability to do so. In the next section we will consider this dilemma in more depth.

3. SOCIAL SYSTEMS AND COMPLEXITY

In this section, we will consider the assertion that the complexity of social systems within enterprise systems introduces epistemic limitations that restrict the hypothetical enterprise engineer’s ability to predict the impact of his or her interventions. The term complexity is widely used in the scientific, engineering, and business communities. But as Alderson and Doyle [2010] note, its usage by different communities of researchers can be diametrically opposed. To that end, we need to discuss just what is meant when we say a system is complex.

3.1. The Usage of Complexity

Alderson and Doyle [2010] present a two-dimensional matrix of complexity (evolved from earlier work by Weaver [1948]). The first dimension indicates whether the system is described by a simple or a complex model. The second dimension indicates whether the system exhibits robust or fragile behavior. This results in four categories:

- Simplicity : simple model, robust behavior
- Organized complexity: complex model, robust behavior
- Disorganized complexity: complex model, fragile behavior
- Fragility : simple model, fragile behavior
• Disorganized complexity: simple model, fragile behavior
• Irreducible complexity: complex model, fragile behavior

In short, disorganized complexity describes the aggregate behavior of a large collection of randomly interacting entities while organized complexity describes the behavior of a large, highly organized collection of interacting entities. Examples of disorganized complexity would be the swarming behavior of insects or wave patterns in traffic. Examples of organized complexity include biological organisms or complex engineered systems. Systems that exhibit disorganized complexity may be described with a simple model but exhibit fragile behavior whereas systems that exhibit organized complexity may exhibit robust behavior but require a complex model to describe them. Alderson and Doyle assert, reasonably, that misdiagnosis of the type of the complexity exhibited by a system can result in erroneous conclusions about that system.

Another way to state the terminology problem is this: Modern science and engineering are predicated upon creating a compact description of a system that we can use to make accurate predictions about the future state of that system. The more compact the description and the more accurate the resulting predictions, the more useful the description. A description that is not compact is uneconomical in terms of making the prediction. It requires too much time and/or resources to obtain the prediction. A description that is inaccurate is uneconomical in terms of the response. The greater the spread of possible outcomes, the greater amount of resources and time we need to devote to covering them. Whenever we have difficulty achieving either of these objectives for a particular system, there is a tendency to refer to that system as complex.

Even so, some have argued that complex systems may exhibit regularities that can be exploited. For example, Boisot and Mc Kelvey [2011] assert that complex systems can exhibit scale-free regularities that may be more expensive to exploit than traditional reductionist regularities because they require an adaptive response, but doing so can be better than guessing or waiting. However, Alderson and Doyle [2010] argue that scale-free concepts apply to disorganized complexity but not organized complexity.

In a similar vein, Poli [2013] makes a distinction between complex and complicated systems. He argues that complicated and complex systems are not differences of degree but are instead two different types of system that require different approaches. Decision makers often confuse the two and apply the wrong approach.

Thus, the problem with the term complexity is that there can be different reasons for why we cannot achieve compactness and predictive accuracy. The blanket term complexity is applied for all of these cases, it leads some to mistakenly apply a method developed to address one cause of complexity to a system that is complex for a different reason.

3.2. The Implications of Complexity

Enterprises, as we will subsequently argue, likely exhibit a mixture of complexity types. Thus, as we move forward, it will be important to try to identify the underlying issue so that the right approach can be applied to the right problem. Even so, the implication of all forms of complexity is that there is a resulting epistemic limitation that must be explicitly recognized. Complexity limits what we can know about a system. Proceeding under the assumption that we know when we do not can result in counterproductive actions.

It is worth discussing some of the issues that can result from the various forms of complexity, particularly those that impact prediction and control. While a complete survey of the complexity literature is outside the scope of this paper, what follows are some representative examples provided with the aforementioned caveat that these implications may be the result of one or more different types of complexity.

Casti [2012] provides a broad summary of the consequences of complexity with the following complexity principles (as summarized by the authors):

• Emergence: Properties emerge at the system level that are not present at the level of the components
• The Red Queen Hypothesis: Competitive systems must keep evolving just to avoid extinction
• No Free Lunch: Generally speaking, the more efficient you make your system, the more susceptible it becomes to shocks
• The Goldilocks Principle: Complex systems operate on the edge of chaos: Not enough chaos and the system is frozen in place. Too much chaos and the system is destroyed.
• Unpredictability/Incompleteness: There are events that cannot be predicted by logical deduction. The structure of the system is not sufficient to predict all possible outcomes
• The Butterfly Effect: A seemingly insignificant event can cascade through the system with dramatic effect
• The Law of Requisite Variety: If the underlying system is more complex than the control mechanism, then control will be lost.

These principles are related to our discussion in three ways. First, they imply that complex systems are constantly adapting and changing. This makes it difficult to model them, and it makes it difficult for engineered control systems to keep up. Second, “optimizing” a system in the face of complexity may be the worst thing that one can do. Third, there are epistemic limitations. No theory or model will be able to predict all possible outcomes.

Helbing and Lämmer [2008] note that complex systems may exhibit (as summarized by the authors):

• History-dependence: Starting the system with a different set of initial conditions may cause it to end up in a different state
• Multiple local optima: This means that it may be extremely difficult to find the global optimum
• Instability and cascading effects: When the system enters a critical state, failures may ripple through the system
• “Guided self-organization is better than control” [Helbing and Lämmer, 2008: 7]: The system may resist deliberate attempts to force change yet change radically following a seemingly insignificant event.
Consequently, traditional control may be ineffective, and it may be better to try to guide the system’s natural tendency to adapt.

Essentially, Helbing and Lämmer assert that (from a disorganized complexity standpoint) traditional prediction and control are largely futile. It is difficult to predict what the system is going to do. It is difficult to determine the best possible state for the system to be in, and it would be difficult to push the system to that state even if one knew what it was.

In contrast, when a system exhibits organized complexity, Alderson and Doyle [2010] assert that complexity results from attempts by the system to achieve robust behavior in response to a changing environment. In particular, “most of the complexity in highly engineered or evolved systems is in control processes that regulate the internal state and respond to external changes.” [Alderson and Doyle 2010: 842] As a result, these systems tend to be “robust yet fragile” in that they can respond effectively to a wide range of events but are vulnerable to attacks on their signaling and control systems [Alderson and Doyle 2010; Doyle and Ceste, 2011]. A good example of this phenomenon is the emergence of cancer, which results from a disruption in the body’s signaling and control system that suppresses uncontrolled growth.

Finally, Poli [2013] asserts that the difference between a complicated system and complex system is that in a complicated system, a problem can be associated with a particular cause. As a result, one can develop a permanent solution. For a complex system, problems result from multiple causes that interact. There is no way to identify a single cause. Consequently, one cannot control a complex system and, instead, can only influence it.

What we can draw from the preceding is that whenever a system is complex (whatever the reason), modeling, prediction, and control become difficult. Consequently, traditional engineering approaches become problematic at best and counterproductive at worst. From an enterprise standpoint, the complexity that we are most interested in is the complexity of the social system, both in terms of the internal social system within the enterprise bounds and the external societal system that exists within the enterprise’s ecosystem.

3.3. Social Systems are Complex

Asserting that social systems are complex is hardly an original or controversial position. Rather our interest here is in understanding the implications of that complexity for the enterprises associated with them. The interesting feature of social systems is that they exhibit aspects of both disorganized and organized complexity. Herding behavior and idea propagation are examples of disorganized complexity, yet human developed organizations, governments, and enterprises often evolve to exhibit organized complexity.

