Applying multi-modeling to enterprise strategic planning: What can we actually learn?

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***Abstract*—What makes enterprise strategic planning so challenging is the complexity of the enterprise and its environment. This complexity results in phase transitions that necessitate corresponding shifts in strategy. Ideally, strategic planners would like to identify these transitions so that they can plan accordingly. An increasingly popular way to attempt to identify these turning points is multi-modeling, the composition of models that represent the same system with different abstractions. In this paper, we consider whether we learn anything from this approach above and beyond other common approaches such as system dynamics and scenario planning. What we conclude is that multi-modeling occupies a similar epistemological status to system dynamics. We can use it to attempt to identify potential policy turning points, but we cannot be sure that these points are real without an empirical investigation. Multi-modeling has the potential to identify turning points that system dynamics and scenario planning might miss, but at a cost of creating artificial linkage relationships among the system views that cannot be derived logically. Consequently, both techniques can be used to target further investigations or identify risks to be hedged, but neither should really be used for prediction when the subject is an enterprise. In the end, multi-modeling is another tool in the strategic planner's toolbox as opposed to a revolutionary new source of knowledge.**

***Index Terms*—Multi-modeling, strategic planning, scenario planning, system dynamics, complex systems**

I. Introduction

The intrinsic complexity of the social system that makes up an enterprise and its environment is what makes strategic planning difficult. Anyone can extrapolate a trend; the challenge is to forecast or establish the possibility of turning points in the trend. If decision makers can at least achieve the latter, then they can plan to adapt to or hedge against the contingency. Of course, the very complexity of the enterprise itself makes identifying these turning points a daunting task. In past work, the second author argued that modeling and simulation efforts to support decision making for enterprise systems should focus on determining the existence of these turning points to support the formulation of "adapt and hedge" strategies as opposed to finding the "optimal" policy [1], [2].

Yet, the question still stands as to how to actually go about doing this. Multi-modeling has become an increasingly popular approach to support strategy development. However, the assertion that enterprises are complex would seem to argue against the feasibility of this approach. One could make the argument that the fields of system dynamics and scenario planning attempted to accomplish the same thing, and achieved mixed results. So what is different this time? Why would multi-modeling fare any differently?

What we will subsequently argue is that modeling and simulation, in general, can only explore the logical implications of what we know about complex systems. Thus, it can establish the possibility of a turning point but it canno,t establish its existence. This requires empirical evidence. Furthermore, there will be turning points that the simulation misses because they are not the logical consequences of what we know. Our knowledge is always incomplete. Thus from an epistemological standpoint, multi-modeling is probably on the same footing as system dynamics modeling. The chief difference is that it attempts to leverage more sources of knowledge than a system dynamics model would, albeit at the cost of a more complicated model. Still, it avoids some of the subjectivity of scenario analysis. Thus, it is yet another tool in the toolbox as opposed to a revolutionary new approach. As long as it is used appropriately, it can aid analysts and decision makers with strategic planning.

The remainder of this paper is organized as follows. First, we briefly discuss the application of multi-modeling to strategic decision making for enterprise systems. Next we will discuss how the aforementioned turning points are a result of bifurcations or phase transitions driven by the complexity of the enterprise and its environment. Then we will briefly discuss how system dynamics and scenario planning both attempt to identify these turning points. Based on the lessons learned from these two areas, we will reconsider multi-modeling with respect to how it differs from these two approaches and the resulting implications for its application to strategic decision making. Finally, we conclude with a discussion of the status of multi-modeling and future work.

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II. Multi-modeling for strategic decision making

Multi-modeling is becoming an increasingly popular way to support decision making for enterprise systems. In short, the basic idea is that a complex system such as an enterprise cannot be represented via a single abstraction. There are phenomena that are relevant to strategic decision making that occur at different levels of abstraction. Of course, these levels interact in the sense that are all ultimately different representations of the same system. Thus, what happens in one level of abstraction may be relevant to what happens in another. The goal of multi-modeling is to make the relationships among the different levels of abstraction explicit. This, in principle, would allow one to compose models representing each relevant layer of abstraction together into a single model and explore the interactions. This is essentially the approach advocated by Rouse [3]. To illustrate how this works in practice, let us consider a few representative examples.

Park, et al. [4] developed a multi-level simulation to examine policy alternatives for an employee prevention and wellness program. Their model consists of four levels: ecosystem, organization, process, and people. The ecosystem level consists of a set of parameters that could be adjusted to support what if analyses. Some of the parameters include the economic inflation rate, the healthcare inflation rate, and the payment system employed. The organization level also consists of a set of decision parameters that could be adjusted to explore policy options. Some of these parameters include the entering age, the risk thresholds for medical conditions, and the program length per participant. The process level is modeled using a discrete event simulation of the process that patients follow as they move through the care system. Finally, the people level is modeled using an agent-based approach to represent the patients.

