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Multi-Level Modeling of Socio-Technical Systems – Volume 1

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ABSTRACT

This report discusses the initial development of a methodology for modeling complex socio-technical problems. A companion report discusses an in-depth case study of the occurrence of counterfeit parts in the supply chains for Department of Defense weapon systems. These two reports reflect the balance of this research between more theoretical developments and in-depth case studies. This report presents a proposed ten-step methodology for modeling complex socio-technical systems. We elaborate an example of the use of the methodology for ground vehicle design and control that illustrates the nuances of the methodology. We then explore in depth issues associated with representation and composition. This leads to elaboration of a model composition framework. This is followed by consideration of eventual use of the modeling methodology. Use considerations provide the basis for subsequent discussion of approaches to supporting the use of the methodology. Finally, we outline a development roadmap for iteratively advancing and applying the methodology.

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INTRODUCTION

Many of the challenges that confront the Department of Defense (DoD) today are characterized by the intersection of complex social, political, economic, and technical phenomena. Some of these challenges include combating the proliferation of counterfeit parts in military systems; managing joint and international acquisition programs; coordinating disaster and humanitarian responses involving governments, NGOs, and US agencies; and sustaining the defense supplier base in the face of declining acquisition quantities. Each of these situations involves the interaction of independent organizations with differing objectives with direct impacts on the performance, operation, and sustainment of technical systems.

For example, in the area of counterfeit parts, counterfeiters are economically incentivized to surreptitiously feed recycled parts into defense and commercial supply chains under the guise of being new (Villasenor & Tehranipoor, 2013). These parts can then find their way into operational military systems with adverse effects on performance and reliability. Understanding this problem requires insights into the economic incentives of the counterfeiters and suppliers, the interactions between these organizations and the DoD, as well as the ultimate impact of these parts on the performance of military systems. In order to mitigate the problem with counterfeit parts, the DoD needs to understand what factors drive behaviors and outcomes within this socio-technical system. Such an understanding would allow decision makers to craft policy options to combat the counterfeit problem. The DoD would then need a mechanism to “test drive” these policies in order to evaluate their efficacy before incurring the costs of implementation.

More generally, understanding a socio-technical system requires building a model of the system. The notion of a model is fairly broad, ranging from a high-level conceptual model to a detailed simulation. The particular manifestation depends on the nature of the questions being asked and the system being modeled. Regardless, the model allows decision makers to explore the salient features of the system. More capable models allow decision makers to perform “what if” analyses to assess potential policy options.

Understanding complex socio-technical systems often requires understanding how a variety of natural and designed phenomena interact to yield system behaviors and performance. The challenge is that modeling these types of systems often requires selecting and combining modeling formalisms from what have traditionally been separate disciplines. For example, understanding the financial incentive of a counterfeiter of an electronic part would require formalisms from economics. Understanding the movement of the parts through the supply chain requires formalisms from industrial engineering while understanding the impact of the counterfeit part on system performance would require formalisms from information technology, electrical engineering, and systems engineering. The difficulty is that these formalisms were developed within stove-piped disciplines to suit the objectives of those disciplines. Consequently, any immediate compatibility between these formalisms is incidental.

Therefore, to address the complex socio-technical challenges that face DoD[1], decision makers need a means to select and compose formalisms from multiple disciplines in a valid way. The objective of this research effort is to develop a methodology that will accomplish that goal. The methodology should allow a decision maker to assess the problem, determine the relevant phenomena, select the formalisms to model the phenomena, understand the rules for combining the formalisms to achieve valid results, and "test drive" policy options.

Fortunately, there is a substantial foundation upon which to build. The representation of these phenomena have been addressed by models that include varying levels of abstraction and aggregation, with the particular choices depending on the problem of interest. Our Phase 1 report (Rouse & Bodner, 2013) addressed the foundations of this type of modeling, drawing upon very rich literature over the past several decades.

This report discusses the initial development of a methodology for modeling complex socio-technical problems. A companion report discusses an in-depth case study of the occurrence of counterfeit parts in the supply chains for Department of Defense weapon systems (Bodner & Ramirez, 2013). These two reports reflect the balance of this research between more theoretical developments and in-depth case studies. We believe that this balanced approach is the best way to advance our abilities to understand and manage complex socio-technical systems.

This report articulates a vision for methodological support for modeling socio-technical systems. The essence of this vision is an interactive environment that supports a set of nominal steps in the process of modeling. These steps are "nominal" in that users are not required to follow them. Advice is provided in terms of explanations of each step and recommendations for methods and tools that might be of use. Compilations of physical, organizational, economic and political phenomena are available, including standard representations of these phenomena, in terms of equations, curves, surfaces, etc., but not software. Advice is provided in terms of variable definitions, units of measure, etc., as well typical approximations, corrections, etc. Visualization tools are available, including block diagrams, IDEF, influence diagrams, and systemigrams. Software tools for computational representations are recommended, with emphasis on commercial off-the-shelf platforms that allow input from and export to, for example, Microsoft Excel and Matlab.

In keeping with contemporary approaches to user support, this methodological support is not embodied in a monolithic software application. Instead, this support framework operates as fairly slim application that assumes users have access to rich and varied toolsets elsewhere on their desktops. The support provides structured guidance on how to best use this toolset to address the phenomena associated with the problem that has motivated the modeling effort at hand. We assume that model development occurs within the confines of one or more desktops or laptops, with capabilities to export interactive visualizations to much more immersive simulation settings. The support will not, however, be premised on users having access to such settings.

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[1] The Appendix provides a summary of how non-defense industries approach these challenges.

This report proceeds as follows. We next present a proposed ten-step methodology for modeling complex socio-technical systems. We elaborate an example of the use of the methodology for ground vehicle design and control that illustrates the nuances of the methodology. We then explore in depth issues associated with representation and composition – steps 5-7 of the proposed methodology. This leads to elaboration of a model composition framework. This is followed by consideration of eventual use of the modeling methodology. Use considerations provide the basis for subsequent discussion of approaches to supporting the use of the methodology. Finally, we outline a development roadmap for iteratively advancing and applying the methodology.

PROPOSED METHODOLOGY

Experience has shown that models should be developed with a clear intent, with defined scope and givens. Initial emphasis should be on alternative views of phenomena important to addressing the questions of interest. Selected views can then be more formally modeled and simulated. The following ten-step methodology provides a structure to support this approach to modeling.

STEP 1: DECIDE ON THE CENTRAL QUESTIONS OF INTEREST

The history of modeling and simulation is littered with failures of attempts to develop models without clear intentions in mind. Models provide means to answer questions. Efforts to model socio-technical systems are often motivated by decision makers' questions about the feasibility and efficacy of decisions on policy, strategy, operations, etc. The first step is to discuss the questions of interest with the decision maker(s), define what they need to know to feel that the questions are answered, and agree on key variables of interest.

STEP 2: DEFINE KEY PHENOMENA UNDERLYING THESE QUESTIONS

The next step involves defining the key phenomena that underlie the variables associated with the questions of interest. Phenomena can range from physical or organizational, to economic or political. Broad classes of phenomena across these four domains include continuous and discrete flows, manual and automatic control, resource allocation, and individual and collective choice. Mature domains often have developed standard descriptions of relevant phenomena.

