Agent-directed Simulation Systems Engineering

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Abstract
This article emphasizes the application of system engineering principles to the development of Modeling and Simulation (M&S) applications. Clear distinction between M&S for system engineering and system engineering (SE) for M&S is presented to clarify the need for simulation system engineering. Furthermore, the characteristics of emergent open, complex, and adaptive M&S applications are overviewed to make the case for agent-directed simulation system engineering. An agent-directed simulation view of developing such applications is presented within the framework of a cognitive system engineering perspective.

Keywords: agent simulation**,** agent-based simulation, agent-supported simulation, systems engineering, simulation systems engineering.

1.0 Introduction

Complexity is a pervading phenomenon in natural, social, business, artificial, engineered or hybrid systems. Cells, organisms, the ecosystem, markets, societies, governments, cities, regions, countries, large scale software and hardware systems, the Internet, all are examples of complex systems (Parunak 1999). Scientists use various forms of measurements and models to explore, understand, and elucidate the characteristics of such systems, while engineers build and design working artificial complex systems. As the engineered phenomena become more and more complex, we are observing a convergence as engineers try to model the systems in an attempt to analyze them. However, there is another trend that makes these models extremely complex.

Complexity research mainly happens at the borders between various disciplines and thrives on interactions between engineering and the sciences. Predictive modeling comes from the context of theoretical science, with a bias toward deductive reasoning and a resulting preference for validity as a standard quality (Bankes 1999). The current trend in M&S treats the use of computer models as experimental science. In this new era, the purpose of M&S in dealing with complexity is not necessarily to predict the outcome of a system, rather it is to reveal and understand the complex and aggregate system behaviors that emerge from the interactions of the various individuals involved (Yilmaz 2006). This viewpoint is based on the observation that emergent engineering applications are becoming dynamic, adaptive and open systems (Little 2005), for which the tools of traditional closed systems viewpoint are limited. More specifically, it is suggested in (Little 2005) that if our critical infrastructures are to continue to provide vital services safely and reliably, the linkages between people, organizations, and technology need to be fully understood and managed holistically. As we start exploring the state space of such systems, the types of M&S applications, as espoused in this paper, will gradually increase and find their place within the engineering domain.

In this paper we discuss the synergy of M&S and SE by overviewing the role of M&S in SE and the need for SE for M&S in the large. In particular, we examine types and characteristics of systems that are complex, adaptive, and open. Agent-directed simulation (ADS) is presented as a candidate for addressing the challenges raised by modeling and simulation of such systems. A cognitive system engineering perspective is proposed to engineer such M&S applications.

2.0 What is a System?

A system is a construct or collection of different elements related in a way that allows the achievement of a common objective (Thayer 2005). The elements of the system include hardware, software, people, facilities, policies, and other factors coordinated to achieve system objectives.

2.1 What is System Engineering?

System engineering (SE) involves the application of engineering and management practices to transform the user needs into a system specification and realization that most efficiently meets the need. SE entails the technical management functions that controls and coordinates the overall system development activities. As such, it revolves around a generic problem solving process that gradually evolves specifications toward a realization of the requirements that satisfy objectives set forth at the beginning of a project.

2.2 The Functions of System Engineering

SE involves

- *System conception* that deals with the process of involving users in conceiving an application and identifying tentative requirements.
- *Problem specification*, which identified and formulates the needs and constraints imposed by the problem domain. Domain analysis constitutes the fundamental component of problem specification. Application analysis entails the description of the parts of the system that are visible to the user.
- *Solution analysis*, which determines the set of possible ways to satisfy requirements, overviews the solutions, and selects an optimal strategy.
- *Process planning* that identifies the tasks, their scheduling and interdependencies, estimates the size and cost of the project, and determines the required effort to complete the project.
- *Process control and product evaluation* that determines the strategies to control and measure the progress and evaluates the product via testing, inspection, and analysis.