The next example, SPLASH, is an effort by IBM Research to develop a framework for loosely coupling models from different domains to support decision making regarding complex socio-technical systems [5]. While SPLASH is not intended solely for health care applications, the team presented an example model that considered the impact of the placement of a health food store on obesity. In the example four different models are composed: VISUM, a proprietary off-the shelf transportation model, an agent-based simulation of buying and eating, a discrete event simulation of exercise, and a differential equation based model of Body Mass Index (BMI). SPLASH mainly focuses on achieving a methodologically valid combination of different modeling formalisms by developing methods to coordinate inputs and outputs, synchronize time, etc.

Finally, the last example we will consider is the Dynamic Multilevel Modeling Framework (DMMF) [6]. DMMF was an effort by the US Department of Defense to leverage its enormous investment in models and simulations. DMMF viewed existing defense models and simulations as falling into one of four levels: campaign, mission, engagement, and engineering. The idea was that if one decided to make a change in a system at the engineering level (say improve its performance), then one should be able to see the impact of that change at the campaign level. Since DoD already had many simulations at each of these levels, the challenge was to create a framework to allow these simulations to interoperate in order to answer such questions.

Ultimately, the DMMF effort ended at the feasibility study stage. The problem was that the study found that such a framework is fundamentally infeasible without substantial human-in-the-loop effort to rectify inconsistencies among the models. The DMMF study raises the important issue of the risks involved when combining such models. We will discuss this notion further in Section V.

With all of these such efforts, we will argue that the intent is to find policy turning points or tipping points. That is a point at which you would want to switch from one policy regime to another. If that were not the case, you more than likely would not need the different abstractions. One abstraction would suffice.

To illustrate the point let us consider the DMMF example. What if an air force is interested in whether or not it should perform an upgrade on its fighter engines to increase speed? Increasing speed is just a means to an end. The reason why they would consider such an upgrade is to improve their chances of winning a war or some other similarly high-level objective. Consequently, decision makers would want to know what the impact of this upgrade would be on the probability of winning a war. So the thought is by linking the engineering simulations to the mission simulations to the engagement simulations, and so on, one could determine what the impact of this low-level engineering change would be on the ability to win a war. However, unless this change is near a tipping point to magnify its impact, the effect will be effectively undetectable due to epistemic uncertainty inherent in models of socio-technical systems [2]. If every small change in the low-level model produced a noteworthy effect in the high-level model, we would not have the high-level model. It would be too unstable to be useful. The rationale behind these assertions will be explained in the subsequent sections.

III. Turning points as phase shifts

Let us assume for now that our interest in multi-modeling is driven by the concept of turning points. It turns out that this is not a new concern. Most notably this concept emerged in the study of dynamics as a bifurcation and in physics as a phase transition. The history of dynamics can be traced back to mid XVII century when Isaac Newton invented differential equations and discovered the laws of motion and universal gravitation [7]. The combination of these laws solved the two-body problem and offered an explanation for Kepler's laws of planetary motion. During the following decades, many mathematicians and physicians attempted to expand Newton's analytical approach to the three-body problem such as the motion of the Sun, Earth, and Moon but found it to be analytically intractable.

A giant leap came in late 1800s when Henri Poincaré changed the overall character of the discussion from a quantitative to a qualitative nature. Instead of focusing on questions such as the precise position of the planets at all times, Poincaré questioned himself about the stability of the solar system. By doing so, he developed a geometric way to approach such problems. While writing a publication on the topic, Poincaré unintentionally found that deterministic systems may exhibit aperiodic, or chaotic behavior as a result of high sensitivity to the initial conditions [8]. This conclusion not only rendered long-term predictions impossible but also prompted the emergence of a new field of studies - the field of dynamics [7].

Dynamics is a branch of mathematics that deals with the behavior of a system over time. A dynamical system consists of an abstract state space whose elements describe the state of the system at any point in time. These systems are often represented by differential or difference equations whose solutions result in a trajectory from an initial point. Along the trajectory we can find *attractors* or stable points toward which the system tends to evolve, and *repellers* or unstable points from which the system tends to deviate. Implied here is the idea that a state evolves to another state (deterministic) or to a number of possible states (stochastic) at a later time [7]. This is also a convenient lens with which to view phase transitions.

Phase transitions may place systems in states in which microscopic symmetries and microscopic equations of motion are violated [9]. In fact, it seems difficult to derive microscopic models able to describe the behavior of large and complex systems; instead, simplified models of reality may be useful [10]. Mean field theory has this aim: by replacing all interactions in a system by an average interaction, it reduces a multi-body problem to a one-body problem [11]. It is important to understand, however, that such approximation ignores important aspects of reality such as the nature of the interactions among the elements of a system or the importance of fluctuations [10]. So, why does a simplified model produce useful results? The simplicity of the model enables the formulation of important qualitative questions that shed light on the conditions under which transitions may occur [11]. This is only possible because different complex systems seem to share *universal* features (called *critical exponents*) near continuous phase transitions. Observing critical exponents in complex systems indicates that complexity (and inherent phase transitions) arises close to instability points [12].