STEP 3: DEVELOP ONE OR MORE VISUALIZATIONS OF RELATIONSHIPS AMONG PHENOMENA

Phenomena can often be described in terms of inputs, processes, and outputs. Often the inputs of one phenomenon are the outputs of other phenomena. Common variables among phenomena provide a basis for visualization of the set of key phenomena. Common visualizations methods include block diagrams, IDEF, influence diagrams, and systemigrams.

STEP 4: DETERMINE KEY TRADEOFFS THAT APPEAR TO WARRANT DEEPER EXPLORATION

The visualizations resulting from Step 3 often provide the basis for in-depth discussions and debates among members of the modeling team as well as the sponsors of the effort, which hopefully includes the decision makers who intend to use the results of the modeling effort to inform their decisions. Lines of reasoning, perhaps only qualitative, are often verbalized that provides the means for immediate resolution of some issues, as well as dismissal of some issues that no longer seem to matter. New issues may, of course, also arise.

STEP 5: IDENTIFY ALTERNATIVE REPRESENTATIONS OF THESE PHENOMENA

Computational representations are needed for those phenomena that will be explored in more depth. These representations include equations, curves, surfaces, process models, agent models, etc. – in general, instantiations of standard representations. Boundary conditions can affect choices of representations. This requires deciding on fixed and variable boundary conditions such as GDP growth, inflation, carbon emissions, etc. Fixed conditions can be embedded in representations while variable conditions require controls such as slider bars to accommodate – see Step 9.

STEP 6: ASSESS THE ABILITY TO CONNECT ALTERNATIVE REPRESENTATIONS

Representations of phenomena associated with tradeoffs to be addressed in more depth usually require inputs from other representations and produce outputs required by other representations. Representations may differ in terms of dichotomies such as linear vs. nonlinear, static vs. dynamic, deterministic vs. stochastic, continuous vs. discrete, and so on. They may also differ in terms of basic assumptions of Markov vs. Non-Markovian processes. This step involves determining what can be meaningfully connected together.

STEP 7: DETERMINE A CONSISTENT SET OF ASSUMPTIONS

The set of assumptions associated with the representations that are to be computationally connected need to be consistent for the results of these computations to be meaningful. At the very least, this involves synchronizing time across representations, standardizing variable definitions and units of measures, and agreeing on a common coordinate system or appropriate transformations among differing coordinate systems. It also involves dealing consistently with continuity, conservation, and independence assumptions.

STEP 8: IDENTIFY DATA SETS TO SUPPORT PARAMETERIZATION

The set of representations chosen and refined in Steps 5-7 will have parameters such as transition probabilities, time constants, and decay rates that have to be estimated using data from the domain(s) in which the questions of interest are to be addressed. Data sources need to be identified and conditions under which these data were collected determined. Estimation methods need to be chosen, and in some cases developed, to provide unbiased estimates of model parameters.

STEP 9: PROGRAM AND VERIFY COMPUTATIONAL INSTANTIATIONS

To the extent possible, this step is best accomplished with commercially available software tools. The prototyping and debugging capabilities of such tools are often well worth the price. A variant of this proposal is to use commercial tools to prototype and refine the overall model. Once the design of the model is fixed, one can then develop custom software for production runs. The versions in the commercial tools can then be used to verify the custom code. This step also involves instantiating interactive visualizations with graphs, charts, sliders, radio buttons, etc.

STEP 10: VALIDATE MODEL PREDICTIONS, AT LEAST AGAINST BASELINE DATA

The last step involves validating the resulting model. This can be difficult when the model has been designed to explore policies, strategies, etc. for which there is no empirical data. A weak form of validation is possible by using the model to predict current performance with the "as is" policies, strategies, etc. In general, models used to explore "what if" possibilities are best employed to gain insights that can be used to frame propositions for subsequent empirical study.

Not all problems require full use of this ten-step methodology. Often visual portrayals of phenomena and relationships are sufficient to provide the insights of interest. Such views are also valuable for determining which aspects of the problem should be explored more deeply.

AN EXAMPLE

The purpose of this example is to illustrate the line of reasoning typically associated with use of the ten-step methodology outlined above. Specific representations chosen and computational results are not presented for this notional example, as our intent is focused solely on how to think about modeling socio-technical systems using the proposed methodology.

STEP 1: DECIDE ON THE CENTRAL QUESTIONS OF INTEREST

The questions of interest concern the design of congestion pricing models to discourage personal use of cars in the central city during times of potential peak demand. This involves the design of the magnitude and timing of congestion pricing, including the implication of alternative designs.

STEP 2: DEFINE KEY PHENOMENA UNDERLYING THESE QUESTIONS

The phenomena of potential interest initially include:

- Traffic Control: Magnitude and timing of prices per unit time for use of targeted inner city zone(s)
- Traffic Congestion: Traffic densities, delays, and accidents in these zones at different time of the day with and without congestion pricing
- Vehicle Control: Driver-vehicle performance as a function of varying levels of congestion

- Vehicle Performance: Acceleration and braking performance in varying levels of stop-and-go driving
- Powertrain Performance: Energy efficiency and pollution emissions as a function of vehicle performance and control as a function of varying levels of congestion

STEP 3: DEVELOP ONE OR MORE VISUALIZATIONS OF RELATIONSHIPS AMONG PHENOMENA

Development of a systemigram of this set of phenomena leads to two important conclusions. First, powertrain and vehicle performance are key to predicting the likely energy consumption and pollution emission outcomes of a congestion pricing model, but are not central to designing the model. Thus, these two phenomena can be shelved, at least until energy and pollution issues are of interest.

The second conclusion is that two important phenomena are missing. One is driver decision making in response to congestion pricing. More specifically, what percent of drivers choose to avoid the central city as a function of the pricing level? Second, what alternative modes of transportation do drivers who chose to avoid the central city chose instead? Do they avoid traveling, or take public transportation, or drive via different routes. Thus, driver decision making is a critical phenomenon.

STEP 4: DETERMINE KEY TRADEOFFS THAT APPEAR TO WARRANT DEEPER EXPLORATION

The key issue was first seen as determining what level of pricing would discourage driving in the central city during high-demand periods. With a little reflection, it is obvious that exorbitant prices will discourage everyone. But this will eliminate all traffic and generate no revenue for the city. Inner city merchants certainly do not want to eliminate all traffic and city mayors do not want to eliminate all revenue. Thus, pricing versus outcomes is a key tradeoff.

Another key tradeoff relates to the impacts of drivers' decisions on other modes of transportation. The pricing, as well as convenience, of public transportation will affect its use. Pricing levels and convenience of use will also affect the use of alternative routes. There is significant risk of just moving the congestion problems elsewhere. Thus, a key tradeoff involves levels of incentives for alternative choices and the impacts of these incentives across all alternatives.

STEP 5: IDENTIFY ALTERNATIVE REPRESENTATIONS OF THESE PHENOMENA

Three representations are needed. The route structure of the city can be represented as a directed graph, with directions of arcs indicating two-way and one-way streets. A traffic flow model is needed to predict the impacts of demands on flows along arcs, as well as the impacts of these flows on congestion. Third, an agent-based model of driver decision making is needed to model driver choices relative to pricing levels and alternative modes and routes of travel.