3.0 Modeling and Simulation (M&S)

M&S, as a discipline, is vital for the success of many applications areas in a multitude of disciplines (Ören 2002). M&S has many facets; often specialists in one area have a tendency to ignore other aspects. At one extreme this leads the point of view of “Anything other than war is simulation” (STRICOM). Of course, this point of view stressing on the main task is understandable; however it does not allow a top-down decomposition of the elements of a simulation system to be able to develop advanced simulation environments and applications. Most probably due to this type of view, the importance of contributions of simulation to science and engineering, known to practitioners for several decades, is rediscovered recently (NSF 2006). However, this is a very good indicator of the acceptance of the value of M&S from another perspective.

Simulation is used for two categories of applications: (1) to gain experience (simulation in training) with the following types of usages: live, virtual, and constructive simulations and (2) to perform experiments (simulation in areas other than training). Simulation can also be perceived as (1) an infrastructure to support real-world activities, a computational activity, a model-based activity, a knowledge-generation activity, and a knowledge-processing activity. A detailed view of the many aspects and different perceptions of M&S are given at the site of the M&SBOK project at (M&SBOK-aspects).

4.0 The Synergy of M&S and SE

In (Ören and Yilmaz 2006), we elaborated on how M&S and SE can support each other. Here, we discuss the role of M&S in systems, why

M&S requires SE, and why Simulation Systems Engineering (SSE) is necessary.

4.1 The Role of M&S in Systems

Simulation is becoming a dominant technology in many systems engineering applications. In defense-related training systems, simulations are being embedded to create virtual scenarios. Symbiotic simulation systems have been proposed as a way of solving this problem by having the simulation and the physical system interact in a mutually beneficial manner (Fujimoto et al. 2002). As shown in Figure 1, the (multi)simulation (Yilmaz and Oren 2004) is driven by real time data collected from a physical system under control and needs to meet the real-time requirements of the physical system.

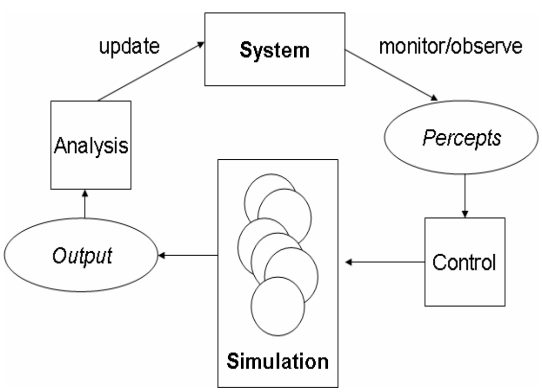

Figure 1: Symbiotic Simulation

For instance, symbiotic simulation of network systems could be used to make use of measurements obtained from the physical network to optimize and reconfigure the physical network in order to improve its performance and avoid bottlenecks.

4.2 Why does M&S Require SE?

As discussed above, M&S systems are becoming more and more complex and they are being embedded with other system in a system of systems context to serve larger objectives. In developing such simulations the solution space must be defined before assigning functionality to various components. The SE perspective provides an opportunity to specify the solution for the acquirer prior to allocation of functionality onto hardware, software, and simulation systems.

4.3 Why is SSE Necessary?

M&S development costs are rising partly due to increased complexity. Craftsmanship approach to M&S in the small does not scale to M&S in the large. Consequently, such complex and extremely large simulation systems require technical system management and SE oversight. Unless such oversight is present, the following problems are likely to emerge.

- Simulation system becomes unmanageable.
- Costs are overrun and deadlines can be missed.
- Greater risk exposure arises.
- Requirements may not be met.
- The simulation fails to satisfy its objectives.
- Maintenance costs increase.

Hence, given the functions of SE (see section 2.2), the SE perspective to M&S in the large is needed.

5.0 Agent-directed Simulation (ADSSE) Systems Engineering

The emergent types of problems addressed by simulation systems are requiring more and more open, adaptive, and flexible solutions. For instance, in most realistic scientific problems, the nature of the problem changes as the simulation unfolds. Initial parameters, as well as models can be irrelevant under emergent conditions. Relevant models need to be identified and instantiated to continue exploration. However, manual exploration is often not cost effective and realistic within a large problem state space. Dealing with uncertainty is paramount to analyzing complex evolving phenomena. Adaptivity in simulations is necessary to evolve systems in a flexible manner. The use of intelligent agents is advocated, and agents are applied (Parunak 1999) in numerous application domains to avoid limitations of conventional methods.