In his study of societal collapse, Tainter [1988] contends that a complex society is essentially a problem solving organization. However, each new problem it solves requires the addition of a new layer of complexity. Eventually, society becomes so strained by the burden of its own complexity that it becomes vulnerable to crises it would have previously found manageable. Enterprises may be no different in that they similarly avoid discarding previous investments. Marticello [2012] supports this notion with an analysis of the U.S. Air Force acquisition system through the lens of Tainter’s theory. Additionally, this viewpoint is consistent with the previously discussed work of Hannah and Freeman [1984].

Harvey and Reed’s work, “Social Science as the Study of Complex Systems” [1996] examines the implications of social complexity on the study of social science. They postulate a layered, ontological hierarchy (Table I) of a social system that starts from the “regularities of the physical universe” at the bottom to “societal evolution via historical modes of production” at the top. In essence, the complexity increases as we move up the layers of the hierarchy. As Harvey and Reed note, this results in “several epistemological breaks as we move along this abstraction dimension” [308].

This recognition is critical to the epistemic dilemma previously described. Any social system that we will deal with can be legitimately considered at multiple layers of abstraction. Furthermore, the behavior of the social system at each layer may be critical to the operation of the enterprise. Unfortunately, the behavior of the social system becomes increasingly complex as we move up the layers, and this limits what we can know about the system. Consequently, it becomes increasingly difficult to model and make precise predictions. It also means that a method we use to model the physical universe may be incompatible with a method to model the social universe. We should note that we are not asserting that this inconsistency exists in the universe itself. Rather it is the direct consequence of the necessary but incompatible simplifications required to accommodate the epistemic limitations introduced at each layer.

Recognizing these limitations, Harvey and Reed introduced levels of modeling abstraction that map different modeling approaches to their appropriate ontological level. These include: predictive modeling, statistical modeling, iconological modeling, structural modeling, ideal type modeling, and historical narratives. They note that predictive modeling is really only appropriate on the lower levels of the ontological hierarchy. Given the importance of prediction to engineering,
this would seem to be a significant inhibitor to engineering an enterprise unless we accept that the goal of design is to influence rather than control.

It is also interesting to note that while we might reasonably argue that the lower and middle levels involve mixtures of organized and disorganized complexity, the upper levels seem to approach irreducible complexity. They can only be described by a historical narrative, which is essentially a verbal description of what appears to have happened without any real prediction of future states.

To illustrate the impact of social complexity, consider a social system that is extremely important to most enterprises, the economy. Here, the work of the economist W. Brian Arthur in instructive. Arthur contends that the economy itself is a complex adaptive system [Arthur 1999]. Neoclassical economics assumes that the economy consists of only negative feedback loops that force economic agents to make decisions that lead to static equilibria. However, the real economy also contains positive feedback loops. Consequently, neoclassical economic models can lead to inaccurate predictions. More importantly, many economic phenomena become path dependent. The result is that outcomes can be intrinsically unpredictable because they become sensitive to small changes in inputs.

For example, Arthur found that in circumstances with increasing returns, technology selection becomes path dependent and inferior technologies can actually be “locked-in” by incidental events [Arthur 1989]. Another study that employed an agent based model of the stock market found deviations from the standard rational expectations hypothesis and was able to replicate bubbles and crashes similar to what is seen in the real stock market [Palmer et al. 1994; LeBaron et al. 1999].

In an analysis directly applicable to enterprises, Christen et al. [2008] considered different control strategies at both the firm and economy level. Their results suggest that an over emphasis on efficiency may actually reduce the robustness of a firm by limiting the flow of information in the social network. They also found that, at the macroeconomic level, complex control schemes may actually exacerbate instabilities in a market versus a fixed-limiter control mechanism.

Kempf [2008] considers the illusion of control in managing enterprises. While traditional optimization approaches can be used to maximize the efficiency of production processes, an inability to forecast market behavior accurately limits the gain from this optimization. As the complexity of an enterprise increases, prediction becomes even more difficult, and decision makers may mistake noise for signal, resulting in wasted effort.

Thus, it would seem that most enterprises are embedded in a highly unpredictable social system, the economy. Adding cultural and political phenomena to the picture are unlikely to improve the situation.

Recognizing the difficulty of management decisions under such circumstances, Snowden and Boone [2007] developed the Cynefin framework to guide leaders in shifting their decision making approach depending on the circumstances. This framework consists of five domains: simple, complicated, complex, chaotic, and disordered. Leaders should alter their approach to problem solving depending on which of the domains they find themselves in.

While not phrased this way by Snowden and Boone, their framework essentially advocates adjusting strategy based on the epistemic limitations of the current situation. The idea of shifting strategy based on the context is certainly applicable to enterprise engineering. In particular, determining whether one is dealing with organized or disorganized complexity is critical. As we will consider in the subsequent sections, it is likely that one will have to implement a mixture of strategies to influence an enterprise.

4. EXAMPLES OF ENTERPRISE SYSTEMS

It is very difficult to discuss enterprise systems in general. A major difficulty is that context matters. In the absence of context, the discussion is, at best, rather abstract. This section elaborates six examples of enterprise systems that were carefully chosen to stretch the overall intellectual framework presented in this paper.²

We first discuss deterring or identifying counterfeit parts in aerospace and defense systems. In this case, the systems of interest were engineered, as was the organizational system for procuring these systems. The second example concerns financial systems and the bursting of bubbles. The investment products of interest were engineered or designed, as was the context of investment, although the context was not typically thought to be an example of engineering.

The next two examples focus on cities. First, we consider human responses to urban threats (e.g., hurricanes) and urban resilience. Then, we focus on one specific urban system in the context of traffic control via congestion pricing. In both cases, we have engineered networks of urban infrastructure embedded in the complex behavioral and social contexts of contemporary cities. For these examples, much less is designed in a formal sense. Many phenomena are emergent.

The final two examples address healthcare. First, we address the impacts of investments in healthcare delivery and how payment schemes affect investments and consequent health outcomes. We then address a particular health threat – human biology and cancer. This is an enterprise system in that the biological system succeeds or fails in the context of human lifestyles and environmental risks and consequences. Overall, these examples range from broad socioeconomic systems to individual humans functioning in a broader context.

4.1. Deterring or Identifying Counterfeit Parts

Thousands of suppliers provide millions of parts that flow through supply chains to subsystem assembly and then final assembly of the overall system. Performance and reliability of these parts determines performance and availability of the overall system to serve its intended purpose, for example, transportation, defense, etc. Downward pressures on suppliers’ pricing of parts potentially undermine suppliers’ profit margins, motivating them to cut costs somewhere. Leaning of materials and production costs reaches diminishing returns

²Earlier versions of the analysis of these enterprise examples were presented in Pennock and Rouse [2014a, 2014b].
for one or more suppliers, which causes them to intentionally decrease quality of parts. Counterfeit parts are detected by increased and tightened inspection and/or inhibited by economic incentives for suppliers, both of which exacerbate cost problems.

