INTERNATIONAL JOURNAL OF INTELLIGENT CONTROL AND SYSTEMS
VOL. 14, NO. 1, MARCH 2009, 4-19

On the Synergy of Simulation and Agents: An Innovation Paradigm Perspective

Tuncer ÖREN and Levent YILMAZ

Abstract –**The advances of modeling and simulation as well as agent systems have been phenomenal. The premise of the agent paradigm, its related theory and methodologies together with advances in multi-level modeling of complex systems are opening new frontiers for advancing the studies of the physical, natural, social, military, and information sciences and engineering. This survey paper provides a comprehensive analysis of the evolution of the synergy of modeling and simulation and agent systems and their applications to various fields. The analysis framework explores the evolution of the application and technology of agent-directed simulation. We present a unified and comprehensive perspective regarding the broad range for the synergy of simulation and agents. In drawing the trace of the evolution of agents and simulation to a close, we offer comments on three aspects. The first involves the breadth and extent of agent simulation applications; the second relates to the role of agent simulation in computational experimentation and exploratory analysis; and the third pertains to the future of the use of agents in simulation, as well as simulation for agents.**

Index Terms – **agent-directed simulation, agent simulation, agent-based simulation, agent-supported simulation, agent technology**

1. INTRODUCTION

1.1 Background

Simulation offers a very reach paradigm and has many aspects. So far as *purposes of applications* of simulation are concerned, simulation can be summarized by double E, namely, Experimentation and Experience. In fact simulation is used: (1) to perform experiments by using a model of a dynamic system (for several types of decision support, understanding, and education) and (2) to provide experience for entertainment and for training; the last type of use is to enhance three types of skills, i.e., motor, decision making, and operational skills. A comprehensive and integrative view of simulation is given by Ören [60].

Recent trends in technology as well as the use of simulation in exploring complex artificial and natural information processes [11] have made it clear that simulation model fidelity and complexity will continue to increase dramatically in the coming decades. The dynamic and distributed nature of simulation applications, the significance of exploratory analysis of complex phenomena [41], and the need for modeling the micro-level interactions, collaboration, and cooperation among real-world entities are bringing a shift in the way systems are being conceptualized.

Using intelligent agents in simulation models is based on the idea that it is possible to represent the behavior of active entities in the world in terms of the interactions of an assembly of agents with their own operational autonomy. The emergent need to model complex situations whose overall structures emerge from interactions between individual entities and cause structures on the macro level to emerge from the models at the micro level is making agent paradigm a critical enabler in modeling and simulation of complex systems [16]. This survey article provides a comprehensive analysis of the evolution of the synergy of simulation and agent systems.

1.2 Innovation Paradigm

We would like to analyze the evolution of the synergy of simulation and software agents within a larger paradigm of innovation processes in technical communities and elaborate on different elements that were influential within these processes. As it was stated in a previous publication:

> "If the state-of-the-art, in any field, is satisfactory, it may be worthwhile to preserve it. But, no advancement is ever possible by preserving the status quo. Furthermore, for a creative mind, the world view pertaining to a topic cannot be limited by the current state-of-the-art. Generation of new ideas which might lead to a worthwhile change, i.e., innovation, requires a rare ability to conceive and perceive reality from radically different perspective(s). Modes and characteristics of innovation are summarized in Table 1 where the possibilities range from innovate to oppose, passing through support, pseudo-support, and ignore. There is no substitute to the intellectual disposition to innovate. Furthermore, to increase the value of innovative thinking, the ideas have to be transformed into wealth production through generation, promotion, and distribution of appreciated products and/or services in a timely and competitive way. To be able to achieve these goals, the philosophies of institutions (academic, commercial, and governmental) as well as countries need to be nurtured to promote both innovative thinking and the transformation of ideas into wealth production. In doing so, the agencies should also realize that innovation is a highly non-linear phenomenon." [53]

Figure 1 is a schematic representation of the innovation processes in technical communities. The innovation processes consist of three components which are: technical contributions or factors, applications, and organizational factors [9].

Tuncer Ören, M&SNet: McLeod Modeling and Simulation Network of SCS, School of Information Technology and Engineering, University of Ottawa, Ottawa, ON, K1N 6N5, Canada, oren@site.uottawa.ca.
Levent Yilmaz, M&SNet: Auburn Modeling and Simulation Laboratory, Computer Science and Software Engineering, Auburn University, Auburn, AL, 36849, yilmaz@auburn.edu

Table 1: Modes and characteristics of innovative thinking (from Ören [53])

Modes	Characteristics
Innovate	- Intellectual disposition to perceive and conceive reality from radically different perspective(s)
Support	- Intellectual disposition - Commercial or other benefit(s)
Pseudo-support	- Support or follow anything fashionable
Ignore	- Uninformed - Not realizing consequences - Unrelated field
Oppose	Due to: - Mental inertia - Commercial or other interests - Not Invented Here syndrome - Opposite views

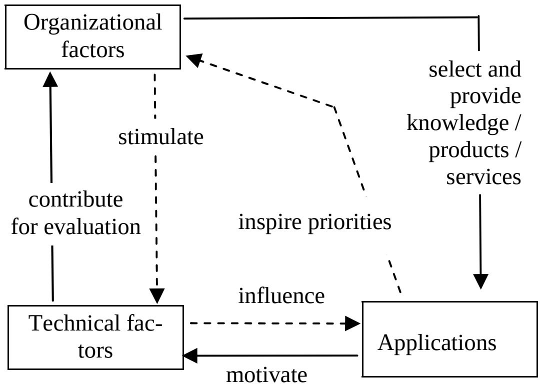

Figure 1: Innovation process: Components and relationships

The *technical factors* pertain to contributions made by individuals that produce creative solutions to problems. Such technical factors induce novel variations in the domains and constitute the scientific culture. Existing or anticipated *applications* motivate technical contributions and can be realized trough selection and transmission of knowledge by organizational factors. *Organizational factors* may stimulate technical factors which in turn contribute for evaluation by organizational factors and can be inspired from application domains to evaluate and stimulate technical factors. Even though organizational factors are important to stimulate technical innovations, they may also be hindering them; hence causing lost opportunities. See for example [90], for a reported case of the importance and influence of corporate culture with reference to: "Why didn't Sony invent iPod?" As it is explained in [90]: "There is a story in Japan that some engineers came up with a concept similar to that of the iPod, but management would not permit it to go forward because it would cannibalize sales of the existing product (the Walkman)"

In addition to mutual relationships of these three components, as can be seen in Figure 1, there are two feed-forward cycles –worth exploring– among them.

We are going to present the evolution of the synergy of simulation and agents in terms of interactions between the technical, organizational, and application factors which have been affecting them.

1.2 Innovation Paradigm for the Synergies of Simulation and Agents

Technical factors pertain to the contributions made by individuals or groups that produce innovative solutions leading to advancements in modeling and simulation, advanced computational paradigms –including agents and cognitive informatics– and their mutual contributions. We elaborate on them in section 3.

Applications (1) can benefit by adopting relevant advanced knowledge / products / services, (2) can motivate technical innovations – by raising their standards, and (3) the existence of technical contributions may influence the requirements of applications. Elaborations on advanced applications are given in section 4.

Organizations and communities of interest help stimulate technical factors and contribute to the development of the scientific domain. As such, active communities in simulation that focus on the use of agent technologies are overviewed to clarify their role in advancing the state of the art. Realization, acceptance, and declaration of the importance of modeling and simulation are important steps to benefit from the relevant advances. One of the important organizational factors is funding agencies. For this reason, even 30+ years ago, it was stated [50] that "Grant officers responsible to screen simulation language realization (definition / development / implementation) projects should take the time to familiarize themselves with the importance of simulation techniques and the related challenging implementation problems. As Bell, who explains that in post-industrial societies the methodologies are abstract theories: models, simulation, decision theory, and system analysis, states it: 'The key political problems in post-industrial society are essentially elements of science policy' [3]. Of course, in the 21st century, the emphasis of "simulation language" should be replaced by other concerns. However, in mid 1970s, even the definition of CSSL, the most influential simulation language –at that time– was severely flawed by grammatical errors [49].

US Congress, set an important example by its resolution in 2007 [87]. We hope that several countries and regions having knowledge-based economies –including European Union and P.R. of China– will pass soon similar resolutions to raise modeling and simulation to the right level.

An important aspect of professionalism in sustainable civilizations is to adhere to an appropriate code of *ethics*. Even, as posited by Dowling:"Adherence to a code of ethics is, in fact, a key element in the definition of a profession" [13, p. 91]. Currently there is no such code to give the users necessary trust for using agent systems [13]; hence a code of ethics needs to be developed for software agents and developers of software agents. Until such time and even afterwards, the simulationists can use the code of professional ethics of their own profession [61] in studies dealing with any aspect of the synergy of simulation and agents.

1.4 Organization of the Article

The rest of the article is organized as follows. In section 2, we provide background information and categorize the use of modeling and simulation (M&S) for agents in and the use of agents for modeling and simulation. Sections 3, 4, and 5 focus on technical factors, application domains, and organizational factors that have influenced the development of the synergy between M&S and agent systems. In drawing the trace of the evolution and growth of the synergy of simulation and agents to a close, we offer comments on two main aspects: (1) the role of applications, organizations, and emergent technologies on innovations regarding agents and simulation and (2) potential avenues of future research at the intersection of simulation and agent technologies.