The notion of stability and instability is tied to the idea of change. Generally speaking, stable systems do not vary over long time scales whereas unstable ones do [10]. To capture the dynamics of a complex system, nonlinear differential equations are frequently used; indeed, linear differential equations rarely provide an accurate description of complex systems. However, finding the analytic solution to differential equations is not always feasible. For this reason, a popular approach is to understand the behavior of the solutions near equilibrium points using a linear approximation to the nonlinear dynamics - *Linear stability analysis*.

It turns out that these concepts apply to more than just physical systems. Similar behaviors were noticed in ecological systems. From an ecological perspective, it might seem natural to focus on shifts triggered by major perturbations to the system. For example, the Cretaceous-Paleogene extinction, generally believed to have been caused by a massive asteroid impact million years ago, is a rare, high-impact event that led to significant qualitative changes in ecosystems. Such deep changes, however, may also result from gradual changes that impact a system's capacity to recover from disturbances, and eventually trigger a shift to an alternative equilibrium.

One such case can be found in shallow lakes. The increased nutrient concentrations in lakes, for instance, does not seem to have a significant impact on water clarity until a given threshold - critical turbidity - is reached. At this point, the lake shifts abruptly from clear water dominated by submerged vegetation to a turbid state with high algal concentration [13], [14]. The reverse process, i.e. the shift to a pristine water, requires a significantly lower nutrient concentration than the critical threshold at which the transition occurred. Yet such effort may succeed through a combination of nutrient reduction and ecosystem disturbance such as food web manipulation.

The increased nutrient loading also contributes to the degradation of coral reefs that tend to shift from plentiful coral to abundant macro-algae. This transition, however, is unlikely to be triggered by nutrient overload alone, but rather by its combination with other factors such as reduction in herbivorous fishes, reduction in habitat complexity, effects of natural disturbances (e.g. hurricanes) and eutrophication or overfishing [15]. Similarly to shallow lakes, coral recolonization may also be difficult as adult algae, less palatable to herbivorous fishes, prevent the establishment of coral larvae [14].

Alternative stable states and threshold effects have also been identified in terrestrial grazing systems. Some parts of the Sahel region in Africa, for instance, shifted from perennial grasses to annual vegetation and herbs, and eventually to desertification. The same happened around six thousand years ago in the Sahara, the largest desert on Earth. These transitions can be explained by two main mechanisms: herbivore saturation and soil degradation. As human population increases in size also does the grassing pressure by livestock. Because herbivores consume mostly low plant standing crop, plant losses naturally exceed plant growth, which invariably leads to a more critical decrease in plant standing crop. Despite its importance, herbivore saturation is not the sole cause for terrestrial grazing transitions. These shifts may also result from extreme soil degradation that inhibits plant growth. Indeed perennial vegetation plays a crucial role in the retention of rain water by the topsoil (a necessary condition for plant survival). A decline in vegetation results in an increase in surface runoffs and, thus, in a reduction of absorbed rainfall and consequent loss of nutrients. The increasing deterioration of soil conditions leads to irreversible vegetation destruction [16].

Complexity does not diminish as we move from physical systems to biological systems to social systems. Consequently, the same principles apply to social systems such as an economy. Consider, for example, crashes and rebounds in financial markets, where *bubbles* are a common regime. A bubble can be interpreted as a state in which the growth rate is also growing, accelerating the price hyperbolically. This regime is often explained by the increasing build-up of market collaboration between investors [17]. Nonetheless, as bubbles increase they enter unstable states where small disturbances can trigger unprecedented collapses. Classic examples are the United States housing bubble that preceded the 2008 financial crisis (or collapse) and the dot-com bubble in late 1990s. Contrasting theories support different explanations for these crashes: while the *Efficient Market Hypothesis* suggests that crashes result from new negative information being added in prices at short time scales, others make use of phase transition theory (together with economic and behavioral finance theories) to support the hypothesis that the underlying factors of the crash should be present in the prior years to the crash.

All the above examples illustrate the existence of phase transitions and are included here as a motivation to address the same question in the context of enterprise systems. Based on these examples, we can see that once a specific set of parameters crosses a threshold, the dynamics of the system changes, i.e. the system transits to (and operates in) a new regime or phase. A *critical transition* can thus be defined as an abrupt shift between contrasting states. This implies the existence of alternative stable states separated by unstable equilibrium points that represent boundaries between *basins of attraction*, i.e. set of states toward which a system tends to evolve [14]. The identification of these transitions lies at the core of approaches such as scenario planning.

IV. Identifying Turning Points in Social Systems

Even though they may not have been framed as a problem of identifying phase transitions, turning points have long been an important topic. We contend that formal approaches to identify turning points in social systems such as enterprises can be found in it least two disciplinary areas: system dynamics and scenario planning. We will discuss each of them in turn. In each case, we will argue why the identification of turning points is its main purpose, as well as cover some of their shortcomings toward this goal.