4.2. Financial Systems and Bursting Bubbles

Demand for high-quality investments exceeds available supply. The financial sector is incentivized to increase supply by selling low-quality investments. Financial engineers create new derivatives that combine previously high-risk investments in a way that is intended to reduce the overall risk based on the assumption of low correlation among assets. These derivatives are sold as high-quality investments. This lowers the cost of capital to previously low-quality investments. This results in over-investment in low quality assets, which increases prices and consequently returns on investment for asset holders. Demand for additional low-quality assets increases. As the demand for low-quality assets exceeds supply, suppliers lower minimum standards and/or create fraudulent assets. The resulting positive feedback loop creates an asset bubble that introduces a systemic risk that increases the underlying risk of the “high-quality” derivatives, that is, the bubble increases correlation among the assets. Eventually, the lowest quality assets begin to default, causing a chain-reaction resulting in a crash of financial markets.

4.3. Human Responses and Urban Resilience

A projected storm surge leads to predictions of flooding within a specific urban topography. Projected flooding leads to anticipated deterioration of infrastructure for transportation, energy, etc. Projections are communicated to inhabitants and subsequently communicated among inhabitants, resulting in altered perceptions. Perceptions (and later experiences) of impending deterioration lead people to adapt by planning to move to higher ground or to leave the area. Plans are shared among inhabitants, resulting in altered intentions. Intentions to move or leave enable projections of demands on urban infrastructure. Projections result in altered communications to inhabitants as well as among inhabitants. The results can range from resilient responses to complete gridlock.

4.4. Traffic Control via Congestion Pricing

Congestion in particular urban areas causes increased transit times in these areas. Time-varying time-unit pricing is adopted for use of these roads. Government likes the revenue. Business in these areas may be concerned about loss of traffic. Motorists respond by avoiding these areas and using other roads or modes of transportation. Increasing demands for alternatives affects congestion in these areas. Motorists communicate with each other in search of shortcuts and avoiding tolls. Thus, flows affect pricing, and pricing affects flows, with no guarantee of equilibrium.

4.5. Impacts of Investments in Healthcare Delivery

Demand for services (e.g., chronic disease care) and payment models (e.g., by Medicare) drive investments in capacities to provide services by healthcare providers. Capacities in the form of people, equipment and facilities are scheduled to meet demands. Use of capacities as scheduled results in outcomes, costs, and revenue. Quality of outcomes results in decreased demands for some services (e.g., reduced Emergency Department visits and in-patient admissions), but increased demands for others (e.g., out-patient chronic disease management). More subtly, decreased capacities to care for diseases with low payments can cause increased prevalence of other diseases – for instance, poor care for early diabetes mellitus leads to increases in coronary heart disease.

4.6. Human Biology and Cancer

Human genes express proteins that result in 50 trillion cells, with several hundred distinct types, that compose tissues that, in turn, compose organs, muscles, etc. within cardiovascular, pulmonary, vestibular, etc. systems. The nervous system, a network of specialized cells, coordinates the actions of humans and sends signals from one part of its body to another. These cells send signals either as electrochemical waves traveling along thin fibers called axons, or as chemicals released onto other cells. Signaling aberrations result in dysfunctions in the control of cellular processes, for example, cell growth and death, resulting in diseases such as cancer. Targeted therapies, for example, signal transduction inhibitors, can be used to treat cancers that result from aberrations to signaling pathways involved in cell growth. Cancers evolve in how they react to therapies.

4.7. Comparison of Examples

Table II compares the six examples in terms of historical narratives, ecosystem characteristics, organizations and processes, and people or basic elements. The framework of Harvey and Reed [1996] influenced the terminology chosen for this tabulation.

From these comparisons, we can see that these six examples have several common characteristics:

- All involve behavioral and/or social phenomena, directly or indirectly
- All involve effects of human variability, both random and systemic
- All involve economics (pricing) or financial consequences
- All include both designed (engineered) and emergent aspects

There are also important distinctions:

- Counterfeit Parts and Financial System involve deception by a subset of the actors
- Healthcare Delivery and Human Biology involve aberrant functioning by a subset of the actors
<table>
<thead>
<tr>
<th>Levels of Phenomena</th>
<th>Counterfeit Parts</th>
<th>Financial System</th>
<th>Urban Resilience</th>
<th>Congestion Pricing</th>
<th>Healthcare Delivery</th>
<th>Human Biology</th>
</tr>
</thead>
<tbody>
<tr>
<td>Historical Narrative</td>
<td>Aerospace/defense ecosystem in terms of decision processes and incentives</td>
<td>Evolution of financial ecosystem in terms of investment instruments, regulations, etc.</td>
<td>Evolution of urban ecosystem in terms of social development, communities and neighborhoods</td>
<td>Evolution of transportation ecosystem in terms of technologies, demographics and expectations</td>
<td>Evolution of healthcare ecosystem in terms of ends supported and means provided</td>
<td>Evolution of humans in terms of genes, proteins, cells, tissues, organs, systems and signaling</td>
</tr>
<tr>
<td>Ecosystem Characteristics</td>
<td>Aerospace/Defense ecosystem -- norms, policies, values and supplier economics</td>
<td>Financial ecosystem -- what is assumed, allowed, illegal, and enforced</td>
<td>Urban ecosystem -- norms, values and elements of social resilience</td>
<td>Transportation ecosystem -- norms, values and expectations of convenience</td>
<td>Healthcare ecosystem -- norms, values and resource competition</td>
<td>Human biological ecosystem, including factors such as lifestyle and environment</td>
</tr>
<tr>
<td>Organizations and Processes</td>
<td>System assembly and deployment networks and controls; test and evaluation</td>
<td>Commercial and investment banks, mortgage companies, and regulatory agencies</td>
<td>Urban infrastructure networks and flows -- water, food, energy, and people</td>
<td>Transportation infrastructure networks and flows, and control systems</td>
<td>Provider, payer and supplier organizations -- investments, capacities, flows, outcomes</td>
<td>Cardiovascular, pulmonary, digestive, nervous, reproductive, etc. systems</td>
</tr>
<tr>
<td>People or Basic Elements</td>
<td>Flow of parts in supply chain to assembly and deployment</td>
<td>Investors, financial engineers, traders, and homeowners</td>
<td>Peoples' evolving perceptions, expectations and decisions, as well as shared beliefs</td>
<td>Individual vehicles and driver decision making in response to flows and controls</td>
<td>People's health and disease incidence, progression and treatment</td>
<td>Cellular processes and signaling mechanisms; therapy decisions</td>
</tr>
</tbody>
</table>
● Congestion Pricing and Urban Resilience involve aggregate consequences (e.g., traffic) of all actors.

Another important distinction is between two classes of problems:

● **Bottom-Up:** Detection and remediation of aberrant actors involves stratifying actors and exploring behaviors of each stratum in different ways.
  ○ Aberrant actors tend to react to remediation strategies, eventually undermining their effectiveness.

● **Top-Down:** Economic strategies, for example, pricing, payment models, procurement practices, based on aggregate behaviors.
  ○ Individual actors tend to react to aggregate strategies, often undermining the desired consequences.

Considering how the phenomena associated with these examples might be represented, three common features should be noted. First, the set of phenomena associated with a problem can be represented at different levels of abstraction, for example, individual instances of counterfeiting versus macroeconomic policies that motivate counterfeiting. Second, each example has phenomena of interest that emerge within each layer of abstraction. This would suggest that a different representation of the enterprise system would be relevant for each layer. Third, each example exhibits feedback loops that cut across two or more layers. For example, the incentive to counterfeit increases with declining supplier profit margins. High-level policies designed to combat counterfeiting could raise costs at the lower levels. This could further erode profit margins and actually increase the incentive to counterfeit. Thus, the counterfeiting problem cannot be addressed without considering the relationships between the different layers of the enterprise system.