2. SYNERGY OF SIMULATION AND AGENTS

This section aims to provide a basic overview of potential synergy of simulation and software agents. Agent systems are defined as systems that are composed of a collection of goal-directed and autonomous physical, human, and logical software agents situated in an organizational context to cooperate via flexible and adaptive interaction and cognitive mechanisms to achieve objectives that cannot be achieved by an individual agent. Even more comprehensive concept, i.e., "infohabitant," need to be used. "The players in the distributed and connected information systems are not limited to individuals and software agents, but include infohabitants in general. Infohabitants of the connected information systems include individuals, organizations, smart appliances, smart buildings, and other smart systems, as well as virtual entities acting on their behalf. Hence their behaviors are important for the sustainability of the overall system. The virtual entities acting on behalf of individuals and organizations are (or can be) implemented as software agents (and avatars) [59].

Agent-Directed Simulation (ADS) is promoted as a unified and comprehensive framework that extends the narrow view of using agents simply as system or model specification metaphors. Rather, it is posited that ADS is comprehensive in the integration of agent and simulation technologies. In a simulation study, the model, experimental framework, and simulator (or behavior generator) [108] agents can be used in supporting model conceptualization (e.g., agent-based modeling), behavior generator design (e.g., agent-based simulation), as well as the realization of the context within the experimental frame (e.g., agent-supported simulation).

We start exploring the evolution of the synergy of simulation and agents by categorizing the use of agents under a unified framework, called Agent-directed simulation [55], [98]. Agent-directed simulation is comprehensive in the integration of agent and simulation technology, by including models that use agents to develop domain-specific simulations, and by also including the use of agent technology to develop simulation techniques and toolkits that are subsequently applied, either with or without agents. Hence, as shown in Figure 3, agent-directed simulation consists of three distinct, yet related areas that can be grouped under two categories as follows: (1) Simulation for agents (*agent simulation*), namely, simulation of agent systems in engineering, human and social dynamics, military applications etc. (2) Agents for simulation which comprises two possibilities: *agent-supported simulation* that deals with the use of agents as a support facility to enable computer assistance in problem solving or enhancing cognitive capabilities; and *agent-based simulation* that focuses on the use of agents for the generation of model behavior in a simulation study.

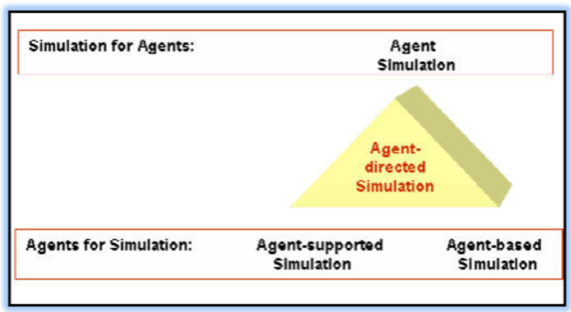

Figure 2: Agent-directed simulation:
A unified and comprehensive framework

2.1. Agent Simulation

Agent simulation is the use of agents as design metaphors in developing simulation models. Agent simulation involves the use of simulation conceptual frameworks (e.g., discrete-event, activity scanning) to simulate the behavioral dynamics of agent systems and incorporate autonomous agents that function in parallel to achieve their goals and objectives. Agents possess high-level interaction mechanisms independent of the problem being solved. Communication protocols and mechanisms 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 [93], 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 [92]. If agents are used as design metaphors in model conceptualization and realization, this is called *agent-based modeling*.

2.2. Agent-based Simulation

Agent-based simulation is the use of agent technology to generate 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). Development of novel and advanced modeling and simulation methodologies such as multisimulation and multimodeling [42], [63], [97] suggests the use of intelligent agents as coordinators of behavior generation, where run-time decisions for model as well as simulation run staging and updating take place to facilitate dynamic composability of models and simulations. Agents are often viewed as design metaphors in the development of models and scenarios for simulation and gaming. Yet, this narrow view limits the potential of agents in improving various other dimensions of simulation. A special issue edited by Yilmaz and Ören [98], followed by an article published by Yilmaz et al. [101] aimed expanding horizons on the synergy of simulation and agents. It is clarified in [101] that sometimes a term is used to denote different concepts. For example the term Monte Carlo simulation is used to mean stochastic simulation as well as the use of probabilistic techniques to solve deterministic problems such as integration problems. Another example is the term "computer simulation" which is used to mean simulation of computers as well as "computerized simulation." Similarly, the term "agent-based simulation" is used by many, to mean simulation of systems described by agents. Similar to AI-supported simulation and AI-based simulation, the terms "agent-supported simulation" and "agent-based simulation" can be used as explained in the unified and richer framework of Agent-directed simulation. Based on this new perspective, Yilmaz has organized the first meeting of the Agent-directed Simulation conference series in 2005 [95] to provide a forum to bring together researchers and practitioners from diverse simulation societies within computer science, social sciences, engineering, business, education, human factors, and systems engineering. The involvement of various agent-directed simulation groups enabled the cross-fertilization of ideas and development of new perspectives by fostering novel advanced solutions, as well as enabling technologies for agent-directed simulation. The use of agents in contributing to the theory and methodology of modeling and simulation is a noteworthy impact of the extended view is advocated by Agent-directed Simulation.

2.3. Agent-supported Simulation

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 enrich simulation and gaming infrastructures or environments. The distinction between agent-based simulation and agent-supported simulation becomes clearer in the context of systems engineering where simulation systems are defined in terms of a collection of hardware, software, people, procedures, facilities, and other factors organized to accomplish a common objective. In this perspective agents associated with components external to simulation software play critical roles to sense, perceive, and understand the environment to steer the simulation, while providing facilities to collect, analyze, and visualize data to support decision-making. With these potential support mechanisms in mind, agent-supported simulation is used for the following purposes:

(1) to provide computer assistance for front-end and/or back-end interface functions; (For example, in augmented reality, agent support may be useful in selecting pictures in photosynth applications where pictures have to be selected from 100s of pictures with different version and zooming [100].)
(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.

3. Technical Factors Affecting Synergy of M&S and Agents

The evolution of the synergy of simulation and agents lies at the intersection of: modeling and simulation (including system theories, complex adaptive systems, emergence, systems engineering, and control theory); artificial intelligence (including distributed artificial intelligence); agents, and the emerging cognitive informatics discipline. These core disciplines have been giving direction to technology, languages, and possible applications, which then influenced the evolution of the synergy between simulation and agents. A comprehensive coverage of the evolutions of these disciplines and their contributions to each other would be interesting. However, due to space limitations, we would like to limit the highlights of their developments and elaborate on the main traits of the synergy.

3.1 Modeling and Simulation

A milestone publication in the evolution of modeling and simulation has been [65] where simulation is promoted as a model-based activity and the need for the specifications of models and experimental conditions (experimental frames) were pointed out.

Documents on history of M&S differ on whether they concentrate on application areas or tools, techniques, or methodologies. Some references are given in the sequel: *Nance and Sargent* (2002): Perspectives on the evolution of simulation [45]. *Zobel* (2000): A Personal history of simulation in the UK and Europe, 1964-2001 [109]. *Hollocks* (2006): 40 years of discrete-event simulation–A personal reflection [26]. *Nance* (1993): A history of discrete simulation programming languages (and several early references) [44]. *Robinson* (2005): Discrete-event simulation: From the pioneers to the present, what next? [71]. *Mack* (2005): 30 years of lithography simulation [37]. Several other references exist on the history of simulation in flights, in health care, etc. Several researchers and advanced user communities pointed directions to advance state-of-the-art, e.g. [12].

3.2 Computational Paradigms

One way to conceive the synergy of modeling and simulation and agents is to consider the spectrum of computational paradigms [100]. In Table 2, three types of knowledge processing can be identified: procedural, intentional, and goal-directed knowledge processing. In each type, the roles of people and the computational systems are different and the more advanced systems take over more computational responsibilities. There are still tremendous possibilities for progress along this line.

Procedural knowledge processing is exemplified by algorithmic computational paradigm which includes unstructured, structured, and object-oriented programming. Modeling and simulation has been involved with all types of procedural knowledge processing.

In *intentional knowledge processing*, computational paradigm is declarative and the role of the user is to specify the problem. In the case of simulation, this corresponds to the specification of the model; than a program generator generates the program. Simulation has been the first discipline to free the users of writing programs. In both intentional and procedural programming, the *whole program* (written by the user or generated by the system) is activated for execution.

Three main categories of *goal-directed knowledge processing* are possible. They are: interactive (or event-based); AI-based (heuristics, rule-based, or frame-based); and agent-based computational paradigms.

- In *interactive* (event-based) *programming*, user activates functions to be performed hence indirectly activates the module(s) to be executed. (In discrete event system simulation, events can be created, scheduled, and activated by other events.). System executes only the modules thus activated.

- In *AI-based computation*, user specifies the goal and the facts (initial conditions); than the system determines the order in which the rules have to be executed and execute them in this order. Even before the advent of software agents, synergy of simulation and artificial intelligence was at a very mature level. Some details will be elaborated in the sequel.

- In *agent-based computational paradigm*, problem is specified in agent-based modeling and the user specifies the goal and delegates finding a solution of the problem to agents. In this paradigm, agents: (1) process the goal (identifies sub-goals, sequence them, and determine additional knowledge requirements); (2) perceive their environments; (3) perform goal-directed knowledge processing; and (4) decide which (other agent or non-agent software module(s) to activate or sub-delegate the task(s).