A. System Dynamics

Complex systems such as the ones presented in section III can contain a great number of feedback loops coupled to one another. To establish causality, humans make use of heuristics such as spatial and temporal proximity of cause and effect, the order in which the events occurred, correlation and likeliness of cause and effect [18]. In complex systems, however, cause and effect tend to be distant in time and space and the impact of our actions in the long term, if at all perceptible, tends to be significantly different from that in the short term. Moreover, the interconnectedness of complex systems forces variables to be correlated with one another further complicating the process of establishing causality.

Research has shown that the human brain is unable to cope with such dynamic complexity [18]. Therefore, the use of informal maps and formal models as input to computer simulation, central to a system dynamics approach, has the potential to help to overcome the aforementioned cognitive limitations. System dynamics is an interdisciplinary approach grounded on the theory of nonlinear dynamics and feedback systems. Its fundamental principle is that the behavior of systems is dictated by their internal structure, which can be captured by a network of feedback loops. The overall dynamics depends upon which feedback loop is dominant. Implied here is the idea of a closed boundary around the system or, in other words, an endogenous viewpoint. By forcing the dynamics to be endogenous, causality becomes circular, which provides a means to understand the feedback effects [19]. As illustrated in section III, phase transitions are sometimes caused by feedback effects (recall, for instance, the shift from clear to turbid water in shallow lakes). The point here is straightforward: if we can capture these feedback effects we could identify the existence of turning points in the system. Yet, models, by definition, are simplifications of reality and, as such, cannot fully represent systems.

A recurrent critique to system dynamics is its inability to generate curves that fit historical data [20]. However, doing so does not guarantee that the model captures the structure that gives rise to the dynamics of the real system [21]. In fact, curves of historical data are specific cases of how the system responded to a series of random events. Stated differently, if we were to ”restart” a real system under different conditions, we would certainly arrive at different curves in spite of the underlying structure being the same. Comparison of modeling results and real data is still useful and desirable [22]. What is being emphasized here is that a model's output validity is of little value if its structure is fundamentally wrong. Moreover, from a structural shift viewpoint, the concern is rather to establish the potential existence of a turning point as a logical extrapolation of what we know as opposed to when exactly that shift will occur.

Structural shifts result from changes in the dominance of the feedback loops. They can also be triggered by unexpected events whose impact in the system results in new feedback loops being formed and becoming dominant [20]. Whereas the former situation can be anticipated with a system dynamics model (assuming the right feedback loops are incorporated in the model), the latter seems difficult to accomplish given the focus of the approach on an endogenous modeling of the system. Is it thus the case that the main feature of the system dynamics approach is also its most significant limitation?

It has been proposed in the literature that the use of scenarios could be useful in building up a methodology to account for structural shifts arising out of external, unexpected events [20]. This reasons from the fact that scenario planning does not aim at the development of scenarios in the form of parameter variation. Instead, the approach focuses on the development of scenarios of completely different system structures. We will discuss this approach next.

B. Scenario Planning

Scenarios are narratives of hypothetical but plausible future states that help us structure uncertainty by looking at its driving forces [23]. The origins of scenarios can be traced back to World War II as a form of war theater strategies to evaluate possible enemy actions [24]. With the end of World War II and the beginning of the Cold War, the US government found itself at an unstable equilibrium point. The question of how to keep - if not dominate - this equilibrium, led the US government to found the RAND corporation [25]. At RAND, theatrical scenarios were being converted into war planning scenarios by a military strategist named Herman Kahn. Kahn's perspective on scenarios was rather different from the well-established forecasting mindset. For him, scenarios were an opportunity for people to explore different futures through the logical combinations of events and to *"think about the unthinkable"* [26]. This approach was extended to the business environment by Ian Wilson and Pierre Wack, who, at the time, worked at General Electric and Royal Dutch/Shell, respectively. Here, scenarios were reasonable descriptions of different futures for a given time horizon [25].

Over the years, many scenario methodologies and techniques have been proposed resulting in what was coined as "methodological chaos" [27]. This chaos is overcome if we cluster most of the methodologies and techniques into three main schools of thought [24]: the *intuitive logics*, the *probabilistic modified trends* and the *la prospective* schools. In the intuitive logics school, scenarios are organized as a set of equally likely, theme-oriented narratives, supported by graphics and limited quantification of the main variables of interest. The narratives provide a means to describe both the evolution and end state of plausible future environments. Early warnings that signal the unfolding of the scenarios can be incorporated. The probabilistic modified trends school includes two groups of techniques - the *trend impact analysis* and the *cross impact analysis* - that share the same mathematical foundation. The first technique takes time series data pertinent to the question of interest and considers different events that may have an impact on it. Domain experts assess the probability of occurrence of these events, as a function of time, as well as their anticipated impact. Scenarios result from the combination of the extrapolation of the time series data with the expected impact of the selected events at different points in time. Narratives may be added to provide a more contextual description of the scenarios. The cross impact analysis further refines this approach by also computing the conditional probabilities of the selected events. The *la prospective* approach is probabilistic in nature and relies on computer-based analysis and mathematical modeling to develop scenarios. These models share the same mathematical roots as the probabilistic modified school. Yet, the resulting set of scenarios is both qualitative and quantitative, which suggests that this school is, to a large extent, a combination of the intuitive logics and the probabilistic modified trends schools. It is also deemed as the most complex and mechanistic schools of scenario thought.