The analysis of these six problems is consistent with the difficulties identified during the discussion of complex social systems. Therefore we would expect challenges to modeling and prediction including but not limited to:

● Multiple, overlapping layers of abstraction
● Evolving behavior
● Path dependence
● Multiple potential equilibria
● Cascading effects
● Vulnerabilities in signaling and control

Examples of how each of the six enterprise systems exhibits these attributes are provided in Table III.

5. IMPLICATIONS FOR ENGINEERING ENTERPRISE SYSTEMS

As discussed previously, a hypothetical enterprise engineer would like to design interventions to steer the enterprise system in a desirable direction. However, the discussion and examples have made clear that the complexity of social systems, both internal and external to the enterprise, introduce epistemic limitations that make it difficult to do so. The enterprise engineer simply would not know everything that he or she would need to know to produce a reliable “design” for the enterprise.

The difficulties associated with modeling enterprises have strategy implications. At a high level, traditional engineering entails searching the design space for a solution that, while perhaps not truly optimal, is good enough with some degree of confidence. We often use models to aid us in this search. But for the previously described enterprise problems, we may have difficulty building valid models to assist in the search for solutions. Even if we can build a functioning model, it may require so many assumptions that we have very low confidence in its outputs.

Unfortunately, the real world is indifferent to our ability to model, and the challenges that exist in the enterprises previously described must still be addressed. The limitations on our ability to model may limit our ability to assess the efficacy of an engineered solution in advance of its employment. Consequently, coping with these challenges requires complementing engineering solutions with context driven strategies that allow for dynamic responses to emerging events.

5.1. Context Driven Strategies

Our examination of the six enterprise examples revealed that a would-be enterprise engineer may be concerned with any number of phenomena ranging from the adverse actions of external actors to aberrant human behavior to a breakdown in communications. For any given enterprise, there are likely to be multiple such phenomena, each seeming to merit a response.

Two questions logically follow: what strategy options do the decision makers have available to them and what criteria determine when they should select one strategy over another? Two criteria seem immediately relevant: 1. the ability of the decision maker to accurately predict the response of the enterprise and/or enterprise ecosystem to a design or strategy decision and 2. the ability of the decision maker to actually implement the decision. If the decision maker could predict all future responses to the decision, then there is no reason to ever make a change. He or she could determine the optimal policy for every possible circumstance and design the enterprise accordingly. No changes would ever be required. If the decision maker could respond to every new development instantaneously and costlessly, he or she would not need to predict anything. He or she could continuously adapt the engineered interventions as needed.

Obviously, real life lies in between these extremes. For any given enterprise and phenomenon of interest, there will be a different ability to predict and different ability to respond. The implication is that the decision maker’s strategy will change based on the relative values of these two attributes. The predictability of social phenomena has already been discussed extensively. The ability to respond merits additional discussion.

Several factors influence a decision maker’s ability to respond to a development in the social system. The first is the ability to detect that a change has occurred. This may seem trivial at first, but consider the difficulty of measuring
<table>
<thead>
<tr>
<th>Levels of Phenomena</th>
<th>Counterfeit Parts</th>
<th>Financial System</th>
<th>Urban Resilience</th>
<th>Congestion Pricing</th>
<th>Healthcare Delivery</th>
<th>Human Biology</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overlapping Layers</td>
<td>Economic and political conditions; supply chain structure; system design</td>
<td>Economic conditions; regulatory structure; financial markets; consumer decision-making</td>
<td>Economic conditions; political institutions; physical infrastructure; urban population</td>
<td>Economic conditions; transportation network; driver decisions</td>
<td>Economic conditions; regulatory structure; government policies; provider structure; disease progression</td>
<td>Ecosystem; lifestyle choices; genetics; anatomical systems; cell biology</td>
</tr>
<tr>
<td>Evolving Behavior</td>
<td>Counterfeiters change strategies in response to interventions</td>
<td>Participants develop new derivatives and strategies in response to changing regulations</td>
<td>Changes in behavior, polices, and infrastructure in response to past events; deferred maintenance</td>
<td>Drivers change routes, departure times, and living and working locations based on experienced conditions</td>
<td>Providers and patients alter behavior in response to changes to government regulation</td>
<td>Biological evolution in parallel with evolution of medical practices and technologies</td>
</tr>
<tr>
<td>Path Dependence</td>
<td>Opportunities for large scale electronic counterfeiting arose from specific geopolitical conditions; e.g., offsets</td>
<td>Regulatory changes, economic circumstances, available technology, and globalization determine the nature of the bubble</td>
<td>Population responses depend on recent experiences and prevailing conditions; impacts of pervasive communication technologies</td>
<td>Established commuting patterns impact efficacy; social media enables immediate communication of short-cuts</td>
<td>Established capital investments (e.g., hospital capacity) affect care approaches and responses to regulatory changes</td>
<td>Inreversible lifestyle choices and genetics affect the likelihood of cancer and other conditions in the future</td>
</tr>
<tr>
<td>Multiple Equilibria</td>
<td>Counterfeiting profitable; counterfeiting unprofitable</td>
<td>Stable financial system; Failed financial system</td>
<td>Recovered city; diminished / abandoned city;</td>
<td>Free flowing traffic; congestion; constant adaptation</td>
<td>Universal healthcare; wealth based health care</td>
<td>Cancer free; stable cancer; terminal cancer</td>
</tr>
<tr>
<td>Cascading Effects</td>
<td>System failure due to counterfeiter part intrusion; costs of interventions exacerbate motivations</td>
<td>Bubble bursting leads to financial crisis; declining state revenues drive up higher ed costs; student debt undermines home buying</td>
<td>24×7 news, rumors, and misinformation, propagate leading to counterproductive population responses</td>
<td>Pricing and congestion levels lead to the long-term relocation of businesses and residences</td>
<td>Rising costs lead to care avoidance, which leads to more expensive and less effective corrective procedures</td>
<td>Cancer can lead to cascading failures of anatomical systems and ultimately death</td>
</tr>
<tr>
<td>Signaling and Control</td>
<td>Deception of inspection methods</td>
<td>Gaming of investment risk rating systems</td>
<td>Communication failures and misinformation</td>
<td>Price viewed as proxy for congestion level</td>
<td>Gaming of payment and reporting structures</td>
<td>Cancer is the result of failure of the body’s signaling and control system</td>
</tr>
</tbody>
</table>
Strategic framework for enterprise decision makers

![Figure 2. Strategic framework for enterprise decision makers (Updated from Pennock and Rouse [2014b]).](image)

macroeconomic phenomena. Metrics such as unemployment, gross domestic product, and inflation are often subject to long measurement time lags and multiple revisions. Furthermore, there are often biases inherent in the measurement techniques. Consequently, determinations such as whether or not an economy is in a recession are often contentious and not settled until long afterward.

The second factor is the capacity to respond. In other words, does the decision maker know what to do, and is he or she capable of doing it? If there is no known way to respond to an event or the decision maker is not capable of implementing the response, the outcome is the same. For example, changes to a foreign country’s import policies may have a substantial impact on a firm, but there may be nothing that the firm can do about it.

The third factor is the speed of response. The decision maker must be able to implement the response before the consequences of the event are too severe to recover from. For example, if a competitor introduces a rival product that is vastly superior, a firm may have the ability to introduce a comparable product, but if it does not introduce it quickly enough, the firm may lose too much market share to recover.