Cognitive informatics is an emerging discipline and applied to agents becomes relevant in the synergy of simulation and agents. In use of simulation for agents, simulation of cognitive behavior is in order. In advanced applications of both agent-based and agent-supported simulations, cognitive abilities are needed and should be included in the computational abilities of agents. Abilities to understand [62] and to learn are two of the important cognitive abilities. Intelligent software assistants are required to be task oriented and it is reported –as one of the ten emerging technologies in 2009– the position that "In order to get a system that can act and reason, you need to get a system that can interact and understand" [46].

3.3 Agents and Computation beyond Turing Machines

Recent research on computational paradigms, as published among others in [14], results in the claim that Turing Machines are inappropriate as a universal foundation for computational problem solving. Turing Machines have the following properties that model algorithmic computation:

(1) The computation is closed, i.e., there is no interaction happening with the world.
(2) The resources are finite, i.e., time and memory are limited.
(3) The behavior of the computational system is fixed, i.e., there is no self-configuration and adaption, but all computations start at the same configuration.

The work of Alan Turing in general, and his well-known paper from 1936 [84], in particular, led to the Church-Turing Thesis. This thesis is still fundamental for computer scientists' education. The thesis states that whenever there is an effective method for obtaining the values of a mathematical function, the function can be computed by a Turing Machine. In its strong form, the thesis reads: A Turing Machine can compute anything that a computer can do. The work summarized in [23] claims that – while the Church-Turing Thesis was valid for early computers – the introduction of concurrent computing changed the underlying assumptions significantly. Concurrency theory positions interaction as orthogonal to computation. If Turing Machines are extended by adding input and output actions that support dynamic interaction with an external environment, they are transformed into Interaction Machines. While this is only a small change, it changes the characteristics of the machines significantly and increases the expressiveness beyond simple mathematical models. In their published work [23], the scientists around Peter Wegener claim that *Interaction Machine behavior is not reducible to Turing Machine behavior*. As they furthermore claim that computational tasks situated in the real world which includes human agents are not solvable algorithmically, but that interaction theory can support to the solution of these problems, they introduce the phrase of *Super-Turing Computing*. If these claims are correct, artificial agents as representatives of human agents can lead to a paradigm shift in computation. Similarly, agents in simulations can radically change the face of modeling and simulation. Adding current developments in the domain of supercomputing and massive parallel core technologies, as described in [66], the technical developments that we observe will contribute to the evolution of agents and simulation to a degree surpassing the recent years by far.

3.4 The Synergy of AI and Simulation

The synergy of AI and simulation has been well established for some time [51], [52]. The simplest type of AI-based simulation is knowledge-based simulation (kbSim) [70] and qualitative simulation (QSim) [34]. As another level of advancement machine learning may enhance the associated knowledge base(s). In its simplest form, only one behavior generation paradigm (single paradigm) can be used and the simulation system may exist as the only knowledge generation system. The next step is multi paradigm simulation systems where two or more of knowledge-based simulation, qualitative simulation, and numerical simulation can be used. In addition to AI techniques, several types of soft computing (e.g., neural nets, fuzzy systems, and evolutionary computing) paradigms are also successfully used in modeling and simulation.

3.4.1 AI and Simulation

Fundamental discussions on the synergy of AI methodologies and simulation can be traced back to Methodology in Systems Modeling and Simulation [106] and Modeling and Simulation Methodology in the Artificial Intelligence Era [15]. The discussion as to the benefits of using AI in simulation continued for the years to follow. As one of the earliest advocates of using AI in simulation, [51] pointed out how AI could help in model building, specification of model behavior, interface design, as well as model parameters. Following these early proposals, [91] compared AI and simulation in terms of knowledge representation, learning, and natural language understanding. Based on the promising avenues pointed out by these earlier studies, an idealistic perspective on integrative use of simulation and AI techniques to facilitate tasks such as model design, input scenario selection, experimentation, and result analysis is delineated [76]. A detailed treatment of the subject followed in the edited volumes on Modeling and Simulation Methodology in the Artificial Intelligence Era [15] and AI Applied to Simulation: Proceedings of the European Conference at the University of Ghent [30]. Later, the conference series on AI Simulation and Planning in High Autonomy Systems established an annual gathering place for researchers, who are active in fields at the intersection of AI and simulation.

3.4.2 Knowledge-based Simulation

A noteworthy development in the AI and simulation community, as it relates to the evolution of the synergy between agents and simulation, is the introduction of Knowledge-based Simulation [31]. Given that agents are often designed in terms of rule-based decision making and adaptation mechanisms such as found in the ECHO system [25], the development of Knowledge-based simulation is a significant milestone. To this end, Rozenblit and Zeigler [72] defined intelligent simulation as a component of a complete conceptual framework for knowledge-based, computer-aided environments for system design. ROSS (Rule-Oriented Simulation System) [40] was one of the earliest knowledge-based simulation languages. It was developed by RAND Corporation to be used as a military planning simulator. The similarities between specification of objects and frames were recognized by Nielsen in 1987, who demonstrated the applicability to the modeling process of object-oriented paradigm and frame-based reasoning. A slightly different approach to the use of objects in simulation was discussed by Robertson in 1986, who proposed that object-oriented intelligent simulation could be performed by defining a collection of intelligent agents, where each agent has a number of expert rules that support its behavior and an agenda that defines its goals. Similarly, Spiegel and LaVallee [79] describe the use of an expert system to drive a simulation. The expert system is provided with a number of rules which specify, qualitatively, how various simulation parameters affect specific simulation results. DEVS-Scheme [104] is a knowledge-based simulation framework based on Scheme. DEVS-Scheme uses a declarative representation of the simulation domain objects, and uses IF-THEN rules to provide knowledge about modeling constraints, objectives, and requirements. Using a generate-and-test procedure, DEVS-Scheme creates simulation models and families of models, and then stores them in a hierarchical, object-oriented model base. Models can then be retrieved and reused in other simulation instances [107].

3.4.3 Endomorphic Models and Simulation

Distributed knowledge-base that represents for each agent the mental model that characterizes beliefs about the environment, the self, and other agents in the system is a significant requirement for the design and implementation of agent systems. For instance, in [18], an illustration of the elements of agent systems depicts the need for an explicit representation in the mental model of an agent of the environment, as well as other agents. Zeigler [104], [105] used the term endomorphy to refer to objects (systems, models, agents) in which some sub-objects use models of other sub-objects. An endomorphic simulation model might contain an agent and environment such that the agent has, and uses, a model of the environment and models of (parts of) itself in its decision making. Such self-embedding agents are termed endomorphic agents. This abstraction approach was later used for modeling the context in high autonomy systems [105].

3.5 Agent Simulation Frameworks

As the simulation community developed a nuanced understanding of the theory and methodology of agent-based simulation modeling, efforts in developing environments and tools for simulation programming ensued. The following text presents a selected list of common simulation environments developed by the simulation community as contributions to agent modeling and design. The Swarm environment played a critical role in influencing the design rationale and development of various next generation tools such as RePast [48] and Mason [36]. On the other hand, Sesam [32] and PolyAgents [89] are widely used platforms in the multi-agent systems community to develop simulation applications. PolyAgents framework introduces a new modeling construct, the polyagent, which represents each entity with a single persistent avatar supported by a swarm of transient ghosts to deal with uncertainty in complex adaptive systems. Among the tools that are commonly used by the agent simulation community, we realize lack of sophistication in specifying and implementing cognitive architectures. BRAHMS' Belief-Desired-Intentions oriented architecture [9] is an exception, as it provides limited support in representing beliefs and their revision in behavior generation. On the other hand, there exist studies on integrating cognitive modeling and agent-based social simulation [81]. Research on cognitive systems research resulted in various tools and architectures such as ACT-R [80], Soar [94], and [82], which aim to capture socio-cultural aspects of cognition and cognitive processes involved in multi-agent interaction.

3.6 Agent Architectures

One of the first agent-oriented programming languages is called AGENT-0 [77]. AGENT-0 and its interpreter provided a framework that enabled the representation of beliefs and intentions of agents. Unlike object-oriented simulation languages such as SIMULA 67 [10] which introduced class and object concepts and is the first object-oriented language for specifying discrete-event systems, AGENT-O and McCarthy's Elephant2000 language incorporated speech act theory to provide flexible communication mechanisms for agents. While DAI and cognitive psychology [43] influenced the development of cognitive agents such as those found in AGENT-0, Belief-Desires-Intentions (BDI) framework [69], Procedural Reasoning System [21], and control theory provided a basis for the design and implementation reactive agents. Classical control theory enables the specification of a mathematical model that describes the interaction of a controller and its environment. The analogy between an agent and controller facilitated the formalization of agent interactions in terms of a formal specification of dynamic systems. The shortcomings of reactive agents (i.e., lack of mechanisms of goal-directed behavior) and cognitive agents (i.e., issues pertaining to computational tractability in deliberative reasoning) led to the development of hybrid architectures such as the RAP system [20], and Touring Machines [19]. Detailed discussion on various cognitive and reactive agent architectures can be found in [43]. In the early days –when even the term agent was not used in currently used software agent meaning– Andras Javor did pioneering work by using demons in M&S. [28] [29].