The multitude of scenario approaches conceals some of their similarities. They all start by clarifying the question or decision of interest, intentionally challenging people's mental models and perceptions. Relevant information from different sources is always collected and processed. And the most analytical, common steps include the identification of the driving forces underlying the question of interest, the predetermined elements (i.e. what is predictable) and the critical uncertainties. The underlying logics and structure to all scenarios are also detailed to highlight the significant differences between the scenarios [28].

Scenarios reduce complexity and uncertainty by establishing the cause and effect relationships between plausible future events. Doing this while contemplating multiple, structural different futures, forces decision makers to rethink radically the underlying hypotheses of their strategies, also compensating for overconfidence and tunnel vision [28], [29]. Moreover, the development process itself promotes strategic conversations as goals, opportunities, threats and strategies are discussed [30]. Ultimately, the value of scenarios seems to be the establishment of bifurcations in the behavior of complex systems [31]

Overall, the development of scenarios is an interactive, intense, time-consuming and imaginative process [28]. Because scenarios were born from practical concerns, their development is based more on informal rather than scientific evidence, a fact that does not please many in the academic community [31]. At the same time, the emphasis on a subjective and heuristic nature places a huge burden on the selection of the scenario developers. In order to accomplish quality results, the developers have to have a deep knowledge and understanding of the field - the definition of a domain expert - and cannot advocate for political derailing, personal agendas or suffer from myopia [28], [31]. Perhaps an even more important criticism to scenario development is its reliance on a subjective selection of key uncertainties. Were these different, very different scenarios could emerge. A different set of scenarios would, in turn, establish the possibility of different turning points and phase transitions.

V. Revisiting Multi-modeling

In light of our discussion of system dynamics and scenario planning as two existing approaches to identifying policy turning points in support of enterprise strategic planning, where does the type of multi-modeling discussed in section II fall? It seems like it attempts to accomplish the same thing as these other two techniques, so why do researchers and practitioners engage in it? Why is it advocated? One way we might motivate that discussion is to briefly describe a standard control theory view of the problem of choosing a strategy. The intent here is not be literal in our application of control theory, but rather to motivate a comparison between multi-modeling and the other techniques.

A. A control theory perspective

A controlled system is often represented as an ordinary differential equation (ODE) of the form [32]:

$$\dot{\mathbf{x}}(t) = f(t, \mathbf{x}, \mathbf{u}) \tag{1}$$

in which t is time, vector $\mathbf{x} \in \mathbb{R}^n$ is the state, and vector $\mathbf{u} \in \mathbb{R}^p$ is the control. $f(t, \mathbf{x}, \mathbf{u})$ is assumed to be continuous in a domain:

$$\mathbf{D} = \mathcal{T} \times \mathcal{D} \times \mathcal{P}, t \in \mathcal{T}, \mathbf{x} \in \mathcal{D}, \mathbf{u} \in \mathcal{P} \tag{2}$$

The control $\mathbf{u}$ can be selected from classes that are functions of time only, $\mathbf{u} = \mathbf{u}(t)$ (open-loop control), and classes that are functions of both time and state, $\mathbf{u} = \mathbf{u}(t, \mathbf{x})$ (closed-loop or feedback control) [32]. From a control design perspective, choosing an open-loop control means that the control strategy $\mathbf{u}$ for each time t is fixed and cannot change over time. Contrarily, a closed-loop control $\mathbf{u} = \mathbf{u}(t, \mathbf{x})$ may be nonlinear and discontinuous in $\mathbf{x}$, constrained by the existence of a solution to the nonlinear differential equation $f(t, \mathbf{x}, \mathbf{u}(t, \mathbf{x}))$.

The controlled system $\dot{\mathbf{x}}(t)$ represented in equation 1 may be subjected to uncertainty. Uncertainty can result from limited information on the system dynamics and uncertainty in the system and measurement inputs as a result of unknown but bounded disturbances [32]:

$$\dot{\mathbf{x}}(t) = f(t, \mathbf{x}, \mathbf{u}, \mathbf{w}) \tag{3}$$

in which t is time, vector $\mathbf{x} \in \mathbb{R}^n$ is the state, vector $\mathbf{u} \in \mathbb{R}^p$ is the control strategy, and vector $\mathbf{w} \in \mathbb{R}^n$ is the process noise or disturbance.