The fourth and final factor is the cost of the response. The decision maker may be capable of responding quickly and correctly, but the response may be unaffordable. For example, an upstart competitor may be using a new, more efficient production technology that reduces costs, but the incumbent firm has such a large established production infrastructure that converting would be cost prohibitive.

Given different abilities to predict what could happen and respond to it, what options are available to enterprise decision makers? We contend that there are four basic strategies that decision makers use: optimize, adapt, hedge, and accept (Fig. 2).²

If the phenomena of interest are highly predictable, then there is little chance that the enterprise will be pushed into unanticipated territory. Consequently, it is in the best interest of decision makers to optimize their interventions to be as efficient as possible. In other words, if the unexpected cannot happen, then there is no reason to expend resources to make the system more robust, resilient, or flexible.

If the phenomena of interest are not highly predictable, but it is relatively straightforward to adapt interventions appropriately, it may be in the best interest of the decision maker to plan to adapt. For example, decision makers may decide to implement an engineered system within an enterprise using a modular architecture that will allow them to change out modules as needed to respond to evolving circumstances. In this case, some efficiency has been traded to improve the ability to adapt. For the social system, the previously discussed guided self-organization approach may be appropriate. General constraints and guidelines may be set, but participants are allowed to adapt to local circumstances.

Models can help us explore the space of possibilities even if we cannot predict what will happen. However, for this approach to work the participants within the enterprise must be able to identify and respond to potential issues faster than the social system changes. For example, when we consider congestion management, new transportation projects often take years to plan and execute. By the time they are complete, traffic congestion may have changed or the project may simply serve to move the congestion around. Drivers can respond much faster than the government can make changes to infrastructure.

If the phenomena of interest are not very predictable and decision makers have a limited ability to respond, it may be in their best interest to hedge their position. In this case we can use our models to aid in exploration of scenarios, but our system may not be able to handle sudden changes without prior investment. For example, a firm concerned about product obsolescence may choose to invest in multiple, potential follow-on products. While the firm does not know which product will ultimately succeed in the marketplace, it will be ready to take advantage of whichever product ultimately does. If the firm were to take a wait and see approach, it would not be able to respond quickly enough, and it would lose out to its competitors.

If the phenomena of interest are totally unpredictable and there is no viable way to respond, then decision makers have no choice but to accept the risk. Accept is not so much a strategy as a default condition. In other words, if one is attempting to address a problem where there is little ability to predict the efficacy of solutions and little ability to adjust the solution once implemented, then there is nothing that engineering can do to address the problem. Any engineered solution would be tantamount to the expenditure of resources on a wild guess.

To illustrate this point, let us consider an extreme example. A global nuclear war would likely destroy many enterprises. However, there is no basis for estimating the likelihood of such an event, and there is nothing that most enterprises can do to respond. Consequently, few nonnational security oriented enterprises are likely to have a contingency plan for a global nuclear war.

To make the strategies more concrete, we can reconsider the six example enterprise systems. Table IV presents examples of each type of strategy that could potentially be applied within each enterprise system. This table is intended to be

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²The optimize, adapt, hedge, framework was first presented in Pennock and Rouse [2014b].
### Table IV. Strategies Applied to Example Enterprise Systems

<table>
<thead>
<tr>
<th>Example System</th>
<th>Optimize</th>
<th>Adapt</th>
<th>Hedge</th>
<th>Accept</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counterfeit Parts</td>
<td>- Optimize supply chains assuming counterfeits are detectable</td>
<td>- Redesign obsolete systems</td>
<td>- Buy a lifetime supply of parts up front</td>
<td>- Buy on the open market and accept the risk of counterfeits</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Employ modular architectures</td>
<td>- Own the manufacturing process</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Adapt inspection approaches as counterfeiters adapt</td>
<td>- Design for fault tolerance</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Redesign obsolete systems</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Employ modular architectures</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Adapt inspection approaches as counterfeiters adapt</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Financial System</td>
<td>- Write fixed laws and regulations governing financial markets</td>
<td>- Bail out firms considered too big to fail</td>
<td>- Enforce reserve requirements</td>
<td>- Deregulate financial markets</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Open market operations in response to changing financial situation</td>
<td>- Stress test financial institutions</td>
<td></td>
</tr>
<tr>
<td>Urban Resilience</td>
<td>- Optimize urban infrastructures and emergency response capabilities against environmental and demographic projections</td>
<td>- Adjust emergency response deployments as events unfold</td>
<td>- Apply zoning rules to limit damage exposure</td>
<td>- Accept that flood mitigation measures will fail for a storm surge greater than a certain level</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Empower personnel on the ground to make decisions</td>
<td>- Purchase spare capacity for both infrastructure and emergency response</td>
<td></td>
</tr>
<tr>
<td>Congestion Pricing</td>
<td>- Optimize road layout and tolls against traffic projections</td>
<td>- Change toll prices</td>
<td>- Build road capacity in excess of projected usage</td>
<td>- Accept congestion pricing may not alleviate traffic due to accidents and disruptions</td>
</tr>
<tr>
<td>Healthcare Delivery</td>
<td>- Optimize facility capacities for expected utilization</td>
<td>- Reschedule patients to accommodate unexpected delays</td>
<td>- Maintain extra facility capacity to accommodate surges in demand</td>
<td>- Accept that variability degrades service</td>
</tr>
<tr>
<td>Human Biology</td>
<td>- Optimize therapeutic regime based on clinical results</td>
<td>- Adapt treatments to patient comorbidities</td>
<td>- Make lifestyle choices that reduce the risk of cancer</td>
<td>- Accept that cancer evolves</td>
</tr>
</tbody>
</table>

Illustrative not comprehensive. It is important to note that strategies will depend on the perspective and the scope of responsibility of the decision maker of interest and the issue of concern. Most real life situations will involve a mixture of strategies.

In a sense, this strategy framework could be viewed as an adaptation of Thompson’s [1967] views on organizations to the enterprise modeling problem. Thompson argued that the decision making approach of an organization is driven by uncertainties and complexities that it faces. When cause and effect relationships as well as objectives are clear, efficiency becomes the driver and decision making becomes computational. As cause and effect relationships become less clear, there is a shift toward judgment. (Thompson also included cases where objectives are ambiguous, but considered them problems of social psychology.) Furthermore, different components of the organization may exhibit different decision making strategies. The difference here is that rather than a clear break between complete and incomplete understanding of cause in effect at different levels of an organization, we are dealing with gradations of uncertainty across levels of abstraction.

### 5.2. Implications of Modeling Difficulties

Given that a decision maker within an enterprise is likely to be concerned with a number of phenomena both internal and external to the enterprise, one would ideally like to develop a family of strategies to address these phenomena. By recognizing the epistemic limitations, one can tailor modeling and simulation efforts to support strategy development. For example, one is likely to build a very different model if one is pursuing a hedging strategy versus an optimize strategy.

There are essentially two objectives for this modeling effort:

- Explore the tradeoffs among strategy options to address a phenomena of interest
- Ensure the consistency of a family of strategies

The intent of the second objective is to ensure that the implementation of a strategy to address one phenomenon does not interfere with a strategy to address another phenomenon or generate counterproductive responses among other phenomena.