3.7 Discrete-event and Activity Scanning Formalisms for Agent Modeling

Discrete-event simulation models specify state changes in discrete points in time. Computer simulation began during World War II in the case of Monte Carlo and continuous simulation. Discrete-event simulation originated in late 1940s [45]. The notion of state changes in reaction to events has been found by researchers in the agent community as a natural way to capture the actions of agents, as well as operations that enable agents to perceive, produce, transform, and manipulate objects in the environment. While continuous simulation can be used to model average behavior in terms of differential equations, the lack of linkage between individual behavior and macro-level properties and difficulty in modeling actions, as well as complexity involved in estimating parameters in continuous simulations led to the use of discrete-event [48] and activity scanning [8] formalisms in agent simulations.

3.8 Systems-theoretic Models of Agents

The development of the DEVS framework [108] led to system theoretic principles and formalization of discrete-event simulation. The influence of system theoretic approaches started with a seminal workshop on agent-based modeling, which was organized by Uhrmacher and published by the Proceedings of the IEEE. Besides the introductory article by Uhrmacher et al. [85], a number of system theoretic approaches to modeling and simulating agents were presented. For instance, using the DEVS framework, Sarjoughian and his colleagues [74] proposed a layered architecture for agent-based system development. Uhrmacher and her colleagues developed JAMES, which is a Java-based agent modeling environment that is based on parallel, distributed version of DEVS. Using JAMES, [75] presented how planning is carried out using the DEVS formalism. On the other hand, in [108], a theory of quantized systems is presented for DEVS simulation of perception mechanisms for agents. In a more recent article Zeigler [103] proposed discrete-event abstraction as a framework for specifying the internal models of complex adaptive systems that are used to anticipate the future as a basis to select actions to reach desirable outcomes. In principle, the proposed approach involves using DEVS formalism to specify predictive models of entities within complex adaptive systems.

3.9 Generative Agent-based Modeling

Early adopters in application areas such as engineering, business, commerce, industry, logistics, transportation, and manufacturing used agent methodologies to develop agent simulations. These communities are widely influenced by the advances in DAI and emergent agent technologies to design simulations through top-down design strategies in conjunction with agent design styles that favor deliberative and cognitive approaches. On the other hand, social science and complexity researchers advocated the use of simple rule-based agents to explore the generation of regularities, as well as emergent patterns and behavior based on local interactions among heterogeneous and autonomous agents [25], [16], [17]. The premise of the strategy, which is known as generative social science [16], is consistent with Herbert Simon's observation that the apparent complexity of our behavior is largely a reaction of the complexity of the environment [78]. In this view, agent-based simulations allow researchers to explore the complexity of the environment by removing complexity of constituent individuals. The intent is to facilitate understanding the minimal conditions, that is, the simplest set of assumptions, for a given phenomenon to emerge at a higher level of organization. Furthermore, while the engineering community predicates the value and utility of simulations on their predictive accuracy and realism, complexity researchers, in contrast, view artificial societies in agent-based models as highly abstract thought experiments.

4. Application Domains

The evolution of the synergy between simulation and agents is also influenced by various application domains that considered agent-based modeling as an instrument for research and development. Simulations of agent systems in various engineering, as well as social and biological sciences are now common. Among these areas are:

- Management/economy applications: economy, e-commerce, and management;
- Engineering applications: manufacturing systems, networks, robotics, software, as well as transportation/logistics;
- Social systems and human behavior and performance modeling applications: social systems, psychology/human behavior, physiology, negotiation, and organization theory;
- Environment applications: ecosystems, land use;
- Computational Biology: computational models to facilitate understandings of functional biological systems.

Due to lack of space, we will not overview each and every domain; rather, major categories that influenced the growth and evolution of the use of agents in simulation are reviewed.

4.1. Complex Adaptive and Self-organizing Systems

The science of complex systems is a rapidly evolving area [41]. Much of the focus in complex systems is on how systems of interacting agents can lead to emergent behavior [63]. A system is characterized as complex, if it is composed of diverse, dynamic, and heterogeneous entities that interact in nonlinear ways. Complex systems are different than complicated systems. Examples of complex systems include behavioral dynamics of voters in elections, economy, vehicles in transportation systems, cellular mechanisms in a body, disease and culture spread, and technology diffusion processes. In complex systems the agents learn and adapt from their activities, and they operate in unstable and non-static environments. Echo system [25], for instance, provides a sound basis for demonstrating how adaptation of agents to their environment builds complexity. To signify the role of adaptation, such systems are often viewed as Complex Adaptive Systems (CAS). The premise of complex adaptive systems is that such systems consists of processes that are dynamic, non-linear, path dependent, and self organizing, in which global (macro) behavior emerges from the local (micro) interactions of entities which influence one another in response to influence they receive.

The characteristics of such system models are as follows:

- Agents are autonomous - they interact with little or no central authority and they are adaptive rather than optimizing.
- Agents are heterogeneous in terms of their properties, actions, and decision making styles.
- Based on the degree of adaptation, the models are either evolutionary or learning. Evolutionary models allow rules to evolve and compete for adoption, whereas learning models allow agents to learn from experience and feedback.
- Agents are organized into groups or hierarchies. As pointed out hierarchic systems are complex systems, and the organizational structures influence how the underlying system evolves over time [78].

As with any emerging field, there is considerable diversity in the application of agent paradigm in studying complex adaptive systems, especially those that pertain to social systems. In the Proceedings of National Academy of Sciences Colloquium on "Adaptive Agents, Intelligence, and Emergent Human Organization: Capturing Complexity through Agent-based Modeling" [4], some approaches take an evolutionary approach, while others use a learning-theoretic strategy. At the core of most applications of agent-based models for complex phenomena is a focus on agents interacting on landscapes that consist of two-dimensional grid. Agents are directed by rules that de- fine their actions over these landscapes, which represent diversity in social environments.

4.2. Human and Social Dynamics

Simulation is playing a critical role in advancing the understanding of human behavior and performance, as well as social and political behavior at the individual, organization, state, and population levels. Two major emergent areas in which agents are used as design metaphors are generative social science and human behavior modeling.

4.2.1. Generative Social Science

With the introduction of Epstein and Axtell's book [17] on Growing Artificial Societies: Social Science from the Bottom-up, the artificial society modeling as a principle scientific instrument emerged as a new form of conducting research in social sciences. The basic premise of artificial society modeling involves "growing" social structures to demonstrate that certain sets of micro-specifications are sufficient to generate macro-phenomena of interest. Sample applications of this new perspective are presented in [16]: the history of ancient communities (e.g., Anasazi), the emergence of economic classes, the timing of retirement, the evolution of norms, dynamics of ethnic conflicts, the spread of epidemics, and organizational adaptation.

4.2.2. Human Behavior Modeling and Simulation

As a result of increasing use of simulations for training, systems analysis, systems acquisition, and decision aiding in military applications, a panel study [67] was organized by the US National Research Council. In the panel's concluding remarks, it is recommended that models of human behavior employed by simulations be based on psychological, organizational, and sociological theory. Simulation community responded to this call by developing alternative strategies. One alternative is the cognitive or agent architecture, which focuses on emulating the actual human decision making processes that involve perception, understanding, anticipation, planning, and goal selection. On the other hand, profile-based approaches utilize a declarative strategy, by which the personality and psychological profile of an individual is captured in terms of variables and their update dynamics. Martinez- Miranda and Aldea [38] describe an agent model that simulates the human behavior in a team. Urban and Schmidt [86] present a reference model for the construction of human-like agents. Ghasem-Aghee and Ören [22] extend on these early studies to present a profile-based approach to specify personality in agents using fuzzy logic. Others illustrate how models of emotion and personality can improve the believability of agents [2]. These studies collectively demonstrate how agent-based modeling facilitates bridging the gap between psychological knowledge about personality and human behavior and modeling and simulation. Silverman's contribution in this volume provides a patent example on specifying cognitive human agents. Some additional challenges are the representation of irrationality in human behavior, as clarified by Ariely with ample examples for behavioral economics [1].

4.3. Artificial Life

Artificial life research, which is the study of evolution of agents, or in general societies of computer-generated simulated life forms in artificial environments, contributed to the study of complex systems using mainly the techniques of cellular automata and agent paradigm. Santa Fe Institute led the efforts by bringing researchers in complexity science in various Artificial Life Workshops to pursue a specific thread of research that revolves around the concept of a simulation-based iterative population approach using generations of agents that can mutate and become fitter over time. The major contribution of the Artificial Life community to agent systems simulation is the use of basic and extended versions of Cellular Automata (CA) formalism to model and simulate societies of agents and emergent properties in complex systems. CAs are decentralized spatially extended systems consisting of large numbers of simple and identical components with local connectivity [7]. Such systems have the potential to perform complex computations with a high degree of efficiency and robustness as well as to model the behavior of complex artificial and natural systems. CAs have been successfully applied to the simulation of wide variety of dynamical systems such as biological processes, including pattern formation, urban growth, galaxy formation, and most notably in studying fluid dynamics.