These phenomena can be viewed as occurring at four levels or scales – people, process, organization, and ecosystem. The people level includes drivers and their choices. The process level includes traffic flows on the city's route structure. The organization level includes city government, central city businesses, and the agencies managing the transportation infrastructure. The ecosystem level concerns the rules of the game in terms of levels of congestion pricing for various subsets of the route network and different time of the day.

The initial driver agent models might be simply probabilities of avoiding the central city as a function of prices. However, this representation will quickly be inadequate for two reasons. First, drivers' choices of alternatives will depend on what it is assumed they know. If we assume that they all have smart phones, they will know quite a bit. Consequently, the agent models will have to include mechanisms for using this information to make decisions.

The second shortcoming of the initial simple model is its lack of depiction of the social networks among drivers. Drivers are well known for quickly identifying and sharing shortcuts with friends and family. It should be expected that drivers would quickly discover holes in any pricing models and exploit these opportunities. Models that provide mechanisms for such discoveries will be invaluable for uncovering unintended consequences.

STEP 6: ASSESS THE ABILITY TO CONNECT ALTERNATIVE REPRESENTATIONS

The route structure model will define what routes are feasible. The traffic flow model will predict the spatial flows (vehicles per unit time) for each arc in the network at each point in time, including congestion levels for each arc. The agent based model will predict the decisions of each driver as a function of pricing and any other information they are assumed to have.

To connect these models, a mechanism is needed to translate thousands of individual decisions into consequent vehicle flows. More specifically, we need to connect a large number of agent-based models of drivers' decision making with partial differential equation models of vehicle flow and congestion. Thus, we need to somehow combine thousands of decisions about vehicle routes, as well as execution of those routes, with models that represent flow spatially in terms of vehicles per unit time.

This combination problem might be addressed heuristically were it not for the fact that drivers' perceptions of flows will influence their decisions. Thus, put simply, decisions affect flows, and flows affect decisions – all across thousands of agents. Thus, we need to translate back and forth between the two rather different types of representation. This will require careful thought – see later section on Representation and Composition.

Another connection issue concerns not only the movements of variables among the component representations of the overall model, but also the fact that perceptions of variables, correct or not, will influence agents' decisions. This might be handled by providing agent models with rudimentary perceptual capabilities. As a consequence, agents would be acting on approximate or perhaps even distorted information from the process level.

STEP 7: DETERMINE A CONSISTENT SET OF ASSUMPTIONS

The accuracy of the predicted levels of congestion will be highly affected by the validity of assumptions about agents' sources of information, perceptions of information and decision making rules. Making this even more complicated is the fact that drivers will differ along these dimensions. Thus, the accuracy of assumptions about agents will be affected by the accuracy of the distributional assumptions about these dimensions. This is an area where sensitivity analyses will be invaluable.

STEP 8: IDENTIFY DATA SETS TO SUPPORT PARAMETERIZATION

The topic of traffic congestion in general, and congestion pricing in particular, has been heavily studied. Thus, there are likely to be substantial data sets that can be accessed. However, the validity of these data to the particular city and driver population of interest may be questionable. Nevertheless, this is the right place to start, at least in terms of prototyping an initial model and exploring the parameter sensitivity of model predictions to key parameters.

Step 9, Program and Verify Computational Instantiations, and Step 10, Validate Model Predictions, at Least Against Baseline Data, were not performed for this example.

REPRESENTATION AND COMPOSITION

Of the ten steps in the methodology, steps five through seven present some of the biggest challenges from a theoretical standpoint. These steps deal with the identification and composition of modeling formalisms. While combining formalisms is certainly not a new problem, it is one that has been problematic historically. This is especially true when composing models that contain human and social aspects.

In recognition of the difficulty of composing models, Tolk and Muguira (2003) introduced the Levels of Conceptual Interoperability Model (LCIM). This model was subsequently updated in Wang, et. al. (2009) to the seven layer model depicted in Figure 1. As with other types of interoperability model, the greater the number of layers over which two models are compatible, the lower the risk of error due to composition. Depending on the phenomena being modeled and the question being asked, not all of the levels are necessary (Tolk & Muguira 2003). It should also be noted that while LCIM was developed to facilitate simulation interoperability, a simulation is simply an executable model. The same principles can apply to non-executable models.

Level 6 Conceptual Interoperability
Level 5 Dynamic Interoperability
Level 4 Pragmatic Interoperability
Level 3 Semantic Interoperability
Level 2 Syntactic Interoperability
Level 1 Technical Interoperability
Level 0 No Interoperability

Figure 1- The Levels of Conceptual Interoperability Model from Wang, et. al. (2009)

Levels 1 and 2 constitute the traditional view of interoperability: can the models exchange data, and do they agree on the format of that data? For example, this could be viewed as exchanging data using an agreed upon XML schema. Level 3 introduces semantic interoperability. In other words, the two models agree on the meaning of the data exchanged. Achieving semantic interoperability is a well-recognized problem and can sometimes be addressed via common dictionaries or common reference models such as the DoDAF Meta-model 2 (DM2).

Levels 3 through 6 introduce non-traditional forms of model interoperability. Pragmatic interoperability means that the models agree on how data is used. To accomplish this, the models must share a common view of the workflow. This common view could be captured in something akin to a sequence diagram in UML.

Dynamic interoperability means that the models agree on how the context and meaning of data changes over time. This type of interoperability could be captured in a modeling specification such as DEVS. Finally, conceptual interoperability means the models agree on modeling assumptions and constraints. For example, aspects of the conceptual model could be captured in a DoDAF architecture.

Achieving interoperability on a given level reduces the risk of a certain class of errors. For example imagine that an analyst would like to evaluate the performance of a particular sensor at tracking projectiles. He has two models that he would like to compose. He intends to use the first model to generate the trajectory of the projectile and then feed it into the second model, which assesses the performance of the sensor against that trajectory. Unfortunately, unbeknownst to the analyst, the two models do not share the same conceptual model of the earth. The projectile model assumes that the earth does not rotate, an acceptable assumption over short distance trajectories. However, the sensor model assumes that the earth rotates because it was designed to deal with long distance trajectories. When the two models are combined they are likely to produce erroneous results if performance is evaluated over long distances. If the two models were conceptually interoperable, this error could have been avoided.

It is these types of “higher level” interoperability issues that lead to shortcomings in some existing frameworks for model composition. For example Wang, et. al. (2009) noted that High Level Architecture (HLA) standard for federating simulations (IEEE 1516-2010) has exhibited a number of shortcomings in part because it only reaches level 2 on the LCIM scale.

How does one achieve the higher levels of interoperability? There has been a great deal of discussion regarding the use of ontologies as a means to improve model composition and interoperability (Hoffman 2011, Hoffman 2013, McGinnis et al 2011, Partridge, et al 2013, Tolk 2011). The term ontology originated in philosophy and refers to the study of what exists. The concept has been adapted in the domain of computer science as well as the domain of modeling and simulation to refer to a formal specification of concepts and the relationships between them within a particular knowledge domain (Hoffman 2013).