Most of today's systems, however, require a more sophisticated setting. This means being defined by a collection of standard systems such that the active dynamics results from only one of them, with immediate switching from one to another [32]. The overall controlled dynamics progresses in time as those generated by alternating individual continuous dynamics due to systems (with its own controllers) whose order depends upon existing conditions - hybrid systems:

$$\dot{\mathbf{x}}(t) = f(t, \mathbf{x}^i, \mathbf{u}^i, \mathbf{w}^i) \tag{4}$$

with $i = 1, ..., k$ being a collection of systems. Represented differently:

$$\dot{\mathbf{x}}(t) = \begin{cases} f(t, \mathbf{x}^1, \mathbf{u}^1, \mathbf{w}^1), & \text{if } \mathbf{x}^1 \in C_1 \\ f(t, \mathbf{x}^2, \mathbf{u}^2, \mathbf{w}^2), & \text{if } \mathbf{x}^2 \in C_2 \\ \cdots \\ f(t, \mathbf{x}^k, \mathbf{u}^k, \mathbf{w}^k), & \text{if } \mathbf{x}^k \in C_n \end{cases} \tag{5}$$

in which t is time, vector $\mathbf{x}^i \in \mathbb{R}^n$ is the state for the system i, vector $\mathbf{u}^i \in \mathbb{R}^p$ is the control strategy for the system i, vector $\mathbf{w}^i \in \mathbb{R}^n$ the process noise for the system i, and C_1, C_2, ..., C_n the conditions for which the different systems apply.

The control theory perspective highlights the key problem: the control regime switches under different system states. These are analogous to phase transitions. So a strategy that appears to be adequate over a range of system states suddenly becomes inadequate when a threshold is crossed (C_i to C_j). These are bifurcation points that would be invisible under a simple model. We could argue that system dynamics attempts to identify the bifurcation points by increasing the complexity of the feedback loops in f. Scenario planning attempts accomplish something similar via expert assessment. We could also argue that multi-modeling is similar to system dynamics except that it increases the complexity of f even further by considering multiple ontological views of the system simultaneously. In principle, doing so could result in the identification of more phases (C_i's) and associated bifurcation points than just system dynamics alone, yet in a more systematic and repeatable way than scenario planning. However, as we will subsequently consider, this will come at a cost.

B. Epistemological Status of Multi-Modeling

Rosen's view on measuring and modeling systems is instructive to understand the epistemological status of the type of modeling we are discussing here [33]. Rosen frames the general problem as follows: We have a system with a set of states, S. However, we do not directly interact with the state space, S. Rather we measure observables such as position, temperature, voltage, and so on. These observables are essentially functions that map the state space, S, to another set such as the real numbers. A given set of observables, F, generates an equivalence class, R_F, on S. The result is that the quotient set S/R_F is the reduced state space of the system that is a consequence of which observables are collected. Of course, we do not measure the observables directly. Rather, we use specially configured systems called meters that are designed to dynamically interact with the system of interest and asymptotically approach a value we take to be the measurement of the observable. An example would be using a thermometer to measure temperature.

Rosen uses this setup to explore to implications of trying to measure and model the dynamics of a system, which he frames as an automorphism on the state space, S. Rosen devotes an entire monograph to this exploration, so we can only briefly highlight the relevant conclusions here. First, when we model systems, we typically fractionate the system. This means we break the observables up into groups that are easier to work with (i.e., we do not try to model everything all at once). The presumption is that we can work with the fractions then put them back together and get an accurate understanding of the dynamics of the real system. This works when the observables are completely unlinked. An example is when we can break the dynamics of a mechanical system up into the x, y, and z components, propagate them separately and then put them back together and obtain the correct position.

When the dynamics of a set of observables is not totally unlinked, the composition of the fractional models yields a state space that does not completely correspond with the state space of the real system. Mathematically, the state space of the composed model will be larger than that of the real system. For example, for two sets of observables F and G, the state space of the composed model is actually $S/R_F \times S/R_G$, of which S/R_{FG} is only a subset. We have no way to know for sure which states of this enlarged space are real and which are artifacts of the model. As Rosen notes, "the situation is actually worse than this because we know that in the process of imposing dynamics on a system, we generally establish new linkage relations, involving observables extraneous to the original system. As a result, in terms of our description of the fractionated system, we may have lost states..."

One could argue that both system dynamics and multi-modeling are an implicit recognition of this fact. In short, they both attempt to restore the missing linkage relationships among the fractional views of the systems. In the case of system dynamics, this takes the form of reinforcing and balancing loops. In multi-modeling, this takes the form of linkage relationships among the different modeling ontologies. The problem is that we don't really know what these linkage relationships are, and even if we did, simply introducing them to the composed model would not necessarily solve the problem. Since the composed model has a different state space and dynamics than the real system, these linkage relationships would likely need to be altered or "calibrated" in order for the model to produce accurate results.