4.4. Computational Organization Science

Computational modeling is now widely accepted as a scientific instrument in conducting organizational research [25]. In defining the basic tenets of computational organization science and establishing the synergy of organization science and multi-agent systems, Carley posits that computational systems are organizational by nature [5]. Specifically, she illustrates that entities in organizations are distributed, heterogeneous information processing elements that exhibit adaptive and bounded rational behavior. Exploiting these analogies, organization scientists developed novel agent-based modeling perspectives to study organizational adaptation, culture and norms [23], knowledge diffusion in organizations [33]. Simulation of social networks as models of loosely coupled agents in virtual organizations such as Open Source Software communities [39] resulted in test-beds that facilitated generation of hypothesis pertaining to dynamics of user innovation communities. One of the major contributions of the computational organization science community to simulation modeling, as well as multi-agent systems domain is the conceptual models of organizations in terms of a meta-level social network of agents, knowledge, resources, and tasks [5]. VDT [35] and OrgAhead [6] are two agent-based organizational model development environments that have sound theoretical basis to study organizational effectiveness and efficiency. Ferber's work on multi-agent systems also demonstrates how such systems can be specified in terms of organizational constructs. Ferber [18] also introduces various dimensions of organization analysis in designing multi- agent systems. Similarly, [88] presents organizational principles for multi-agent system architectures. The synergy between organization theory and multi-agent simulation is exploited by others (e.g., [102] to study effectiveness and efficiency of team archetypes in software development organizations.

4.5. Military Applications

Defense Advanced Research Projects Agency (DARPA) is a central and influential research organization that provided impetus to the development of agent technologies and their integration to simulation modeling infrastructures. Among the programs that impacted directly or indirectly the growth of the use of agents in simulation modeling and systems engineering are

- Control of Agent-Based Systems (CoABS) project aims to develop and demonstrate techniques to safely control, coordinate and to manage large systems of autonomous software agents.
- Joint Unmanned Combat Air Systems (J-UCAS) project envisions developing a weapon system that expands tactical mission options and provides revolutionary new air power and penetrating surveillance capability.
- LifeLog is part of DARPA's research in cognitive computing. The research is fundamentally focused on developing revolutionary capabilities that would allow humans to interact with computers in much more natural and easy ways than exist today.
- Mobile Autonomous Robot Software (MARS) aims to develop (learning-based) software technologies required for robust perception-based autonomy.

Synergistic use of simulation and agents are definitely important applications in constructive simulations as serious games, mostly in war gaming. However, in NATO parlance, non-article 5 activities can benefit from advanced modeling and simulation applications. These activities include vitally important applications of M&S, or better yet agent-directed simulation applications in crisis management including peace support training and management [47].

4.6. Space Applications

To reduce the cost of future space flight missions, NASA has been investigating autonomous ground and space flight systems. These goals of cost reduction have been further complicated by, for instance, NASA's plans to use constellations and swarms of nano-satellites for future science data gathering which may entail large communications delays and loss of contact with ground control for extended periods of time. The application of agents in support of these objectives, and consequently the use of agents in simulated environments to prove the concept and feasibility of such ideas, resulted in the Lights-Out Ground Operations System (LOGOS) and the Agent Concept Testbed (ACT) [73]. Another activity worth mentioning is the Mobile Agents Project. Communicating intelligent software agents in backpacks, rovers, and other mobile platforms can greatly enhance planetary extravehicular activity (EVA). The task of the Mobile Agents Project is to develop a distributed architecture for simulation and coordination of human-robotic EVA teams, including model-based control of life support, communications, and spoken-language interfaces to rovers. The system will integrate crew, robots, software agents, and remote operations and science teams into coherent work systems, amplifying human capability.

5. Organizational Factors

Scientific and technical factors influence and shape the methodologies and technologies associated with the synergy of simulation and agents. On the other hand, organizations act as catalysts to stimulate and filter innovations. While some of the scientific societies advocate the improvement of the theory and methodology of multi-agent systems and associated simulation studies, others focus on specific application domains. Some of the societies which have been influential are outlined in the sequel:

5.1 Agent Simulation Conference Series

Agent Simulation Conference Series organized by the Argonne National Laboratory has been focusing on mainly three major areas: (1) Methods, Toolkits, and Techniques, (2) Computational Social Theory, and (3) Social Simulation Applications. The advances promoted by the community that annually convenes in this conference series mainly revolves around the agent-based modeling paradigm and its use in social science applications.

5.2 Center for Research in Social Simulation and European Activities

The growth of agent-based social simulation field is also advocated by the Center for Research in Social Simulation at the University of Surrey in UK, as well as the broader umbrella organization, called European Social Simulation Association (ESSA). The societies that are active in the social simulation domain are facilitating the formalization of behavioral theory in agent models and simulation of social phenomena that emerge from interaction of multiple agents (e.g., evolution of norms and culture).

5.3 North American Activities

The North American Association for Computational Social and Organization Sciences (NAACSOS) has been influential in the development of the computational organization theory by using agent paradigm and simulation modeling as scientific instruments in studying organizations. The evolution of this organization had its roots with a small group of researchers who were interested in how computational models could be applied to theoretical development and empirical analysis in the study of collectives. The early workshops were associated with INFORMS.

The organization has evolved into a formal society with an associated journal (Computational and Mathematical Organization Theory), and it is affiliated with other social simulation organizations such as ESSA and PAAA (The Pacific-Asian Association for Agent-based Approach in Social Systems Sciences). Similarly, the Agent-based Computational Economics (ACE) society aims to promote and advance the studies of economic processes modeled as dynamic systems of interacting agents. Following the tradition of NAACSOS, ESSA, and other simulation communities that focus on social sciences, ACE society seeks to improve empirical and normative understanding of social systems, and in particular, economic systems. Theory generation through exploration and insight via agent-based models and methodological advancements are among the objectives of these societies.

Organized by the Autonomous Agent and Multi-Agent Systems (AAMAS) community, the Multi-Agent-Based Simulation (MABS) workshop –which is held since late 1990s– is an important venue that brings researchers from the agent system and agent-based social simulation (ABSS) communities. The theme of the MABS workshop series is based on the observation that: (1) the focus on agents for the solution of complex engineering problems related to the construction, deployment and efficient operation of agent-based systems and (2) the focus of ABSS for simulating and synthesizing social behaviors in order to understand real social systems via development and testing of new theories. It is considered desirable that these two communities synergistically so as to mutually advance their own disciplines.

5.4 Agent-directed Simulation (ADS) Community (North America and Europe)

A recent organizational development to provide international platforms to share knowledge on the synergy of simulation and agents is the emergence of the Agent-Directed Simulation (ADS) community. The ADS community is interested on any one of the three types of the synergy of simulation and agents, namely, simulation for agents (*agent simulation*) and agents for simulation – which consists of *agent-based simulation* and *agent-supported simulation*. Hence, the ADS paradigm is comprehensive and integrative.

The first activities on ADS started in 2000 [54], [55]. In 2001, three activities followed [56], [57], [58] them. As of 2009, three separate platforms are well established for ADS:

(1) In 2003, the first track of sessions on ADS was organized, by Ören within the 2003 Summer Computer Simulation Conference (SCSC) of SCS, held in Montreal, Quebec, Canada. In 2004, another track of sessions on ADS was organized by Yilmaz and Ören within the 2004 SCSC, held in San Jose, CA. Since then, they organize –annually– tracks of sessions or symposia on ADS within each SCSC.

(2) In 2005, the first annual symposium on ADS was organized by Yilmaz within the Spring Simulation Multiconference (SpringSim) of SCS [95]. Starting in 2006, T. Ören and G. Madey joined Yilmaz as organizers of the annual ADS symposium. For 2010, the executive committee of the ADS symposium has five members and the Call for Papers has a wide scope of relevant topics.

(3) In 2007, Ören organized a session on ADS within the European Modeling and Simulation Symposium (EMSS) which is part of the International Mediterranean Modelling Multiconference. In 2008 and 2009, Ören and Yilmaz organized tracks of sessions on ADS within EMSS. Plans are under way to continue to make the ADS track of sessions an annual event within EMSS.

The position advocated by the ADS community is that while there exist many agent communities, there are not many simulation communities where agent and simulation technologies are together a central theme.

It is therefore that the ADS community fills a gap in the agent field as well as the simulation community. The theme of agent-directed simulation brings together agent methodologies, technologies, tools, toolkits, platforms, languages, and applications in a pragmatic manner. The theme of ADS is based on (1) the observation of the potential benefits of having a comprehensive and integrative conception of the synergy of simulation and agents and (2) following premises.

(1) The growth of new advanced distributed computing standards is providing a new context that acts as a critical driver for the development of next generation systems. These standards revolve around service-oriented technologies, pervasive computing, web-services, Grid, autonomic computing, ambient intelligence etc. The supporting role that intelligent agents play in the development of such systems is becoming pervasive, and

simulation plays a critical role in the analysis and design of such systems.

(2) To facilitate bridging the gap between research and application, there is a need for tools, agent programming languages, and methodologies to analyze, design, and implement complex, non-trivial agent-based simulations. Existing agent-based simulation tools are still not mature enough to enable developing agents with varying degrees cognitive and reasoning capabilities as well as assurance of trust between agents and between agents and users.

6. Concluding Remarks and Future Research Directions

In drawing the trace of the evolution and growth of the use of simulation for agents and agents for simulation to a close, we offer comments on two aspects: (1) the role of applications, organizations, and emergent technologies on innovations regarding the synergy of simulation and agents and (2) potential avenues of future research. In this article, we advocate the position that scientific, organizational (e.g., community dynamics) and technical factors interact to produce advancements at the intersection of simulation and agents. Specifically, developments occur when individuals or groups of scientists/ engineers make changes in the scientific domain of their study, which are then transmitted to the organizational domain. However, such changes are not adopted unless they are sanctioned by some group that is entitled to make decisions as to what should or should not be included in the domain. In light of this view, we overviewed various technical factors and scientific communities that have shaped the growth and evolution of the synergy of agents and simulation. The contribution, once confirmed and accepted, involves a change in the scientific culture. It is useful to think in this context about scientific culture as a set of interrelated areas shaped by the application domains. As such, we evaluated the major domains that are of significant relevance to agent system design and simulation. We believe that anticipation of the future developments requires understanding of these three components and their synergistic interactions.