However the epistemic limitations have implications for realizing these objectives. In particular:

- There is no complete model of the enterprise or its ecosystem. We will always be leaving something important out.
- One cannot obtain conclusive answers from modeling and simulation. They can only be used to support decision makers and engineers in exploring trades.

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No single ontology can represent a whole enterprise problem. Multiple models will be needed to explore trades.

- Strategies developed to address phenomena in different ontological layers may interfere with each other. Model composition is needed to check the consistency of strategies.

In short, we will need to develop and compose models from multiple domains to support enterprise engineering and strategy development. This approach to modeling goes by several names such as multi-level, multi-scale, and multi-resolution modeling.

As an illustrative example of modeling an enterprise system, consider the health care delivery enterprise examined by Park et al. [2012]. In that work, the authors analyze the performance drivers of an actual employer-based prevention and wellness program. Table V provides a high-level summary of their approach.

First, they decompose the enterprise into four layers ranging from the overarching healthcare ecosystem down to the clinical practices used to treat individual patients. Each of these layers present different phenomena that the health care enterprise must contend with if it is to operate effectively. Second, the authors identified the potential design decisions that a would-be enterprise engineer would need to make to address each of the phenomena. Table V presents some representative examples of these design decisions for each layer. Ultimately, the authors built a simulation of this enterprise and analyzed the impacts of the design decisions. What we can draw from this example is that engineering an intervention to influence an enterprise involves modeling a range of human and social phenomena at different layers of abstraction.

Unfortunately, the very limitations that push us toward a multi-level approach also complicate the composition of these models. The symptoms of a deeper theoretical issue are evident in the modeling and simulation literature. As an example, Wang et al. [2009] posit that the High Level Architecture (HLA) standard for federating simulations (IEEE 1516–2010) has experienced issues in part because it neglects higher level conceptual interoperability between models. In fact, the Journal of Simulation devoted a special issue to the topic of composition entitled “Enhancing simulation composability and interoperability using conceptual/semantic/ontological models,” (Vol. 5, No. 3) [Tolk and Miller 2011]. The use of ontology is key to understanding the challenges.

Coordinating ontologies among simulation models as a means to improve model composition has been examined repeatedly. Hofman et al. 2011, Hofman 2013, McGinnis et al. 2011, Partridge et al. 2013, Tolk and Miller 2011]. Hofman [2013: 77] asserts that, “For many technical domains and artificial systems, ontologies will be able to ensure the interoperability of simulation components developed for a similar purpose under a consensual point of view of the world.”

However, when we expand the scope and attempt to integrate human and social phenomena into a traditional engineering model, difficulties arise. Hofman [2013: 79] points out that, “…in many socio-technical and most social domains the specification of such ‘well defined’ domain ontologies (referential ontologies) will be impossible… Hence, in these cases, there is no easy mapping possible between referential and methodological ontologies… This mapping, if possible at all… would not be a technical matter, but a challenging and subjective task of selection.”

The conclusion we can draw here is that it is unlikely that there is any final theoretical solution that will resolve all of these difficulties. However, this does not mean that it is not possible to selectively model enterprises to address particular questions of interest. Restricting an enterprise modeling effort to just what is needed to address a targeted set of questions can substantially reduce the complexity of the endeavor in terms of reducing the amount of rectification that must occur among model ontologies. This does not make the problems go away; it merely mitigates them, more in some cases than others. Consequently, research is still required to address these difficulties even when the problem scope is managed.

### 6. RESEARCH AGENDA

The intent of this paper was to advocate a shift in perspective. While systems engineering approaches can bring value to efforts to engineer enterprise systems, their emphasis on prediction and control can be counterproductive because of the epistemic limitations inherent in the study of social systems. Consequently, we must shift our emphasis away from control and more toward influence. Even with that recognition there are still substantial methodological challenges to exercising influence on enterprise systems. Several have been highlighted in this work.

Many of the challenges to understanding and influencing enterprises are not new. What has changed in recent decades is the widespread availability of low cost computing capabilities and the automated, large-scale collection of data. These developments seem to have led many to believe that they could address complex, multi-faceted problems by fitting models to each relevant new data source and then simply jamming them together to draw inferences. As this paper and other works [Hofman 2013; Pennock and Rouse, 2014b] make clear, this is a nontrivial undertaking.

While there are some larger questions here with regard to making causal inferences under such circumstances, in this paper we will limit ourselves to how we might address such
issues within the scope of understanding and influencing enterprise systems. To that end, we have developed a research agenda to identify areas where additional work is required. We expect that the expertise of multiple disciplines including the physical sciences, social sciences, and engineering will be required to make progress against this agenda.

In short, our research agenda is driven by three questions:

- How can we effectively model enterprise systems when doing so involves the simultaneous consideration of multiple models at multiple layers of abstraction?
- How can we draw inferences about enterprise systems given the potential gaps and/or inconsistencies among the multiple models?
- How can we leverage enterprise models to develop strategies to influence as opposed to control enterprise systems?

The resulting research agenda is an evolution of a previous set of research questions developed through a series of NSF workshops on complex engineered, organizational, and natural systems and documented in Rouse [2007]. Over the intervening years, this list had been presented and updated via approximately twenty talks given by Rouse. This resulted in a set of research topics regarding the modeling of complex systems and enterprises and documented in Rouse [2015]. However, that set of topics is focused on specific technical issues associated with developing multi-level simulations. Based on the analysis presented in this paper, it was deemed necessary to broaden that research agenda to better capture the epistemic issues and multi-disciplinary nature of the problem.

6.1. Representing an Enterprise with Multiple Models

With regard to modeling enterprise systems, most of the issues revolve around selecting modeling ontologies, developing mutually consistent combinations of models, and inferring models from available data sources. Of particular concern are the challenges associated with establishing conceptual interoperability as discussed in Section 5.2. Composing models is an active area of research within the modeling and simulation community. Of particular note is work to apply a branch of mathematics known as model theory to this area. (See Tolk et al. [2011, 2013] and Diallo et al. [2013] for more information)

From an enterprise modeling perspective, we are concerned with how we can decompose an enterprise system into models at different levels of abstraction and aggregation, and then put them back together again to obtain meaningful insights. It is important to note that it in many circumstances it may not be possible to computationally connect all of the various models that represent the enterprise. Thus, in those cases, we would ideally want guidance on when we can and cannot compose multiple models. When we cannot, we need to understand how we can draw inferences from the various models. This is addressed in the next section. Some aspects that are of particular concern for enterprise systems are:

6.1.1. How Should We Decompose Enterprises?

The starting point for modeling an enterprise system is the decomposition of an overall phenomenon, for example, healthcare delivery, into component phenomena at varying levels of abstraction and aggregation. A central question at this point is what phenomena belong in each of the multiple levels? Further, how does the representation of each phenomenon depend on its level? This can be addressed in part by considering natural part-whole relationships. However, the question remains what wholes and what parts are needed to address the question that motivated the modeling initiative?

One of the implications of this paper is that a traditional reductionist approach may not yield viable results. In other words, trying to reduce the enterprise to the smallest units possible and then putting them back together computationally will either not yield correct results or be computationally intractable. This reality tends to push us toward multiple, overlapping layers of abstraction. But how many levels should we have and at what level of fidelity should they be modeled? While this will vary depending on the particular question of interest, for any given enterprise, there are likely tradeoffs to be made. Adding levels of abstraction increases the likelihood of capturing critical behaviors of an enterprise system but also increases cost of the modeling effort as well as the risk of model induced errors due to incompatibilities and feedback among the layers. Increasing the understanding of such tradeoffs and developing guidelines for selecting the appropriate layers for a given problem would be invaluable for enterprise modelers.