This assertion would seem to correspond to the observations made by Winsberg [34]. He considers the real world case of researchers attempting to build a physics-based multi-model of nano-crack propagation in a material. In short, to model the phenomena, one must simultaneously consider linear-elastic theory, molecular dynamics, and quantum mechanics. The problem is that these three theories are inconsistent and incompatible. To make the simulation work, "handshaking algorithms" that require deliberate fictions must be introduced to translate parameter values back and forth among the three views. For instance, fictitious "silogen" atoms are introduced on the boundary between the molecular dynamics view and the quantum mechanical view. Despite these fictions, the simulation can produce accurate results. However, Winsberg also notes that these linkage relations are not logically determined but rather they are empirically determined. This observation is consistent with the conclusions drawn from Rosen's analysis above.

So what can we learn from multi-modeling when applied to a complex social system such as an enterprise? In short, multi-modeling attempts capture relevant dynamics that would be missed with a single view of the system. In particular, the missed dynamics could be viewed as the result of phase transitions or bifurcations that are invisible to the single view. Essentially, multi-modeling attempts to restore the missing linkage relationships that are lost when the system is fractionated into separate models. Unfortunately, we do not know what these linkage relationships should be, and they cannot be logically determined. Rather they must be hypothesized and evaluated empirically.

If we are dealing with a physics-based multi-model such as the one Winsberg described, it may be feasible to construct controlled experiments to establish working linkage relationships. However, this seems unlikely for a multi-model of a complex social system such as an enterprise. Consequently, if we identify a policy turning point in a multi-model of an enterprise, we cannot be confident that it actually exists. Furthermore, the absence of a turning point we might have expected does not necessarily mean that it cannot occur. We also reach the not surprising conclusion that it is unlikely that we can use such a model to make accurate predictions. Rather, what we can use multi-modeling of enterprises for is to identify potential policy turning points for further investigation. When the identified turning points are unexpected or counter-intuitive to strategic planners, this can be quite useful. The results can be used to target further empirical investigations to determine whether or not the turning point is real. If this is not feasible, then the turning point can be considered in the strategic planning process as a contingency to be hedged against.

VI. Conclusions and Future Work

In this paper, we considered the increasingly popular approach of using multi-models to support strategic planning for enterprise systems. The question posed was whether we learn anything differently from this approach than other approaches such as system dynamics or scenario planning. We concluded that all three approaches are essentially attempting to identify policy turning points that result from phase transitions or bifurcations in the dynamics of the system of interest. Crossing one of these turning points would necessitate a shift in strategy. However, each goes about it in a slightly different way.

Mathematically, we can view each approach as attempting to restore broken linkages among observables that result from our fractionated views of the system. System dynamics does this by introducing reinforcing and balancing loops, while scenario planning does this via human expertise and experience. Finally, multi-modeling does this by introducing linkage relationships among models with different ontologies.

What we can conclude is that multi-modeling has the potential to identify some policy turning points that system dynamics alone might miss while avoiding the subjectivity of scenario planning. However this comes that the price of creating linkage relationships that may be artificial and generate spurious behavior in the model without substantial calibration and empirical validation. Since the latter is often difficult, if not impossible, to do for complex social systems such as enterprises, we contend that multi-modeling occupies a similar epistemological status to the application of system dynamics to strategic planning: it is useful for generating insights that can cue more focused investigations or identify risks that may need to be hedged. Specific prediction with such models is inadvisable.

In the opinion of the authors, this means that multi-modeling for strategic planning is yet another tool in the toolbox of the strategic planner to be used in a complementary fashion with system dynamics, scenario planning, and other approaches as opposed to a fundamentally new source of knowledge. It has the potential to generate insights that might otherwise be missed, but it comes at the cost of establishing artificial linkage relationships. A question that naturally follows is: are there methods or techniques that can be used to minimize the cost of developing these linkage relationships or minimize the risk of spurious model behaviors? This question and others will be the subject of future work.

REFERENCES

[1] M. J. Pennock and W. B. Rouse, "The epistemology of enterprises," *In press, Systems Engineering*, 2016.

[2] M. J. Pennock and C. Gaffney, "Managing epistemic uncertainty for multi-models of socio-technical systems for decision support," *under reivew, IEEE Systems Journal*, 2016.

[3] W. B. Rouse, *Modeling and Visualization of Complex Systems and Enterprises: Explorations of Physical, Human, Economic, and Social Phenomena*. John Wiley & Sons, 2015.

[4] H. Park, T. Clear, W. B. Rouse, R. C. Basole, M. L. Braunstein, K. L. Brigham, and L. Cunningham, "Multilevel simulations of health delivery systems: A prospective tool for policy, strategy, planning, and management," *Service Science*, vol. 4, no. 3, pp. 253–268, 2012.

[5] N. Barberis, P. J. Haas, C. Kieliszewski, Y. Li, P. Maglio, P. Phoungphol, P. Selinger, Y. Sismanis, W.-C. Tan, and I. Terrizzano, "Splash: A computational platform for collaborating to solve complex real-world problems," http://researcher.watson.ibm.com/researcher/files/us-phaas/Splash external 20130319.pdf, accessed 6/16/15, IBM Research - Almaden.

[6] F. E. Mullen, "Dynamic multilevel modeling framework phase 1 – feasibility," US Department of Defense, Modeling and Simulation Coordination Office, Washington, DC.