 ISBN # 1-56555-316-0

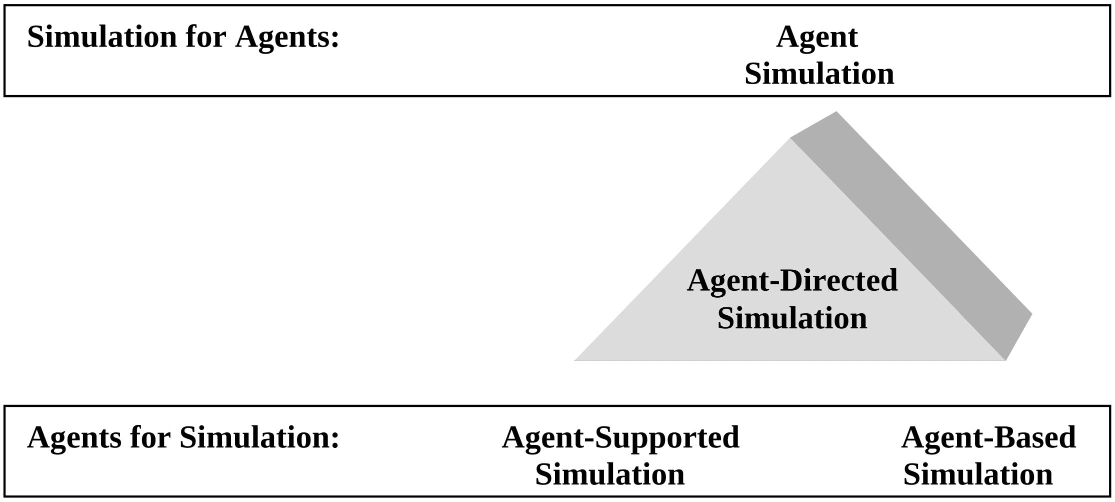

Figure 2: Agent-directed Simulation Framework

In this section, we elaborate on the essence of the complex adaptive systems that integrate people, organizations, and technology (Little 2005) and argue about the merits of ADS. Finally, we discuss characteristics of a systems engineering perspective for ADS.

5.1 The Essence of Complex Adaptive Open Systems (CAOS)

- *CAOS are goal-directed and adaptive*: In well-adapted systems goals and constraints are often implicit and embedded in the process. In a dynamically changing environment, an effective realization depends on self-organizing and adaptive mechanisms that are in place to change properties of the process to meet the current needs.
- *CAOS processes improve over time*: CAOS processes are frequently modified to update the structure and mechanisms to keep some measure elated to the relevant performance objective near an optimum. Control of adaptation, however, is distributed across all components and subsystems. A useful and credible model for the analysis of the process and prediction of responses to changes in the circumstances must reflect the mechanisms underlying the evolution of the process.
- *Many CAOS processes (e.g., sociotechnical systems) are human-centered*: As suggested by Little (2005), if our critical infrastructures are to continue to provide vital services safely and reliably, the linkages between people, organizations, and technology need to be fully understood and managed holistically. Human actors that manage and processes are adaptive and goal-directed agents. What people actually do, how they communicate and collaborate, how they solve problems, resolve conflicts, and learn behavior matters in the outcome of a process. Hence, representing activities requires modeling communication, collaboration, team work, conflict resolution, and tool and technology usage.

Given the above observations, a systems engineering perspective for CAOS should represent not only technical activities, policies, and procedures, but also the resources, preferences, and cognition of staff members, together with functional and social organization and strategic management, all in unified and coherent terms.