Hoffman (2013) notes two types of ontologies in the world of modeling and simulation: methodological and referential. Methodological ontologies refer to specifications of model formalisms, for example, discrete event simulation. Referential ontologies capture knowledge about the parts of the real world that are being modeled, for example, machines, workers, raw materials, power, etc. In other words, a methodological ontology should capture techniques for modeling and a referential ontology should capture what objects and phenomena in the world are being modeled. Standardization in both types of ontologies can facilitate composition and interoperability.

To better illustrate the use of ontologies for composition, imagine you wish to develop a simulation by composing “off the shelf” models that could be used to train a pilot to fly an aircraft. Constructing a referential ontology would mean capturing the salient physical features of the aircraft, the pilot, and the relationship between them. One might imagine that there would be a different referential ontologies for different classes of aircraft. For example, a Boeing 747 airliner behaves very differently in the air that a Boeing F/A-18 fighter aircraft. As far as methodological ontologies, the flight characteristics of the aircraft might be modeled using differential equations while the arrival of sudden events such as in-flight emergencies might be modeled using a discrete event formalism.

Suppose that you have two off the shelf models: one that models the discrete arrival of inflight emergencies and one that models the continuous behavior of the aircraft in flight. Your ability to successfully compose these two models depends on their consistency with the appropriate methodological and referential ontologies. First, let us consider the methodological ontologies. If your flight model conforms to an approach called the Differential Equation System Specification (DESS) and your emergency event model conforms to an approach called the Discrete Event System Specification (DEVS), then there is a valid mechanism to combine the two modeling formalisms. Zeigler, et. al. (2000) developed an entire book that explains how to accomplish this composition.

As Zeigler, et. al. (2000) point out, when we combine formalisms in this manner, we are essentially creating a new formalism that subsumes them. So by employing well defined methodological ontologies and following certain rules, we can create a new, methodologically valid formalism. But this isn't the whole picture. If the referential methodologies are misaligned, composition may still fail.

For example, if the inflight emergency model represents the incidents that one would expect while flying an F/A-18 and the flight model represents the behavior of a 747, the final composed simulation is not going to be representative of what the pilot would experience in the real world. While this example is a fairly obvious case of misalignment for illustrative purposes, one can imagine more subtle misalignments that could be difficult to detect without a full understanding of the referential ontologies. For example, what if instead the models represented two different variants of the 747. Would they be close enough to compose? Consequently, it is entirely possible to combine two off-the-shelf models in a methodological valid way but have the composition fail because they don't represent the real world in a consistent fashion. Sufficient alignment of both methodological and referential ontologies is necessary achieve interoperability.

Hoffman (2013) observes 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." So it would seem that the use of standardized ontologies could be a useful means to facilitate the composition of modeling formalisms.

Unfortunately, when humans come into play, the situation becomes more challenging. Hoffman also notes that, "…it might be difficult, if not impossible, capture many purposeful human actions in formal systems – including referential ontologies." He goes on further to state 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 difficulties with creating referential ontologies in the socio-technical domain that Hoffman cites can be summarized as follows: Human beings are capable of dealing with logical contradictions by bypassing formal logic, but a formal ontology is designed to be a logical representation. Furthermore, there are many possible representations of a social system with little agreement among experts in the domain. To complicate matters further, the appropriate representation often depends on the problem being addressed which entangles what is being modeled with how it is being modeled. This leads Hoffman to assert that there is no independence between referential and methodological ontologies in the social domain.

The conclusion that can be drawn from this discussion is that there is no truly objective, standardized way to ensure the valid composition of existing models within the socio-technical domain. However, the discussion to this point has largely been a description of what is required to maximize the reusability of models. If we loosen the demand for reusability and are willing to do some work to compose existing formalisms, we can turn the aforementioned requirements into a prescriptive approach for composing formalisms to analyze socio-technical systems in a valid way. Consequently, the first four steps of the methodology presented in this report prove to be essential because they address the appropriate way to frame the problem. The validity of the subsequent selection and composition of the modeling formalisms will be governed by the outcome of these first four steps.

To better understand this point, it is instructive to critically review other instances where socio-technical systems have been examined via the composition of independent modeling formalisms. What follows is a brief description of two examples from the health-care domain.

Park, et. al., (2012) developed a multi-level simulation to examine policy alternatives for an employer-based 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 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 four levels were composed by treating the discrete event simulation of the process level as the core model. The ecosystem and organization levels served as inputs to the process model. The agent based behavior from the people level was embedded directly into the discrete event simulation. In other words, the representation of the patients as agents impacted their movement through the discrete event simulation.

Park, et. al. then used this simulation to examine the impact of different operational policies on the outcomes of the prevention and wellness program. One of the findings was that the financial objectives of the employer and the healthcare provider are in conflict and should not be independently optimized because, "if either loses significantly, the system becomes dysfunctional."

From a modeling perspective, the effort created a valid composition by first building a conceptual model that defined the levels and described the interactions between them. This served as a referential ontology to ensure conceptual consistency among the levels. As to the methodological ontology, two standard simulation approaches were employed: discrete event simulation and agent based simulation. The two approaches can be combined in a valid way by embedding the agent attributes into the entities that move through the discrete event simulation. Thus, the modeling approach remained consistent with the methodological ontologies for these simulation techniques. The takeaway is that by employing a top-down approach that considered the objectives of the study to identify the relevant aspects of the conceptual domain, the authors were able to compose formalisms in a consistent manner. This in contrast to a bottom up approach that attempts to build a universal means to combine formalisms for any potential problem.

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 (Barberis, et. al. 2012). While SPLASH is not intended purely 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. Consequently, it really only addresses the lower levels of the LCIM model, though the SPLASH Actor Description Language (SADL) does attempt to document semantics and assumptions.

Consequently, SPLASH could be viewed as a toolkit for creating valid combinations of methodological ontologies, but there is little to address the need to create a consistent referential ontology among the models being composed. In the obesity example, the use of the proprietary off the shelf model, VISUM, means implicitly accepting unknown modeling assumptions that, if not fully investigated, could potentially conflict with the referential ontologies of the other models. In short, while the SPLASH effort may result in some useful tools for composing models, SPLASH by itself is not sufficient to ensure the composability of models.

It is important to note that the SPLASH team makes no claim that the framework will ensure composability. In fact, they acknowledge the difficulty of combining heterogeneous models, and the intent is to provide a means to loosely couple models when it is deemed appropriate to do so (Cefkin, et. al. 2010).

What we can extract from the discussion to this point are the attributes we would expect of the proposed methodology with regard to successfully selecting and composing modeling formalisms. First, it should be driven by the research questions being asked. For socio-technical systems, the appropriate representations of the system depend on the context. As noted by

Davis and Bigelow (1998), a simplifying assumption may make sense to answer one question but not another. Thus, it is necessary to establish what Zeigler, et. al. (2000) referred to as the experimental frame.

Second, the methodology should be top down. That is it should start from an exploration of the domain within the context of the research questions of interest. Once the domain and context are understood, the appropriate modeling formalisms can be selected and composed. This is in contrast to a bottom up approach where one starts with the models available and attempts to force them together to answer the research question. This is not to suggest that model reuse is always invalid. Rather, it is to emphasize that order matters. The chance that any given set of off the shelf models will satisfy the upper levels of the LCIM model (i.e., that they have a consistent referential ontology) is extremely low in the socio-technical domain for the previously discussed reasons. However, when one establishes the referential ontology first, one can consider how well existing models align and if deviations are acceptable for a given application.