In light of this framework and the elaborated categories of the synergy of simulation and agents, we anticipate that the use of agents will increase as the technological context extends with emerging trends and critical drivers such as cognitive informatics, augmented cognition, semantic web, web services and service-oriented computing, grid computing, ambient intelligence, and autonomic computing become more pervasive. Simulation-based design of such systems will require seamless introduction of agents and/or agent technologies.

Dealing with inherent uncertainty due to lack of knowledge is a significant challenge in simulation studies. While experimental designs and statistical decision theory have proven useful in controlling variability, exploration of open systems with structural and behavioral uncertainty is difficult. Variability refers to inherent variation associated with the physical system or the environment under consideration. Sources of variability can be defined in terms of the probability distribution functions that can take on values in an established or known range, but for which the exact value will vary by chance from unit to unit or from time to time. This stochastic variation is used to capture the characteristics of the factors and parameters of both the system and the environment in which it is embedded. Uncertainty, on the other hand, arises due to lack of knowledge. Since the cause of uncertainty is partial knowledge, increasing the knowledge base can reduce the uncertainty. This is also known as epistemic uncertainty and reducible uncertainty. By increasing knowledge, the bias of the simulation can be reduced to improve accuracy. However, in the absence of knowledge, a simulation should be capable of identifying solutions that are robust across variation over uncontrollable factors. Application of fuzzy logic is also an important possibility in cases with partial knowledge.

Building on the premise of autonomic computing and the promise of agent paradigm, newly principled agent-based and agent-supported simulation strategies will allow knowledge to emerge and be used during a simulation study [42]. That is, the ADS perspective, in conjunction with autonomic computing principles suggests promising directions to develop next generation autonomic introspective simulation systems [96] that are able to cope with deep uncertainty. Applications for which autonomic simulation systems will prove useful for online symbiotic simulation, real-time decision support in asymmetric and irregular environments, adaptive experience management for training, crisis and disaster management, and dynamic data-driven applications. Specifically, experimenting with evolutionary and/or contingency models in real-time on demand using the autonomic computing metaphor would be critical for decision support in unstructured problems with the characteristics of (1) deep uncertainty, (2) dynamic environments, and (3) shifting, ill-defined, and competing goals. The major challenges pertaining to decision making in such asymmetric and irregular environments include the following:

(1) For most realistic 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 on the fly and instantiated to continue exploration.

(2) Our knowledge about the problem being studied may not be captured by any single model or experiment.

(3) Dealing with uncertainty is paramount to analyzing complex evolving phenomena. Adaptivity in simulations and scenarios is necessary to deal with emergent conditions for evolving systems in a flexible manner.

Systems characterized by non-linear interactions among diverse agents often exhibit emergent behavior that may be very different from what the initial conditions of these systems would suggest [97]. Traditional simulation techniques that rely on accurate knowledge of these conditions typically fail in these cases. Autonomic simulation systems will have the potential to enable robust decision making in real-time for these problems. Furthermore, the insights derived from the autonomic simulation can be used to improve the performance of the system under study. Likewise, as the system develops, observations of emerging conditions can be used to improve exploration of the problem space.

As a final note, we believe that just as there is no single agent-based abstraction that is uniformly better on all types of problems, there is no one technology (e.g., evolutionary computation, artificial neural nets, symbolic machine learning, and mathematical optimization) that is sufficient to account for the complexity and difficulty of most real-world problems. Rather, we have to recognize that complex real-world systems are developed using a broader systems engineering perspective that requires seamless integration of appropriate technologies [64], [99]. Along this line, the synergy of simulation and agent-directed simulation with systems engineering is becoming relevant for two reasons: (1) applications that are becoming large scale and complex, necessitate use of systems engineering principles and (2) modeling and simulation systems – including agent-directed simulation systems– are becoming very large and complex; hence necessitate use of systems engineering principles.

References

[1] D. Ariely. Predictably irrational: The hidden forces that shape our decisions. Harper Collins Publisher.2008.

[2] J. Bates. The role of emotion in believable agents. Communications of the ACM, 37(7):122-125, 1994.

[3] D. Bell. Welcome to the Post-Industrial Society. Physics Today, Feb. 1976.

[4] J. L. Brian, K. Douglas, and E. Elliott. Adaptive Agents, Intelligence, and Emergent Human Organization: Capturing Complexity through Agent-Based Modeling. The National Academies Press, Washington, D.C., 2001.

[5] K. M. Carley. Computational organizational science and organizational engineering. Simulation Modelling Practice and Theory, 10:253-269, 2003.

[6] K. M. Carley and D. M. Svoboda. Modeling organizational adaptation as a simulated annealing process. Sociological Methods and Research, 25(1):138-168, 1996.

[7] B. Cipra. Cellular automata offer new outlook on life, the universe, and everything. In What's Happening in the Mathematical Sciences, vol. 3, pages 70-81, Providence, RI, 1996.

[8] W. Clancey, P. Sachs, M. Sierhuis, and R. van Hoof. Brahms: Simulating practice for work systems design. In Proceedings PKAW '96: Pacific Knowledge Acquisition Workshop, 1996.

[9] M. Csikszenthmihalyi. Implications of a systems perspective for the study of creativity. Handbook of Creativity, pages 313-338, 1999.

[10] O. J. Dahl and K. Nygaard. SIMULA67 Common Base Definiton. Norwegian Computing Center, Norway, June 1967.

[11] P. J. Denning. Computing is a natural science. Communications of the ACM, 50(7):13-18, July 2007.

[12] Defense Modeling, Simulation, and Analysis – Meeting the Challenge. National Research Council of the National Academies, The National Academic Press, Washington, D.C. 2006.

[13] C. Dowling. Intelligent Agents in an e-Literate Society: Some Ethical Considerations. In T.J. van Weert and R.K. Munro (eds.) Informatics and the Digital Society – Social, Ethical and Cognitive Issues. Kluwer Academic Publishers, pp. 85-92.

[14] E. Eberbach, D. Goldin, and P. Wegner. Turing's ideas and models of computation. In C. Teuscher, editor, Alan Turing: Life and Legacy of a Great Thinker, pages 159-194. 2004.

[15] M. S. Elzas, T. I. Ören, and B. P. Zeigler. Modelling and Simulation Methodology in the Artificial Intelligence Era. North-Holland, Amsterdam,1986.

[16] J. M. Epstein. Generative Social Science: Studies in Agent-Based Computational Modeling. Princeton University Press, Princeton, NJ, 2006.

[17] J. M. Epstein and R. L. Axtell. Growing Artificial Societies: Social Science from the Bottom Up. The MIT Press, Cambridge, MA, 1996.

[18] J. Ferber. Multi-Agent Systems: An Introduction to Distributed Artificial Intelligence. Addison-Wesley, 1999.

[19] I. A. Ferguson. Touring machines: Autonomous agents with attitudes. IEEE Computer, 25(5):51-55, 1992.

[20] R. J. Firby. Building symbolic primitives with continuous control routines. In Procedings of the First Int. Conf. on AI Planning Systems, pages 62-29, College Park, MD, 1992.

[21] M. Georgefi and A. Lansky. Procedural knowledge. IEEE Special Issue on Knowledge Representation, 74:1383-1398, 1986.

[22] N. Ghassem-Aghaee and T. I. Ören. Towards fuzzy agents with dynamic personality for human behavior simulation. In Proceedings the 2003 Summer Computer Simulation Conference, pages 3-10, 2003.

[23] D. Goldin and P.Wegener. The Church-Turing thesis: Breaking the myth. Lecture Notes in Computer Science: New Computational Paradigms, pages 152-168, 2005.

[24] J. R. Harrison and G. R. Carroll. Culture and Demography in Organizations. Princeton University Press, Princeton, NJ, 2005.

[25] J. H. Holland. Hidden Order: How Adaptation Builds Complexity. Helix Books (Addison-Wesley), New York, 1995.

[26] B.W. Hollocks. 40 years of discrete-event simulation–A personal reflection. J. Op. Research Society, 57: 1383–1399. 2006.

[27] D. R. Ilgen and C. L. Hulin. Computational Modeling of Behavior in Organizations: The Third Scientific Discipline. American Psychological Association, Washington D.C., 2000.

[28] A. Javor, M. Benko, A. Leitereg, and G. More. AI controlled simulation of complex systems**.** Computing & Control Engineering Journal, Volume 5, Issue 2, Apr 1994 Page(s):79 - 82

[29] A. Javor and G. Szucs. A methodology for the Determination of the Models of Soft Systems by Means of Intelligent Agents. PERIODICA POLYTECHNICA SER. SOC. MAN. SCI. VOL. 11, NO. 1, PP. 57–66 (2003)

[30] J.H. Kerchofis, G.C. Vansteenkiste, and B.P. Zeigler. Proceedings of The European Conference on A1 Applied to Simulation. SCS Press, Ghent, Belgium, 1985.