5.2 The Merits of Agent-directed Simulation

Figure 2 presents a unified paradigm of Agent-Directed Simulation that consists of three distinct, yet related areas that can be grouped under two categories as follows: (1) Simulation for Agents (agent simulation), i.e., simulation of systems that can be modeled by agents (in engineering, human and social dynamics, military applications etc.) and (2) Agents for Simulation that can be grouped under two groups: *agent-supported simulation* and *agent-based simulation.*

Agent simulation involves the simulation of agent systems. Agent systems possess high-level interaction mechanisms independent of the problem being solved. Communication protocols and mechanism for interaction via task allocation, coordination of actions, and conflict resolution at varying levels of sophistication are primary elements of agent simulations. Simulating agent systems requires understanding the basic principles, organizational mechanisms, and technologies underlying such systems. The principle aspects underlying such systems include the issues of action, cognitive aspects in decision making, interaction, and adaptation. Organizational mechanisms for agent systems include means for interaction. That is, communication, collaboration, and coordination of tasks within an agent system require flexible protocols to facilitate realization of cooperative or competitive behavior in agent societies.

Agent-based simulation is the use of agent technology to generate model behavior or to monitor generation of model behavior. This is similar to the use of AI techniques for the generation of model behavior; e.g., qualitative simulation and knowledge-based simulation. The perception feature of agents makes them pertinent for monitoring tasks. Agent-based simulation is useful for having complex experiments and deliberative knowledge processing such as planning, deciding, and reasoning.

Agent-supported simulation deals with the use of agents as a support facility to enable computer assistance by enhancing cognitive capabilities in problem specification and solving. Hence, agent-supported simulation involves the use of intelligent agents to improve simulation and gaming infrastructures or environments. Agent-supported simulation is used for three purposes:

(1) to provide computer assistance for front-end and/or back-end interface functions;
(2) to process elements of a simulation study symbolically (for example, for consistency checks and built-in reliability); and
(3) to provide cognitive abilities to the elements of a simulation study, such as learning or understanding abilities.

5.3 Systems Engineering for ADS: ADSSE

Before we elaborate on the system conception, problem specification, and solution analysis components of a systems engineering framework for ADS systems, we discuss pertinent requirements for such a framework.

- *Distribution and propagation of objectives:* In agent-directed simulation systems decisions and control actions are not only taken by system entities, but also individuals (actors) carrying out functions at various levels. The allocation of roles to decision makers and the propagation of performance criteria to influence local objectives are critical in specifying the behavior of the system.
- *Representation of the monitoring function available to actors*: The perception of the system state by actors influences the goals to attend, the means for interaction, and subsequent actions. A significant challenge in open systems is to determine if the participants are complying with the applicable rules and policies (Singh 2004).
- *Representation of autonomy*: Complete autonomy may have undesirable effects, as in the case of real world situations. The autonomy of the entities in the system needs to be constrained based on interaction protocols.
- *Representation of heterogeneity*: Large complex systems end up being heterogeneous. The linkages of between models of people, organizations, and technology should be carefully planned to facilitate interoperation by design.

		Dimensions of Problem Analysis for ADSS			
Design Space for Solution Analysis of ADSS		Means-ends dimension	Activity dimension	Social dimension	Cognitive dimension
	Goals and constraints	goals, objectives, organizational structure	activity dependency, scheduling constraints	social norms, form of communication and interaction	cognitive complexity, limits, personality structure etc.
	Interaction function	content of communication	activity in decision making terms	Social network	collective decision making
	Operational function	workflow, physical processes	activity in terms of operational terms	cooperative patterns of behavior	human /team behavior representation
	Organizational function	management of communication, collaboration	coordination of activities	control of social interaction	team structure, cohesion, team archetypes
	Meta-level function	strategy update, acquisition and maintenance of resources	planning, (re)allocation of activities	Social network revision/update, organizational adaptation	adaptive cognition

Figure 3: A Problem and Solution Domain Analysis Matrix for ADSS

- *The role of dynamism:* Dynamics refers to independence of the controller or administrator of the system to update and change configuration without notification to other parties associated with the system. Open systems are particularly dynamic, as, in principle, they do not need administrator due to decentralization.
- *The significance of communication*: Communication is the basis of interaction in systems (Ferber 1999). Communication among actors in socio-technical systems helps preserve their autonomy.