Third, the methodology should produce an overarching conceptual model of the domain that is adapted to the research questions. A referential ontology that is described using a formal modeling language (e.g., SysML) may be desirable in some circumstances, but is not always required. Regardless, the conceptual model will be used to guide the selection of modeling formalisms and aid in ensuring model compatibility by governing interoperability at the upper levels of the LCIM model.

Fourth, the methodology should provide guidance for selecting and combining modeling formalisms. While not every possible combination of formalisms can be anticipated and the appropriate way to combine the formalisms may depend on the experimental frame and the referential ontology, the methodology should provide some general guidelines that lead the model developer in the right direction and highlight pitfalls to avoid. This guidance can be captured in a model composition framework. The framework would address the need to combine methodological ontologies in a valid way and ensure interoperability at the lower levels of the LCIM model.

PRELIMINARY MODEL COMPOSITION FRAMEWORK

The objective of the model composition framework is to support the proposed methodology by providing guidance on how to compose models, particularly those from different formalisms. Since the exact means to compose any two formalisms will vary depending on the circumstances, the framework will not provide specific instructions. Instead it will identify conditions that need to be satisfied, pitfalls to avoid, as well as guidelines and heuristics for approaches that have worked well in the past. What follows is an overview of a preliminary version of the framework that will be refined and improved during subsequent research. The rules for composing dynamic models are largely drawn from Zeigler, et. al. (2000), but they have been augmented to cover static models and to provide guidance for special classes of composed models.

There are basically two different ways to compose models: coupling and combination. Coupling two models means that to compose them you only need to link their inputs and outputs as appropriate and coordinate their execution or evaluation[2]. HLA and SPLASH are approaches to coupling models. Coupled models are modular, and they are easier to mix and match assuming that their referential ontologies are consistent for the experimental frame.

Combining two models, on the other hand, means that you are essentially creating a new model with parts of the original models. This can be accomplished in one of two ways. First, in some cases, one formalism can be embedded in another. For example, a discrete time model could be embedded inside a discrete event model by advancing the time by a constant. Embedding can occur when one formalism can be simulated within another formalism (Zeigler, et. al. 2000). A practical example is the prevention and wellness model developed by Park, et. al. (2012) that was described in the previous section. An agent based model of patient behavior was embedded in the discrete event model of the care process.

Second, modeling formalisms can be combined to create a new formalism. For example, a discrete event model can be combined with a differential equation based model into a new formalism that uses thresholds and phases to manage interactions between the two. Zeigler, et. al. (2000) provides a notional example of a barrel filler. The arrival of a new barrel and the departure of a full barrel are discrete events. The actual filling of the barrel is governed by a differential equation of fluid flow.

Generally speaking, coupling models is preferred because it provides greater flexibility and reuse, but what determines when you can couple rather than combine models? The most important determinant is the dependence relationship between the states of the models being composed. It is useful to consider this issue for two different classes of model: dynamic and static.

Coupling and combing dynamic simulation models of the discrete time, discrete event, and differential equation formalisms are covered in great detail in Zeigler, et. al. (2000). Even though the authors only cover those three formalisms, a very large number of dynamic models fall under one of those three, and the concepts presented are fairly general.

For dynamic models, the key determinant as to whether or not models can be coupled or combined is whether or not the state variables of one model affect the state transition of the other. If the models simultaneously affect each other's state transition, the models must be combined. For example, consider the Newtonian gravitation of two objects. The instantaneous acceleration of each mass is dependent on the distance between the two objects. Therefore, to predict their movement, the models of the two objects would need to be combined.

If, on the other hand, the two models only effect each other's state transitions in future times via input/output relationships, then the models can be coupled. For example, consider the case

[2] Note that we are using the term "coupling" in a different manner than Zeigler, et.al. (2000). Zeigler defines two forms of coupling: modular and non-modular. In our usage, all coupling is assumed to be modular coupling and non-modular coupling is assumed to be a form of combination.

of a distributed command and control system. Since the different nodes of the system can only influence each other by communicating via TCP/IP messages, the system can be represented by coupling the models of the individual nodes.

It is important to note that to successfully couple dynamic models, they must be closed under coupling (Zeigler, et. al 2000). That means that the model that results from coupling itself must be a valid model under the formalism.

For static models, the issue is whether there is a one-way or two-way dependency between the models. When there is a one-way dependency, the models can be coupled via an input/output relationship. The independent model is solved first, and its output becomes an input for the dependent model. That model is evaluated second. For example, imagine that you have a model that optimizes an investment portfolio, but it depends on the prevailing interest rate. You also have model that calculates the prevailing interest rate from a set of reported interest rates from the market. The interest rate model can be solved first and then serve as an input to the portfolio optimization model.

When there is a two-way dependency, however, the models cannot be coupled. They must be combined. For example, consider general economic equilibrium. The price of manufactured goods in the economy is dependent on the price of labor and the price of labor is dependent on the price of manufactured goods. The two market models must be combined into a single model and solved simultaneously via an analytic solution or a search algorithm.

The general guidelines for coupling versus combining models are summarized in the table below. By following these general guidelines, more complex phenomena can be examined by composing multiple static and dynamic models. For example, Figure 2 illustrates a notional example of a hybrid static/dynamic model for rebalancing an investment portfolio. The portfolio optimization model is a static optimization model. It can be incorporated into the dynamic model by resolving it at each relevant time instant. While there are many ways to compose models, there are two classes that stand out as particularly important, hierarchical and multi-level models.

Table 1 – Preliminary Model Composition Guidelines

Model Class	Formalism	State Dependence	Composition	Restrictions
Static	Same	One-way	Coupled	Evaluate in the order of the dependencies. If there is a cycle of one-way dependencies, the models would need to be combined
Static	Different	One-way	Coupled	Evaluate in the order of the dependencies. If there is a cycle of one-way dependencies, the models would need to be combined
Static	Same	Two-way	Combined	Simultaneous evaluation required
Static	Different	Two-way	Combined	Simultaneous evaluation required
Dynamic	Same	Input/output	Coupled	Formalism must be closed under coupling
Dynamic	Different	Input/output	Coupled	Subject to input/output conversion rules and there must be combined formalism that is closed under coupling
Dynamic	Same	State Transition	Combined	Combined within the same formalism
Dynamic	Different	State Transition	Combined	Must create a new formalism or embed one in the other

By following these general guidelines, more complex phenomena can be examined by composing multiple static and dynamic models. For example, Figure 2 illustrates a notional example of a hybrid static/dynamic model for rebalancing an investment portfolio. The portfolio optimization model is a static optimization model. It can be incorporated into the dynamic model by resolving it at each relevant time instant. While there are many ways to compose models, there are two classes that stand out as particularly important, hierarchical and multi-level models.