[31] P. Klahr and W. S. Fought. Knowledge-based simulation. In Proceedings of the AAAI-80, pages 350-354, 1980.

[32] F Klugl. Multi-agent Simulation. Addison-Wesley, Reading, MA, 2001.

[33] D. M. Krackhardt. Viscosity models and the diffusion of controversial innovation. In Dynamics of Organizations: Computational Modeling and Organizational Theories, pages 243-268, AAAI, Menlo Park, CA, 2001.

[34] B. Kuipers. Qualitative simulation. In Encyclopedia of Physical Science and Technology, Academic Press, 2001.

[35] J. C. Kunz, T.R. Christiansen, G.P. Cohen, Y. Jin, and R.E. Levitt.Vdt- a computational simulation model of project organizations. Communications of the ACM, 41(11):84-92, 1998.

[36] S. Luke, C. Ciofi-Revilla, L. Panait, K. Sullivan, and G. Balan. Mason: A multiagent simulation environment. Simulation: Transactions of the Society for Computer Simulation International, 81(7):517-527, 2005.

[37] [37] C.A. Mack. 30 years of lithography simulation. 2005. http://www.lithoguru.com/scientist/litho_papers/2005_Thirty_Years_of_Lithography_Simulation.pdf

[38] J.M. Miranda and A. Aldea. A social agent model to simulate human behavior in teamwork. In Proceedings of 3rd Workshop on Agent-based Simulation, Passau, Germany, 2002.

[39] G. Madey, V. Freeh, and R. Tynan. Modeling the free/open source software community: A quantitative investigation. In Free/Open Source Software Development, pages 203-221, Idea Group Publishing, Hershey, PA, 2005.

[40] D.J. McArthur, P. Klahr, and S. Narian. Ross: an object-oriented language for constructing simulations. In Expert systems techniques, tools and applications, pages 70-91, Addison-Wesley, Boston, MA, 1986.

[41] J. H. Miller and S. E. Page. Complex Adaptive Systems: An Introduction to Computational Models of Social Life. Princeton University Press, Princeton, New Jersey, 2007.

[42] B. Mitchell and L. Yilmaz. Symbiotic adaptive multisimulation: An autonomic simulation framework decision support under uncertainty. ACM Transactions on Modeling and Computer Simulation, 2008.

[43] J. P. Muller. The Design of Intelligent Agents: A Layered Approach, volume 1177 of Lecture Notes in Artificial Intelligence. Springer, 1996.

[44] R.E. Nance. A history of discrete simulation programming languages. Technical report TR-93-21, Dept. of Computer Science, Virginia Polytechnic University, Blacksburg, VA. 1993. http://eprints.cs.vt.edu/archive/00000363/01/TR-93-21.pdf

[45] R. E. Nance and R. G. Sargent. Perspectives on the evolution of simulation. J. Op. Research, 50 (1):161-172, 2002.

[46] E. Naone. Intelligent Software Assistant – 10 Emerging Technologies. Technology Review, MIT, April 2009, p. 48.

[47] NATO. Crisis management. 2009. http://nato-otan.org/cps/en/SID-8B2CC8EF-9D3C0880/natolive/topics_49192.htm

[48] M. J. North, N. T. Collier, and J. R. Vos. Experiences creating three implementations of the repast agent modeling toolkit. ACM Transactions on Modeling and Computer Simulation, 16(1):1-25, 2006.

[49] T. I. Ören. Syntactic errors of the original formal definition of CSSL 1967. Technical Report 75-01, Computer Science Department, University of Ottawa, Ottawa, ON, 1975, 57 p.

[50] T. I. Ören. A Personal View on the Future of Simulation Languages (Keynote Paper). Proceedings of the 1978 UKSC Conference on Computer Simulation, IPC Science and Technology Press, Chester, England, April 4-6, 1978, pp. 294-306.

[51] T. I. Ören. Artificial intelligence and simulation. Annals of Operations Research, 53:287-319, 1994.

[52] T. I. Ören. Artificial intelligence and simulation: A typology. Proceedings of the 3rd Conference on Computer Simulation, S. Raczynski (ed.), pages 1-5, 1995.

[53] T. I. Ören. Enhancing Innovation and Competitiveness Through Simulation. Preface of the Proceedings of 1995 Summer Computer Simulation Conf., Ottawa, Ont., July 24-26, SCS, San Diego, CA., pp. vi-vii. 1995.

[54] T. I. Ören. Use of Intelligent Agents for Military Simulation. Lecture Notes of Simulation for Military Planning, 21-22 Sept. 2000, Brussels, Belgium. International Seminars and Symposia Centre.

[55] T.I. Ören. Agent-directed Simulation – Challenges to meet Defense and Civilian Requirements. Proc. of the 2000 Winter Simulation Conference, J.A. Joines et al., eds., Dec. 10-13, 2000, Orlando, Florida, pp. 1757-1762. (2000 - Invited Paper).

[56] T. I. Ören. (ed.) Software Agents and Simulation. Special Issue of Simulation Journal. June 2001.

[57] T. I. Ören. Software Agents for Experimental Design in Advanced Simulation Environments. In: S.M. Ermakov, Yu.N. Kashtanov, and V.Melas (eds.) Proc. of the 4th St. Petersburg Workshop on Simulation, June 18-23, 2001, pp. 89-95.

[58] T. I. Ören. Impact of Data on Simulation: From Early Practices to Federated and Agent-Directed Simulations. In: A. Heemink et al. (eds.) Proc. of EUROSIM 2001, June 26-29, 2001, Delft, the Netherlands.

[59] T.I. Ören, Ethics as a Basis for Sustainable Civilized Behavior for Humans and Software Agents. Acta Systemica, 2:1, 1-5. Also in the Proceedings of the InterSymp 2002 - The 14th International Conference on Systems Research, Informatics and Cybernetics of the IIAS, July 29 - August 3, Baden-Baden, Germany.

[60] T.I. Ören. Modeling and Simulation: A Comprehensive and Integrative View. In L. Yilmaz and T.I. Ören (eds.). Agent-Directed Simulation and Systems Engineering. Wiley Series in Systems Engineering and Management, Wiley-Berlin, Germany, 2009, pp. 3-36.

[61] T.I. Ören, M.S. Elzas, I. Smit, and L.G. Birta. A Code of Professional Ethics for Simulationists. Proceedings of the 2002 Summer Computer Simulation Conference, pp. 434-435

[62] T.I. Ören, N. Ghasem-Aghaee, and L. Yilmaz. An Ontology-Based Dictionary of Understanding as a Basis for Software Agents with Understanding Abilities. Proceedings of the Spring Simulation Multiconference, Norfolk, VA, March 25-29, 2007, pp. 19-27.

[63] T.I. Ören and F. Longo. Emergence, Anticipation and Multisimulation: Bases for Conflict Simulation. Proceedings of the EMSS- 20th European Modeling and Simulation Symposium, September 14-17, 2008, Campora San Giovanni, Italy, pp. 546-555.

[64] T.I. Ören and L. Yilmaz. Synergy of Systems Engineering and Modeling and Simulation. Proceedings of the 2006 International Conference on Modeling and Simulation - Methodology, Tools, Software Applications (M&S MTSA), pp. 10-17. July 31 - August 2, 2006, Calgary, AL, Canada

[65] T.I. Ören, Zeigler, B.P. (1979). Concepts for Advanced Simulation Methodologies. Simulation, 32:3, 69-82. SAGE Journals Online

[66] B. W.J. Park, J. Steinman and N. Delane. A proposed open system architecture for modeling and simulation (osams). Proceedings of the Fall Simulation Interoperability Workshop, 2007.

[67] R. W. Pew and A. S. Mavor. Modeling Human and Organizational Behavior: Application to Military Simulations. National Academy Press, Washington D. C., 1998.

[68] Photosynth http://livelabs.com/photosynth/

[69] A. S. Rao and M. P. Georgefi. BDI-agents: from theory to practice. In Proceedings of the First Intl. Conference on Multiagent Systems, San Francisco, 1995.

[70] R. V. Y. Reddy, M. S. Fox, N. Husain, and M. McRoberts. The knowledge-based simulation system. IEEE Software, 3(2):26-37, 1986.

[71] S. Robinson. Discrete-event simulation: From the pioneers to the present, what next? Journal Operations Research Society, **56**: 619–629.2005.

[72] J. W. Rozenblit and B. P. Zeigler. Concepts for knowledge-based system design environments. In Proceedings of the 17th Winter Simulation Conference, pages 223-231, San Francisco, California, 1985.

[73] C. Roufi W. Truszkowski, J. Rash and M. Hinchey. Some autonomic properties of two legacy multi-agent systems - logos and act. ECBS, pages 490-498, 2004.

[74] H. Sarjoughian, B. P. Zeigler, and S. B. Hall. A layered modeling and simulation architecture for agent-based system development. Proceedings of the IEEE, 89(2):201-213, 2001.

[75] B. Schattenberg and A. Uhrmacher. Planning agents in james. Proceedings of the IEEE, 89(2), 2001.

[76] R. E. Shannon. Intelligent simulation environments. In Proceedings SCS Multiconference on Intelligence Simulation Environments, pages 150-156, 1986.

[77] Y. Shoham. Agent-oriented programming. Artificial Intelligence, 60(1):51-92, 1993.

[78] H. Simon. Sciences of the Artificial. The MIT Press, Cambridge, MA, 3rd edition, October 1996.