6.0 Toward a Framework for ADSSE

It is clear from the discussion that analysis and design of ADSS can not be based on conventional systems engineering problem and solution analysis methods. Instead, the engineering of ADSS must be based on analysis of the behavior that shape the constraints and goals of the application domain in which actors are autonomous and perform on the basis of their local objectives and performance criteria.

6.1 A Social-Cognitive View

A systems engineering approach to ADSS analysis and design need to account for the interdependencies among physical processes, activities, and social and cognitive preferences. Figure 3 presents a matrix that partitions the problem and solution analysis. The four main dimensions represent the means-ends, activity, social, and cognitive perspectives. Specifically, the means-ends perspective identifies the structure and general global knowledge base of the ADSS.

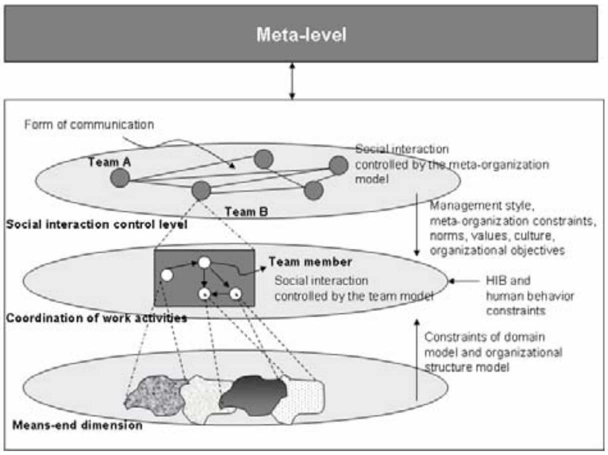

Figure 4: Multiple Dimensions of an ADSS

Activity dimension involves further delimitation of the solution space regarding the meaningful activities that realize task situations defined in the problem domain. The social dimension constrains the form of communication and takes the social norms into account to influence the coordination of interaction. Therefore, the level of control of social interaction and the functional constraints based on activity dependencies together affect the way tasks are carried out. The cognitive domain further refines the analysis by taking the cognitive resource profiles and preferences of individuals and teams into account.

6.2 The Dimensions of Representation

Figure 4 depicts the mechanism by which the interaction between different dimensions ensues. The means-ends dimension at the bottom involves the problem solving activities that carry out the tasks assigned to individual members. The ways these activities carried out are influenced not only by the constraints of the domain model, but also the strategies imposed by human behavior subsystem. This subsystem affects the performance of individuals by inducing human behavior variability in terms of cognitive, affective, and personality traits and factors. The social interaction control level is driven by the social subsystem. The form of communication and interaction styles are governed by the team archetypes, organizational culture, and decision making styles at the social organization level. The structure of the communication net and the content of the communication are based on the functional work organization, and hence they are determined by the control requirements of the problem domain. The social interaction control level along with the activities determines the shape of the coordination of work activities.

6.3 The Functions for Analysis

Each dimension shown in Figure 3 can be analyzed in terms of constraint, interaction, organization, operational, and meta-level functions. The purpose of the constraint function is to formalize the goals, objectives and constraints over the elements of the dimension. The interaction function serves to create a link among elements of the domain and to interface heterogeneous agents. The operational function focuses on the physical processes that pertain to workflow within the system. The workflow is defined at various levels of abstraction (activities in domain terms, activities in decision making terms etc.) depending on the level of decomposition depicted by the dimension. Organizational function concerns the management of the activities and interactions within the organization that represents the configuration of the elements of the ADSS. Meta-level function entails maintenance and preservation of the resources and agents and flexible adaptation of the behavior of ADSS based on the observations and monitoring of the environment and system components.

7.0 Conclusions

Characteristics of emergent open, complex, and adaptive M&S applications are overviewed to make the case for agent-directed simulation system engineering. An agent-directed simulation view of developing such applications is presented within the framework of a cognitive system engineering perspective. Future research involves further development of the ADSSE approach into a sound methodology and to demonstrate its value and utility using a case study.

 ISBN # 1-56555-316-0

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