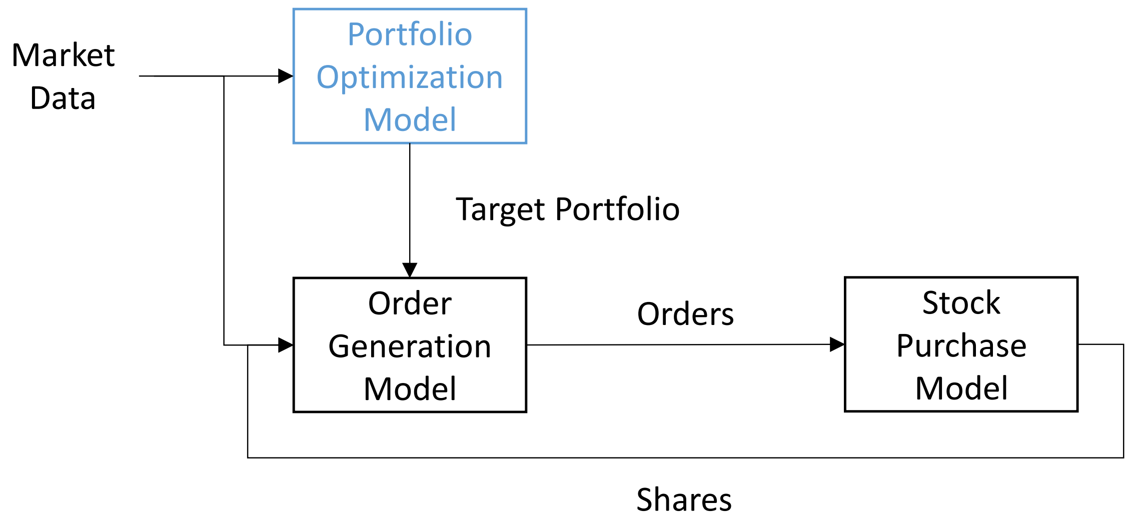

Figure 2 – Notional Hybrid Model of Rebalancing an Investment Portfolio

Hierarchical models involve the aggregation of individual models into larger models via a hierarchical structure. This is analogous to the traditional systems engineering process of combining components into subsystems and subsystems into systems. This can be accomplished via either combination or coupling, but a hierarchy built via coupling is particularly flexible because it allows for mixing and matching as well as distributed execution.

For example, models of machines can be aggregated into a model of a factory, and models of factories can be aggregated into a supply chain (Figure 3). If the hierarchy is modular (i.e., it is built by coupling) the different configurations of the supply chain can evaluated by swapping in out different factory models representing different suppliers.

Another class of composed model that is of particular importance to analyzing socio-technical systems is the multi-level model. A multi-level model is a composition of models at different levels of abstraction. For example, traffic can be represented as a set of flows in one model and as individual vehicles in another. Each model has distinct advantages and disadvantages. Multi-level models attempt to analyze a system by leveraging the advantages of each layer of abstraction.

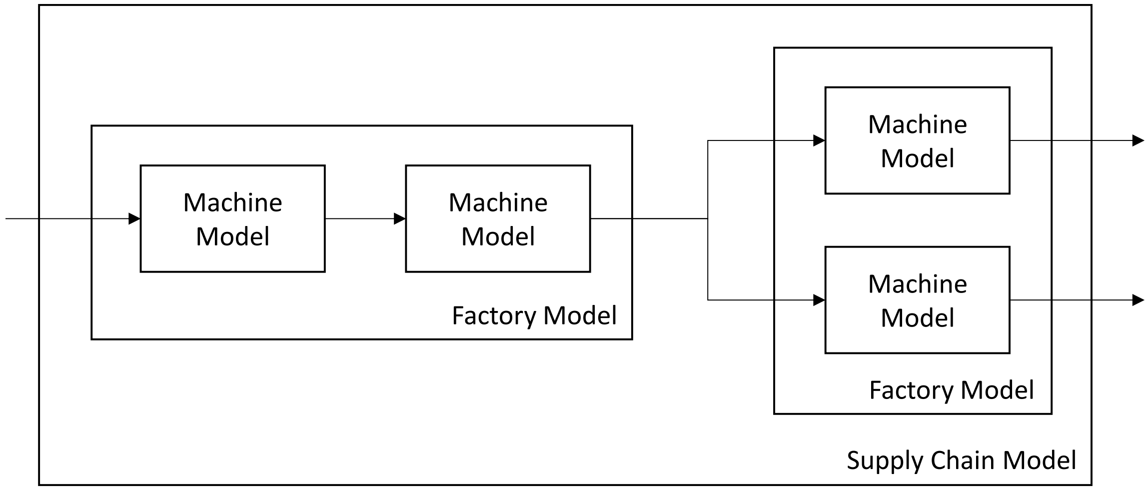

Figure 3 – Notional Hierarchical Model of a Supply Chain

Davis and Bigelow (1998) provide an in depth discussion of the rationale behind multi-level modeling though they use the term multi-resolution modeling. They point out that the most common argument in favor of employing abstraction is economy, but that is really a side benefit. The primary reason for employing different levels of abstraction is that different behaviors emerge at different levels of abstraction. While in principle these emergent behaviors could be replicated via extremely detailed models, in practice the detailed models are scope and data limited. Imagine trying to predict the weather by modeling the behavior of every single atom on Earth. Even if you had the model and the computational power, you would never be able to measure the state of every atom to feed into the model.

The value of abstraction is evident in scientific disciplines. Chemistry has its own laws that are based on the aggregate behavior of atoms. Chemists do not need to constantly turn to quantum mechanical models from physics to do their jobs. However, there is value in understanding the relationship between the models from physics and the models from chemistry. Understanding of one can inform the other.

Multi-level modeling is of particular importance when examining socio-technical systems because the historical difficulty with predicting the behavior of these systems is in part due to the fact that they are the result of multiple layers of emergent behavior. This is evident in the example of congestion pricing presented above.

Unfortunately, building multi-level models presents a daunting set of challenges to model composition. Key among these challenges is that each layer, at least in part, represents the same underlying phenomena. This means that there are always two-way state interdependencies because a change in one layer would imply a change in the others. In the worst case, all of the models for each of the layers would need to be combined and evaluated simultaneously. For a dynamic case, the models would need to be simultaneous "solved" for each time step/instant.

The actual impact depends on the circumstances. The previously discussed prevention and wellness model simply embedded the agent based model into the discrete event model. So computational cost was low, but it came at the expense of losing modularity. However, some situations require the simultaneous solution of several variables. For example, traffic flow rate depends on the decisions of each driver, but the decisions of each driver depend on the current flow rate. Searching for such solutions could be an expensive or even impossible demand depending on the problem.

However, in many practical situations, simplifications can be made to convert two-way state dependencies into one-way dependencies that can be evaluated sequentially. (Though, it should be noted that a cycle of one-way model dependencies would still need to be evaluated simultaneously.) What follows are a few examples of ways that two-way dependencies can be converted into one-way dependencies. Of course, the validity of these assumptions in any given case depends heavily on the referential ontology and the experimental frame.