6.1.2. How should We Integrate Noncomputational Models into the Representation?

As Harvey and Reed [1996] ably noted, the appropriate type of model shifts as we move up the layers of abstraction. Consequently, the range of applicability of computational models decreases as we move away from physics and toward the social sciences. This is not to suggest that there are no applications for computational modeling in the social sciences; there are many. Rather the point is that there are important phenomena within social sciences that we may not be able to capture using a computational model, or if we can, we may not be able to tailor it to specific circumstances. For example, agent-based models of stock markets can reproduce important features of real stock market behavior, but they are often highly simplified to remain tractable (e.g., modeling only a single stock). This limits our ability to directly compose such a model with a computational model of a specific enterprise.

This circumstance introduces a dilemma. Simply throwing out any aspect of the enterprise that we cannot capture computationally introduces a tremendous amount of model-induced risk. The phenomena in question are objects of academic study because they do have important impacts. Neglecting them could have extremely adverse consequences. De Bruijn and Herder [2009] argue that we should simultaneously consider both perspectives and not attempt to directly integrate them. Thus, the challenge is how do we use noncomputational models of an enterprise to influence computational models of enterprises and vice-versa? Of course, this can and has been done on an ad-hoc basis, but it would be extremely useful to enterprise modelers and decision makers to have a systematic approach to accomplish this.
6.1.3. How can We Map the Various Models to Each Other?
When we do have multiple computational models of the enter-
prise, the question remains as to how to map them to one
another in a meaningful way. The choice of which phenomena
will be represented at each level leads to choices of how to
characterize each phenomenon. Each representation will have
defined input-output variables. The next question is what vari-
ables cross the levels between representations? Further, what
transformations are needed to connect across levels? Basic
issues here include units of measure, coordinate systems, and
time. Zeigler et al. [2000] address these issues within the
context of dynamic systems.

It is important to note that resolution of these basic issues
is necessary but not sufficient for assuring Tolk’s [2003] con-
ceptual interoperability. Being able to connect two models
and have them jointly compute some outputs does not assure
that these outputs are valid and meaningful. The issue here
is one of “assumption management.” Are the assumptions
of the two or more interconnected models compatible? This
is sometimes manageable when the same modelers are the
creators of all the component models but far from easy when
some of the component models are legacy software codes.

As noted above, this is an active area of research in the mod-
eling and simulation community, but it is likely that there is
no general solution to the problem. In other words, sometimes
it will work, and other times it will not. Enterprise modelers
need guidelines to understand which circumstances apply to
their situation.

6.1.4. How Can We Scale Enterprise Representations as
We Increase the Scope
of Problems Addressed?
It is often the case that models begin with only a small number
of simulated agents (e.g., patients) or only a fraction of the
entire network that is of interest. The intention is to scale
up such smaller models to address the whole problem of
interest once experience and confidence is gained with the
initial models. Scaling is often very difficult and results in
large unfathomable models that compute very slowly. The
modelers can lose any intuitions of what is happening in the
scaling process.

The first question is, given the targeted scale of the mod-
eling effort, what should be the unit of scale for each phe-
nomenon? A related question is by what quantum does each
unit scale? Perhaps millions of patients are better simulated as
cohorts rather than individuals. Perhaps the flow of thousands
of vehicles should not start with the dynamics of each vehicle,
but instead consider waves of vehicles.

Of particular concern is the risk of uncaptured emergent
phenomena as enterprise models are scaled up. This is one
of the chief concerns of complexity science, and it would
be useful to have indicators of when a system phase shift or
bifurcation is possible so that enterprise modelers can at least
manage the associated model risk.

6.1.5. How Do We Extract Models from Large Data Sets?
With the growing availability of large data sets in both the
commercial and social realms, it would seem natural to at-
tempt to learn as much as we can from these data sets when
modeling a particular enterprise. The question of interest here
is how can structural properties of processes be inferred from
design and operational data sets? This is important because
many complex systems have no “as is” blueprints, that is,
such systems emerged rather than being designed. Instead,
one may have data on millions of transactions throughout the
system’s processes. One needs to have approaches that can
infer processes from such data sets, often without any baseline
process maps to help with validation.

The underlying complexity of enterprise systems, particu-
larly the social aspects, makes it challenging to extract caus-
als models from large data sets. This challenge is actually much
larger than just enterprise systems. An example of active
research work in this area is the DARPA Big Mechanism
Program which seeks to extract causal pathways from indi-
vidually studied phenomena [DARPA 2015a]. For example,
how could one extract potential causal pathways for cancer by
analyzing the extensive cancer biology literature? There are
analogous questions in the realm of enterprise systems. Con-
sequently, any progress in this domain would greatly benefit
enterprise modeling.

6.1.6. How can We Curate and Reuse Effective Approaches
for Enterprise Modeling?
Given that enterprise modeling will frequently involve the
consideration of models from multiple disciplines, it is likely
that an enterprise modeler will need to employ models for
which he or she is not an expert. The natural approach might
seem to be to simply employ the “best of breed” model from
each domain and combine them. As noted by Pennock and
Rouse [2014b], this approach entails considerable risk, not the
least of which is the black-box effect. At the other extreme,
it would clearly be folly to reinvent the wheel for each enter-
prise modeling effort. Consequently, it is necessary to find a
practical way to reuse techniques and models developed by
various disciplines for enterprise modeling. This would mean
at least mitigating the black-box effect.

Rouse [2015] and Rouse and Bodner [2013] outline a
wealth of component models for potential inclusion in en-
terprise models. However, this wealth is not often used.
This is due to both a lack of knowledge of these resources
and difficulty in accessing them [Rouse and Boff, 1998].
Professionals in modeling and simulation seldom access the
academic journals originally reporting these models. Even
when practitioners are aware of such publications, they are
seeking computer codes, not research treatises.

How can component models be represented, archived,
maintained, and accessed to facilitate rapid model integra-
tion? Put simply, these resources need to be curated. There
needs to be one point of access for the many hundreds of
models discussed by Rouse and Bodner. This access should
enable downloading computer codes, documentation on as-
sumptions and use, and original reports of the development
and validation of these models. Of course, this begs the basic
question of how participating organizations can be incenti-
vized to contribute to and make use of the curated archive?

6.2. Drawing Inferences from Enterprise Models
Assuming that enterprise models are amalgamations of mul-
tiple models at different levels of abstraction with some of
these not computationally connected with the others, we are faced with the dilemma of how we can draw inferences from such a Frankenstein’s monster. This is where the epistemic issues really come to the forefront. First, such models are difficult to validate and entail a great deal of model risk. For instance, it might be very easy to make a change in one component model that pushes another component model into a zone where it is invalid. Second, if some of the models are not computationally connected, how can we infer causal pathways between them?

6.2.1. How should We Manage Model Uncertainties?
Structural and parametric uncertainties can have far-reaching effects as they propagate across representations and levels of the overall model. This raises the question of how uncertainties can best be propagated across multiple representations at multiple levels? In particular, how is the variability associated with one level propagated to other levels when simple propagation of point estimates is insufficient?