[79] J. R. Spiegel and D. B. LaVallee. Using an expert system to drive a simulation experiment. In roceedings of the Conference on AI and Simulation, pages 108-112, 1988.

[80] J. R. Spiegel and D. B. LaVallee. Using an expert system to drive a simulation experiment. In Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation, pages 29-52, Cambridge University Press, 2006.

[81] R. Sun. Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation. Cambridge University Press, 2006.

[82] R. Sun. The clarion cognitive architecture: Extending cognitive modeling to social simulation. In Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation, pages 79-102, Cambridge University Press, 2006.

[83] N. Taatgen, C. Lebiere, and J. Anderson. Modeling paradigms in act-r. Science, 185:1125-1131, 1974.

[84] A. Turing. On computable numbers, with an application to the entscheidungsproblem. Proceedings London Mathematical Society, 42(2):230-265, 1936.

[85] A. Uhrmacher, P. Fishwick, and B. P. Zeigler. Introduction to agent modeling and simulation. Proceedings of the IEEE, 89(2), 2001.

[86] C. Urban and B. Schmidt. Agent-based modeling of human behavior. In Proceedings of the AAAI Fall Symposium: Emotional and Intelligent - Tangled Knot of Social Cognition, North Falmouth, MA, 2001.
[87] US House Resolution 487, 2007, July 16. http://thomas.loc.gov/cgi-bin/query/z?c110:hres487
[88] C. van Aart. Organizational Principles for Multi-Agent Architectures. Birkhauser, 2005.
[89] H. van Dyke Parunak and S. Brueckner. Modeling uncertain domains with polyagents. Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems, pages 111-113, 2006.
[90] J. Vardaman. Why didn't Sony invent iPod" Corporate culture is vital, even more than "just research. Circuits Assembly, 2009 Feb. 28. http://circuitsassembly.com/cms/magazine/5-current-columns/7985-why-didnat-sony-invent-the-ipod
[91] J.G. Vaucher. Views of modelling: Comparing the simulation and AI approaches. In Proceedings SCS Multiconference in Artificial Intelligence, Graphics, and Simulation, pages 3-7, 1985.
[92] G. Weiss. Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence. The MIT Press, Cambridge, Massachusetts, 1999.
[93] M. Wooldridge. Introduction to Multiagent Systems. Wiley, 2002.
[94] J. E. Wray and R. M. Jones. Considering soar as an agent architecture. In Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation, pages 53-78, Cambridge University Press, 2006.
[95] L. Yilmaz. The Proceedings of the Agent-Directed Simulation Symposium of the 2005 Spring Simulation Multiconference, volume 37. SCS Press, San Diego, CA, 2005.
[96] L. Yilmaz. Autonomic introspective simulation systems: Concepts and applications. Proceedings of the 2008 Summer Computer Simulation Conference, 2008.
[97] Yilmaz, L. and Ören, T.I. (200_Dynamic Model Updating in Simulation with Multimodels: A Taxonomy and a Generic Agent-Based Architecture, Proceedings of SCSC 2004 - Summer Computer Simulation Conference, July 25-29, 2004, San Jose, CA., pp. 3-8.
[98] L. Yilmaz and T. I. Ören. Agent-Directed Simulation, Special Issue of the Transactions of the Society for Computer Simulation International, volume 81. SAGE, July 2005.
[99] Yilmaz, L. and T.I. Ören (eds.) (2009). Agent-Directed Simulation and Systems Engineering. Wiley Series in Systems Engineering and Management, Wiley-Berlin, Germany, 520 p.
[100] Yilmaz, L., T.I. Ören). Agent-Directed Simulation (ADS). In L. Yilmaz and T.I. Ören (eds.). Agent-Directed Simulation and Systems Engineering. Wiley Series in Systems Engineering and Management, Wiley-Berlin, Germany, 2009, pp. 111-143.
[101] L. Yilmaz, T. I. Ören, and N. Ghasem-Aghaee. Intelligent agents, simulation, and gaming. Simulation and Gaming, 37(3):339-349, 2006.
[102] L. Yilmaz and J. Phillips. The impact of turbulence on the effectiveness and efficiency of software development teams in small organizations. Software Process: Improvement and Practice Journal, 12(3):247-265, 2007.
[103] B. P Zeigler. Discrete event abstraction: An emerging paradigm for modeling complex adaptive systems. In Perspectives on Adaptation in Natural and Artificial Systems, Essays in Honor of John Holland, Santa Fe Institute, Oxford University Press, England, 1989.
[104] B. P. Zeigler. Object Oriented Simulation with Hierarchical, Modular Models: Intelligent Agents and Endomorphic Systems. Academic Press, 1990.
[105] B. P. Zeigler. Endomorphic modeling concepts for high-autonomy architectures. Applied Artificial Intelligence, 6(1):19-43, 1992.
[106] B. P. Zeigler, M. S. Elzas, G. J. Klir, and T. I. Ören. Methodology in System Modelling and Simulation. North-Holland, Amsterdam, 1979.
[107] B. P Zeigler, J. H. Hu, and J. W. Rosenblit. Hierarchical, modular modeling in devs-scheme. In Proceedings of the 21st Winter Simulation Conference, pages 84-89, 1989.
[108] B. P. Zeigler, H. Praehofer, and T. G. Kim. Theory of Modeling and Simulation. Academic Press, 2000.
[109] R.N. Zobel A Personal History of Simulation In the UK and Europe, 1964-2001. International Journal of Simulation. V1, 1-2, pp. 69-79. 2000. http://ducati.doc.ntu.ac.uk/uksim/journal/issue-1/RichardZobel/RichardZobel.pdf

Table 2. Spectrum of computational paradigms (from Yilmaz and Ören [94])

Type of knowledge processing	Computational paradigm	Role of	
		People	Computational system
Procedural	Algorithmic (unstructured, structured, or object-oriented programming)	- *Analyst develops* and algorithm - *Programmer transforms* the algorithm and generates a program. - *User activates* the "whole" program.	- System *compiles* or *interprets* user's program. - System *executes* the compiled or interpreted program code.
Intentional	Declarative	- User *specifies* the problem.	- System *generates* a code (program generator transforms the specification into code) - System *executes* the compiled or interpreted code
Goal-directed	Interactive (Event-based)	- User *activates* functions to be performed. (Indirectly activates the module(s) of code to be executed.)	- System assures the *execution* of the (already-existing problem-independent) *software modules* corresponding to the selected functionalities.
	AI-based (heuristics, rule-based or frame-based computation)	- Knowledge engineer *specifies the rules*. - User specifies *the goal and the facts* (initial conditions). - Problem-independent *inference engine* is prepared only once.	- System (inference engine) *determines the order* in which the rules have to be executed and - *executes* the rules accordingly until the goal is satisfied.
	Agent-based	- *Problem is specified* in agent-based modeling. - User *specifies the goal* and - *delegates* finding a solution of the problem to agents.	Agents: - *process the goal* (identifies sub-goals, sequence them, and determine additional knowledge requirements), - *perceive* their environments, - *perform goal-directed knowledge processing*, and -*decide* which (other agent or non-agent software module(s) to activate or sub-delegate the task(s).

LEVENT YILMAZ is Associate Professor of Computer Science and Software Engineering and Industrial and Systems Engineering at Auburn University. He received his B.S. degree in Computer Engineering and Informa-

tion Sciences from Bilkent University and the M.S. and Ph.D. degrees from Virginia Tech. His research focuses on Agent-directed Simulation and Complex Adaptive Systems with applications in (1) advancing the theory and methodology of modeling and simulation via novel formalisms (e.g., generative multisimulation, autonomic introspective simulation, symbiotic adaptive multisimulation) and their use in decision/ creativity support and (2) exploring and understanding complex adaptive socio-technical/cognitive/cultural systems. Dr. Yilmaz is a member of ACM, IEEE Computer Society, Society for Computer Simulation International (SCS - <www.scs.org>), and Upsilon Pi Epsilon. His email and web addresses are <yilmaz@auburn.edu> and <www.eng.auburn.edu/˜yilmaz >.

TUNCER I. ÖREN is a professor emeritus of computer science at the School of Information Technology and Engineering (SITE) of the University of Ottawa, Canada. He has been involved with simulation for over 40 years. His Ph.D. is in Systems Engineering from the University of Arizona, Tucson, AZ. His *basic education* is from Galatasaray Lisesi, a high school founded in his native Istanbul in 1481 and in Mechanical Engineering at the Technical University of Istanbul. His *research interests* include advanced methodologies for modeling and simulation, agent-directed simulation, cognitive simulation, reliability, QA, failure avoidance, ethics, as well as body of knowledge and terminology of simulation. He has over 400 *publications* including 20 books and proceedings –some translated in Chinese, German and Turkish. He has contributed to over 370 *conferences* and *seminars* held in 30 countries. He has received invitations, fellowships, scholarships, or sponsorships from United Nations, NATO, and 11 countries. Dr. Ören has been recognized, by IBM Canada, as a pioneer of computing in Canada where he has been also the Founding chair of the Executive Committee of the Chairmen of the Canadian Computer Science Departments. Over 20 Who's Who citations. "Information Age Award" from the Turkish Ministry of Culture, SCS Distinguished Service Award, and plaques and certificates of appreciation from organizations including ACM, AECL, AFCEA, and NATO. He is also a distinguished lecturer of SCS. http://www.site.uottawa.ca/~oren/