- *Assume that the impact of one level is negligible on the other*: For example, an individual may make a decision to purchase bread based on the current market price. However, since millions of other people are also purchasing bread, the choice of any one person can be assumed to have a negligible on effect on the price.
- *Assuming that there is a lag in the impact of an event in one level on the state of another:* For example, a large equity order by a major institutional investor will impact the market price of the equity, but it takes time for the news of the order to disseminate and the transaction to execute. Consequently, the institutional investor can make a decision based on the current market price, but the actual impact of the order on the market price will occur at a future time. The two-way dependency is converted to an instantaneous dependency in one direction with a dynamic dependency in the other.
- *Rolling up the state response behavior of the lower level to one that is compatible with the higher level:* For example, consider a parametric performance model of a car. A high fidelity model of the car's engine could be run over a wide range of possible states. Functions could be fit to the output of the high fidelity model, and these functions could be incorporated into the parametric model of the car. The loss in fidelity of engine performance is acceptable given the fidelity of the parametric model. This allows the two models to be evaluated sequentially.
- *Externalizing state variables as decisions:* For example, a CEO would like to assess the impact of his decisions on the operation of the company. Even though, in real-life the state of the company would impact his decisions and his decisions would impact the state of the company, the CEO would like to perform "what if" analyses on decision alternatives. This would make management representation external to the rest of the model and creates a one-way dependency.

As was mentioned previously, the model composition framework and the associated guidelines are preliminary. They will be refined through future research. Refinement means both validating the guidelines in the framework as well as incorporating more specific guidance for common model composition situations. The end goal is to provide a resource to aid practitioners with the execution of steps five through seven of the overall methodology.

USE OF THE MODELING METHODOLOGY

The evolution of this effort will be driven by the needs of two groups: the consumers of analysis products within the DoD and the producers of analysis products within the DoD. The consumers of analysis products consist of high-level policy makers and operational decision makers. Each has slightly different needs. Policy makers, in essence, set the rules of the game. They are interested how the policies they create incentivize the behavior of the organizations and/or individuals that are participating in these complex socio-technical systems. Operational decision makers, on the other hand, are interested in how to best allocate scare resources to achieve desired outcomes within the socio-technical system.

The counterfeit parts example from the introduction illustrates the difference. A policy maker may be interested in identifying policies that would disincentivize counterfeiters from operating and/or incentivize contractors to vet their suppliers. An operational decision maker may be interested in determining how much should be spent on testing for counterfeit parts versus designing systems that are robust against the effects of counterfeit parts. Of course, the needs of the two groups are interrelated as the policies set by the policy maker can influence the resource allocation decisions made by the operational decision maker.

When addressing problems that involve complex socio-technical systems, both groups of consumers require those that produce analyses for them to be equipped with the right tools and methods, and they need a mechanism to explore and understand both the problem domain and the impact of potential solutions. The analyses themselves are developed by a combination of analysts and modeling and simulation (M&S) professionals -- sometimes they are the same person. Analysts require methods and tools to explore the problem, establish the experimental frame, identify relevant phenomena, and develop a conceptual model of the domain (i.e., a referential ontology). M&S professionals require methods and tools to identify the right modeling formalisms to represent the relevant phenomena and compose them in a valid way.

In order to support the needs of both analysis producers and analysis consumers, it is anticipated that the output of this research will provide support in the areas described in Table 2. It is expected that this support will take the form of recommended methods, processes, and tools. Collections of reusable methods and models could be stored in an online archive for future access by analysts and M&S practitioners.

Table 2 – Areas of Methodological Support

Need Area	Rationale
Visualization Methods & Tools	Visualization allows policy/decision makers to explore the problem space and "test drive" potential solutions
Interactive Visualization Infrastructure	Many complex problems involve the input/buy-in of multiple stakeholders. To accomplish this, the visualization infrastructure must allow multiple parties to participate in visualization activities.
Economic and Policy Models	When the purpose driven behavior of individuals and organizations is a salient feature of the problem space, economic, social science, and policy models are needed to explore this behavior.
Physical and Organizational Models	In socio-technical systems, the interplay between organizational structures and the physical systems that they employ translate the decisions made by individuals and organizations into realized outcomes.
Behavioral and Social Models	When people are a critical component of organizational processes, how those individuals execute tasks and communicate with each other can have a substantial impact on the ultimate behavior of the system.

SUPPORTING THE METHODOLOGY

Our vision for methodological support of modeling complex socio-technical systems is an interactive environment that supports the set of nominal steps outlined above. These steps are "nominal" in that users are not required to follow them. Advice is provided in terms of explanations of each step and recommendations for methods and tools that might be of use. This advice can take several forms. At one extreme, it would be copies of this report, as well as previous and subsequent reports. At the other extreme, expert advice and automation might involve streamlined execution of the steps of the methodology. We think a middle ground is more acceptable to users while also being technically feasible.

Compilations of physical, organizational, economic and political phenomena are available, including standard representations of these phenomena, in terms of equations, curves, surfaces, etc., but not software. Advice is provided in terms of variable definitions, units of measure, etc., as well typical approximations, corrections, etc. Of particular importance, advice is provided on how to meaningfully connect different representations of phenomena.

Visualization tools are available, including block diagrams, IDEF, influence diagrams, and systemigrams. Software tools for computational representations are recommended, with emphasis on commercial off-the-shelf platforms that allow input from and export to, for example, Microsoft Excel and Matlab. Examples include AnyLogic, NetLogo, Repast, Simio, Stella, and Vensim.

In keeping with contemporary approaches to user support, this methodological support is not embodied in a monolithic software application. Instead, this support framework operates as a fairly slim application that assumes users have access to rich and varied toolsets elsewhere on their desktops. The support provides structured guidance on how to best use this toolset to address the phenomena associated with the problem that has motivated the modeling effort at hand.

We assume that model development occurs within the confines of one or more desktops or laptops. We also envision capabilities to export interactive visualizations to much more immersive simulation settings. Methodological support will not, however, be premised on users having access to such settings.

DEVELOPMENT ROADMAP

As discussed previously, the challenge of analyzing and modeling complex socio-technical systems is that the appropriate representation of the system gets entangled with the questions being asked. While this is always true to some extent with any analysis effort, the problem is exacerbated when human and social elements are relevant to the experimental frame. To make an admittedly broad generalization, the number of possible alternative representations increases as one loosens the classical assumptions with regard to human and organizational behavior. In other words, as one loosens the assumption that humans and organizations are purely rational, utility maximizing economic agents with perfect forecasting abilities, modeling their behavior becomes more difficult, and there are more modeling alternatives to choose from. In fact, the appropriate alternative may depend on the question of interest.

Unfortunately, there are many complex socio-technical systems of interest to DoD where a classical model of human or organizational behavior could be extremely misleading. For example, one would not expect a classically modeled human being to become a suicide bomber. Another model would be needed to predict that type of behavior. Of course, developing such a model would be outside of the scope of this effort. However, identifying the model and developing the methods to compose it with other models would be consistent with the established research goals.

The challenge is that identifying, selecting, and vetting models that loosen the classical assumptions introduce risk to the successful development of the modeling methodology and associated support. Consequently, the intent is to follow a spiral approach to developing and refining the methodology. The basic approach is to start with classical methods to establish an initial baseline for the methodology. From there, each spiral will attempt to expand and enhance the methodology by loosening additional classical assumptions and integrating another family of models, both conceptual and methodological. In each spiral, the critical risks to accomplishing the incremental expansion will be identified and resolved by conducting targeted case studies.