For physical models, this problem is sometimes termed “uncertainty quantification.” For specific examples of work in this area, see Eldred et al. [2011] and Roy and Oberkampf [2011] for approaches to deal with mixed epistemic and aleatory uncertainty as well as Sandia National Laboratory’s [2015] Dakota Project. For extensive review of the literature combining uncertainty quantification with optimization see Yao et al. [2011]. In an attempt to broaden the application of uncertainty quantification to the propagation of uncertainty through multi-scale physical models, DARPA [2015b] has introduced the EQUIPS program.

While such analysis would be useful for enterprise modeling, enterprise models present some additional complications. The above methods focus on parametric uncertainty. In other words, how does error in a particular parameter or probability distribution propagate through the model? (Though it should be noted that Roy and Oberkampf consider model form uncertainty via extrapolation of error from experimental data.) Enterprise models also entail considerable structural uncertainty. Is the structure of the component model correct for the circumstances? Should the structure of the model change over the space of interest for a particular problem? How might a change in one component model necessitate a structural shift in another component model? How does structural uncertainty in one component model propagate through the combined model of the enterprise? Thus, understanding the propagation of model uncertainty in enterprise systems requires something more than current efforts in uncertainty quantification. For enterprise systems, understanding when and how system bifurcations impact model uncertainty could be critical to managing model risk.

6.2.2. How can We Draw Inferences from Uncoupled Models?
As noted previously, enterprise models are likely to involve multiple component models and these may not all be computationally connected. If that is the case, how do we understand how a change in state of one component model affects the state of another component model? How do we incorporate noncomputational models?

One possibility is to leverage the human mind as the integrating element. Here interactive visualization is key. The objective of enterprise visualizations would be to allow one or more analysts, decision makers, or stakeholders interact visually with the various component models. This is very much in line with physicist Sean Gourley’s [2012] concept of augmented intelligence.

If models are to be used to support a wide range of decision makers, the model outputs have to be accessible by people who are far from modeling and simulation experts. This raises the question of how the “state” of a multi-level system can best be characterized and portrayed. The answer to this question should be determined by the nature of visualizations most meaningful to the key stakeholders in regard to the questions targeted via the multi-level model.

Beyond portraying the state of the system, stakeholders are often concerned with the nature of relationships between levels of the model. How can the relationships within a multi-level system best be portrayed to enable experimentation and insights? This question concerns how best to enable stakeholders to manipulate the relationships between levels of the overall model. Once stakeholders are “in the loop” of choosing assumptions and manipulating parameters, stakeholder buy-in is usually greatly enhanced.

While interactive visualization seems reasonable, substantial research is required to establish the validity of this approach. Just because a user interacting with an enterprise visualization feels that he or she has successfully extracted insights does not mean that these insights are correct. The validity of this approach is likely to depend on the specifics of the problem and enterprise system under consideration. Consequently, research is required to determine which factors affect the efficacy of interactive visualization for enterprise analysis.

6.3. Influencing Enterprise Systems
Of course the ultimate goal of modeling an enterprise and drawing inferences from that model is to then affect the future state of that enterprise. One of the central arguments of this paper is that one cannot expect to control an enterprise and instead can only influence it. As discussed previously, this is due to the underlying complexity of the social component of enterprises that often preclude stable cause and effect relationships. This uncertainty is evident in the enterprise modeling challenges previously outlined.

6.3.1. How can We Operationalize the Strategy Framework with Models?
In this paper, we suggested that decision makers manage this uncertainty using a combination of strategies that optimize, adapt, hedge, and accept as appropriate. However, if we would like to use models of enterprises to support decision makers developing such strategies, then it is necessary to operationalize this framework beyond a concept and develop systematic, model-based approaches. Particularly challenging is Efatmaneshnik et al.’s [2012] observation that engineering based techniques such as flexibility engineering not only do not work for complex engineered systems but can actually
make the problem worse. If flexibility and robustness are difficult to build into a complex engineered system, is it possible to handle these with the social components of an enterprise?

6.3.2. How can We Employ Guided Self-Organization?
Another possible approach is to, whenever possible, simply avoid the risk altogether. This is one of the chief ideas behind guided self-organization. Rather than try to explicitly control an enterprise, create the circumstances such that participants in the enterprise self-organize to achieve the desired outcome. An example of this approach from economics is the well-established field of mechanism design. For instance, how does one design an incentive structure for a CEO such that his interests are aligned with the best interests of the company? For more complex scenarios, the previously discussed work of Helbing and Lämmer [2008] and Christen et al. [2008] describe some of the concepts involved. Of course, the challenge here is to adapt these ideas to enterprise problems. How could multifaceted enterprise models be used to evaluate potential guidance mechanisms? How does the model risk affect the risk of mechanism failure? Are there general principles that could be applied to reduce this risk?

6.3.3. How can We Induce Enterprise Transformation?
Finally, there is the notion of leveraging Schumpeter’s [1942] creative destruction to change the state of an enterprise. The hypothesis here is that human social systems accumulate control structures over time. Each control structure is instituted to solve a particular problem, but eventually the cumulative effect is to destabilize the social system by limiting its capacity to adapt to changing circumstances. Thus, the system becomes increasingly at risk of a collapse. There is a notion within complexity science that one might be able to avoid such a collapse by intentionally triggering smaller scale destructive events that give the system an opportunity to transform without actually destroying it completely. (The authors have seen this idea re-iterated many times, but it is unclear to the authors who originated the idea.) This is somewhat analogous to the use of small controlled burns in forestry to avoid a large catastrophic fire.

If this notion is correct, it would presumably apply to enterprise systems as well, but additional research is required to actually validate this concept. Furthermore, if one were to intentionally trigger one of these disruptive events, there may be a great deal of uncertainty as to which of many possible future states the enterprise would end up in. Thus, one would like to know if it is possible to guide the enterprise into the desired end state. Finally, depending on the nature of the trigger event, there could be substantial legal and social implications.

In short, while the notion of triggering metaphorical controlled burns in an enterprise setting is intriguing, a great deal of additional work would be required to validate and operationalize the concept.

7. CONCLUSION
In this paper, we argued that enterprises are essential to the sustainment of our modern society. However, they rarely receive the level of attention and rigor that technical systems do. The challenge to accomplishing this rigor is that enterprises impose technical systems onto social systems. Due to the inherent complexity of social systems, there are epistemic limitations on our ability to model social systems and predict their behavior. Consequently, the traditional engineering approaches that rely on prediction and control can be ineffective or misleading.

Perhaps the more important implication is that these limitations cannot be overcome by simply increasing the fidelity of our simulations. Even if we knew the correct models to build, the complexity of most enterprise systems means that we would run into data collection limitations, computational limitations, or both. Consequently, we are going to have to learn to deal with the fact that, for all practical purposes, we are stuck with modeling enterprises with multiple, possibly inconsistent models. Both the incompleteness and inconsistency entailed in this approach introduce a substantial amount of model-induced risk. However, questions still need to be answered, and decisions still need to be made. Thus, the question becomes how to manage this model risk.

One approach is to introduce context driven strategies that allow the decision maker to optimize, adapt, hedge, or accept as appropriate. Developing the appropriate mix of these strategies for any given enterprise requires explicitly acknowledging the limitations and adapting modeling approaches accordingly. While doing so may seem simple in principle, there are a number of practical and technical challenges that must be overcome. It is no coincidence that overcoming these challenges will require engagement from multiple disciplines, as the epistemic limitations that complicate modeling enterprises are the very same that lead to the existence of multiple disciplines in the first place.

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