[7] S. H. Strogatz, *Nonlinear dynamics and chaos: with applications to physics, biology, chemistry, and engineering*. Westview press, 2014.

[8] P. Holmes, "Poincaré, celestial mechanics, dynamical-systems theory and chaos," *Physics Reports*, vol. 193, no. 3, pp. 137–163, 1990.

[9] P. W. Anderson *et al.*, "More is different," *Science*, vol. 177, no. 4047, pp. 393–396, 1972.

[10] R. V. Solé, *Phase Transitions*. Princeton University Press, 2011.

[11] L. P. Kadanoff, "More is the same; phase transitions and mean field theories," *Journal of Statistical Physics*, vol. 137, no. 5-6, pp. 777–797, 2009.

[12] R. V. Solé, S. C. Manrubia, B. Luque, J. Delgado, and J. Bascompte, "Phase transitions and complex systems: Simple, nonlinear models capture complex systems at the edge of chaos," *Complexity*, vol. 1, no. 4, pp. 13–26, 1996.

[13] M. Scheffer, S. Hosper, M. Meijer, B. Moss, and E. Jeppesen, "Alternative equilibria in shallow lakes," *Trends in ecology & evolution*, vol. 8, no. 8, pp. 275–279, 1993.

[14] M. Scheffer, S. Carpenter, J. A. Foley, C. Folke, and B. Walker, "Catastrophic shifts in ecosystems," *Nature*, vol. 413, no. 6856, pp. 591–596, 2001.

[15] L. McCook, "Macroalgae, nutrients and phase shifts on coral reefs: scientific issues and management consequences for the great barrier reef," *Coral reefs*, vol. 18, no. 4, pp. 357–367, 1999.

[16] J. van de Koppel, M. Rietkerk, and F. J. Weissing, "Catastrophic vegetation shifts and soil degradation in terrestrial grazing systems," *Trends in Ecology & Evolution*, vol. 12, no. 9, pp. 352–356, 1997.

[17] W. Yan, R. Woodard, and D. Sornette, "Diagnosis and prediction of tipping points in financial markets: Crashes and rebounds," *Physics procedia*, vol. 3, no. 5, pp. 1641–1657, 2010.

[18] J. D. Sterman, "System dynamics modeling: tools for learning in a complex world," *California management review*, vol. 43, no. 4, pp. 8–25, 2001.

[19] G. P. Richardson, "Reflections on the foundations of system dynamics," *System Dynamics Review*, vol. 27, no. 3, pp. 219–243, 2011.

[20] C. R. Featherston, M. Doolan *et al.*, "A critical review of the criticisms of system dynamics," in *Proceedings fo the 30th International Conference of the System Dynamics Society, The 30th International Conference of the System Dynamics Society: St Gallen, Switzerland*, 2012.

[21] J. W. Forrester, "System dynamics: the next fifty years," *System Dynamics Review*, vol. 23, no. 2-3, pp. 359–370, 2007.

[22] Y. Barlas, "Formal aspects of model validity and validation in system dynamics," *System dynamics review*, vol. 12, no. 3, pp. 183–210, 1996.

[23] P. Wack, "Scenarios: uncharted waters ahead," *Harvard business review*, 1985.

[24] R. Bradfield, G. Wright, G. Burt, G. Cairns, and K. Van Der Heijden, "The origins and evolution of scenario techniques in long range business planning," *Futures*, vol. 37, no. 8, pp. 795–812, 2005.

[25] S. M. Millett, "The future of scenarios: challenges and opportunities," *Strategy & Leadership*, vol. 31, no. 2, pp. 16–24, 2003.

[26] H. Kahn, *Thinking About the Unthinkable in the 1980s*. Simon and Schuster, 1984.

[27] A. Martelli, "Scenario building and scenario planning: state of the art and prospects of evolution," *Futures Research Quarterly*, vol. 17, no. 2, pp. 57–74, 2001.

[28] D. Mietzner and G. Reger, "Advantages and disadvantages of scenario approaches for strategic foresight," *International Journal of Technology Intelligence and Planning*, vol. 1, no. 2, pp. 220–239, 2005.

[29] P. J. Schoemaker, "Scenario planning: a tool for strategic thinking," *Sloan management review*, vol. 36, no. 2, p. 25, 1995.

[30] K. Van der Heijden, *Scenarios: the art of strategic conversation*. John Wiley & Sons, 2011.

[31] P. J. Schoemaker, "Forecasting and scenario planning: the challenges of uncertainty and complexity," *Blackwell handbook of judgment and decision making*, pp. 274–296, 2004.

[32] A. B. Kurzhanski and P. Varaiya, *Dynamics and control of trajectory tubes*. Springer, 2014.

[33] R. Rosen, *Fundamentals of measurement and representation of natural systems*. North-Holland New York, 1978.

[34] E. Winsberg, *Science in the age of computer simulation*. University of Chicago Press, 2010.