It is envisioned that these case studies will address problems relevant to DoD and will take one of two forms: examining a new problem where the expansion is necessary or enhancing a case study from a previous spiral by loosening assumptions. Either way, the objective is to simultaneously reduce the risks to the development of the modeling methodology and provide insight to DoD policy makers and decision makers. The advantage to the spiral approach is that it will allow for course corrections based on what works and what does not. The planned spirals are illustrated in Figure 4.

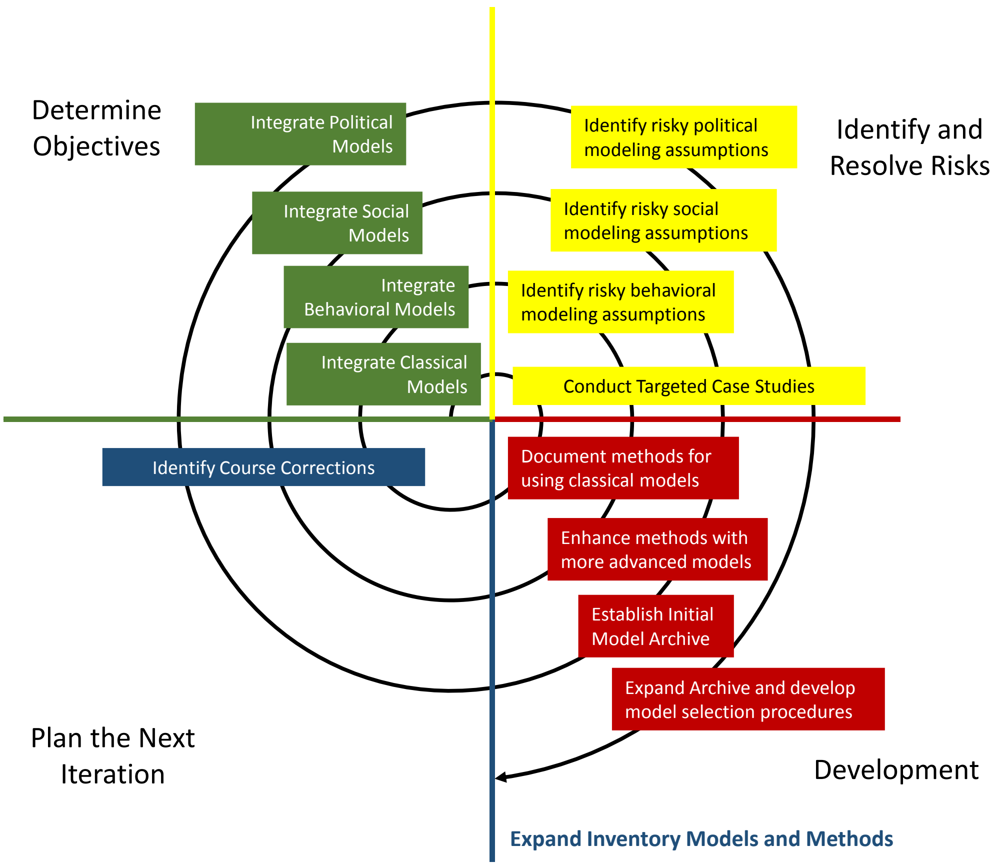

Figure 4 –Planned Spirals for Enhancing the Methodology

Each spiral implies an enhancement to each of the user/customer need areas described in Table 2. While the exact nature of the enhancements will depend on the outcome of each spiral, a notional timeline with projected enhancements is presented in Table 3.

Table 3 – Notional Timeline for Enhancing Each of the Customer/User Need Areas

	2014	2015	2016	2017	2018
Interactive Visualization Infrastructure	Human-in-the loop; individual decision makers	Individual to group decision making; enhanced visualization	Remote access & participation; group support	Multi-site deployment of immersive capabilities	Real-time, distributed operational decision making
Visualization Methods & Tools	Compilation & evaluation of COTS methods and tools	Recommendations for which tools to employ in various contexts	Development of mappings between tools	Exploration & tailoring to new application domains	Exploration & tailoring to new application domains
Economic and Policy Models	Classical economic decision making	Behavioral economic decision making	Initial archive of economic models	Exploration of selected public-sector models	Procedures for selection of economic models
Physical and Organizational Models	Classical physical and organizational process models	Enhanced cross-process linkages & transformations	Initial archive of process models	Expand archive of process models	Procedures for accessing process model archive
Behavioral and Social Models	Individual task-related behaviors & performance	Social networking of task-related information	Expand to broader social phenomena	Exploration & tailoring to new application domains	Exploration & tailoring to new application domains

Based on this roadmap, we propose the following activities for CY-14:

- Case studies will be designed to advance the methodology and user support for classical methods. A separate report will be produced for each case study.
- Models needed to support case studies will be compiled and, if needed, developed, e.g., classical models of human behavior and performance.
- Human, process and economic models will be composed, with careful attention to assumptions, variable flows, etc. A principled approach will be taken, even if heuristic, at the semantic level of composition.
- Conceptual design of the modeling environment in a COTS application, e.g., Excel/VB, will be completed. A report on conceptual design will be produced.

CONCLUSIONS

This report has presented a proposed methodology for modeling complex socio-technical systems. An example of the use of the methodology for ground vehicle design and control that illustrates the nuances of the methodology was elaborated. In depth issues associated with representation and composition – steps 5-7 of the proposed methodology – were explored. This led to elaboration of a model composition framework. Eventual use of the modeling methodology was then discussed. Use considerations provided the basis for subsequent discussion of approaches to supporting the use of the methodology. Finally, a development roadmap for iteratively advancing and applying the methodology was outlined.

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APPENDIX

HOW OTHER INDUSTRIES APPROACH MODELING

The issues raised in this report are not unique to the Department of Defense or the aerospace/defense industry. Other, non-defense industries associated with the design, development, deployment, operation and sustainment of complex systems face these issues as well. To assess how other industries address these issues, we conducted a series of interviews of eight executives in four industries – automobile, commercial aerospace, building equipment, and semiconductors and electronics. The results of these interviews provide insights into modeling complex systems more generally (Mullen, 2013)

All four of these industries use modeling and simulation at multiple levels of abstraction. There are, however, few computational linkages of these representations. This is due in part to the allocation of responsibilities and resources across organizational functions. There is recognition that a solution composed of a set of local optima may not represent the globally optimal solution, but these large companies have difficulty approaching their design and development activities in other than a reductionist manner.

All of these companies consider socio-technical phenomena to be important to the success of their systems. Thus, they address human behavior and performance, social and organizational interactions and economic decisions making, e.g., for airline managers and building managers. However, these models are seldom computationally integrated with the physics-based models of the technology components of their systems.

These companies invest in modeling and simulation capabilities because they intend to manufacture hundreds, thousands, or millions of the systems they design. Further, they are responsible for the consequences of design inadequacies or failures. Modeling and simulation helps them to make better choices, and understand the consequences of these choices.

For the most part, they all employ commercially available software (i.e., Matlab, Simulink, Model Center) as their computational engines, with their system representations being their proprietary information. They approach reuse of models with caution, in particular being wary of "model-induced design flaws." They impose standards on tools, software and documentation. Nevertheless, they report that cross-functional negotiations on models and simulations are quite common.