Multi-Agent Simulation in Organizations: An Overview

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INTRODUCTION

Most economic and business systems are complex, dynamic, and nondeterministic systems. Different modeling techniques have been used for representing real life economic and business organizations either on a macro level (such as national economics) or micro level (such as business processes within a firm or strategies within an industry). Even though general computer simulation was used for modeling various systems (Zeigler, 1976) since the 1970s the limitation of computer resources did not allow for in-depth simulation of dynamic social phenomena. The dynamics of social systems and impact of the behavior of individual entities in social constructs were modeled using mathematical modeling or system dynamics.

With the growing interest in multi agent systems that led to its standardization in the 1990s, multi agent systems were proposed for the use of modeling social systems (Gilbert & Conte, 1995). Multi agent simulation was able to provide a high level disintegration of the models and proper treatment of inhomogeneity and individualism of the agents, thus allowing for simulation of cooperation and competition. A number of simulation models were developed in the research of biological and ecological systems, such as models for testing the behavior and communication between social insects (bees and ants). Artificial systems for testing hypothesis about social order and norms, as well as ancient societies (Kohler, Gumerman, & Reynolds, 2005) were also simulated.

Since then, agent-based modeling and simulation (ABMS) established itself as an attractive modeling technique (Klugl, 2001; Moss & Davidsson, 2001). Numerous software toolkits were released, such as Swarm, Repast, MASON and SeSAm. These toolkits make agent-based modeling easy enough to be attractive to practitioners from a variety of subject areas dealing with social interactions. They make agent-based modeling accessible to a large number of analysts with less programming experience.

BACKGROUND

Computer simulation modeling is an established method in scientific and industrial applications, appropriate for obtaining insight into the dynamics of organizations. Modeling is used to represent a part of reality in sufficient detail, and resulting model is an artificial system used for experimentation. There are several situations when replacement of the real system by an artificial one is helpful or even necessary.

- **Inaccessibility of the real world system:** Sometimes a part of the real world system that should be studied, is not accessible either because the system does not exist any more or is not yet put into operation.
- **Real world system is inappropriate for experimentation:** Some real world systems may be affected in undesired way by experimentation. Examining effects of drastic changes in taxing and pricing policies may for example, disturb the fiscal system, or discourage production and consumption.
- **Time scale or behavior of the system is inappropriate for observation:** A number of systems such as investments in some industries generate results over long periods of time, making it hard to collect enough data from the real system for a meaningful analysis. Simulation is using virtual time that can be accelerated or slowed down as needed in order to observe a particular phenomenon.
- **Intensive dynamics of the system:** All elements of simulation model can be taken under full control. This is especially important in economics for the purpose of studying the impact of changes in one factor on behavior of the whole system, while holding all other factors at the same level. This presumption cannot be achieved in a real life economic system (e.g., system of supply and demand).

The model should be able to answer questions directed to the real system. However, it can produce valid output only for the set of experiments defined by the *experimental frame* (Zeigler, 1976) determined in the early stages of model development. After the model is successfully built, simulation experiments can be performed. In order to gain full control over the experiment, a simulation model is used in a predefined *artificial environment* and a predefined *virtual time* of simulation.

Treatment of virtual time is crucial for selection of the simulation method applied to the model. (1) If virtual time is continuous, then ***system dynamics*** is used. System dynamics focuses on feedback loops of the model whose behavior is represented by differential equations. Model is restricted to macro level, and its properties are described by attributes which represent the state of the system and its changes. System dynamics is used for analysis of the behavior of complex real systems on a macro level, in management, politics, economics, environmental change and so forth. Important advantage of system dynamics is its efficiency due to its high degree of abstraction.

(2) If virtual time is divided into a series of discrete periods, then **event-based simulation** is used (Seila, Ceric, & Tadikamalla, 2003). *Discrete event simulation* advances “time” to the moment (denoted by time stamp) in which at least one model entity needs to execute certain action or change its state. *Simulation clock* defines the beginning and the ending moments of time required for simulation execution. Discrete-event simulation models are primarily used for functional verification and performance evaluation of real world systems.

Standard methods for concurrent processes modeling are queuing networks, Petri nets and cellular automata. (3) **Queuing networks** and **Petri nets** do not include mechanisms for representing inhomogeneous space where the number of entities, their interactions and behavior change over time in dependence on their surroundings. If a conflicting situation occurs in the environment, then probabilistic factors or predefined fixed amounts of system resources and length of activities are used. (4) **Cellular automata** are purely space-based representations where each cell value is calculated on the basis of values of neighboring cells. However, modeling of individual behavior of an entity or modeling of deduction rules using cellular automata requires complex models and overwhelming computing resources (Klügl, Oechslien, Puppe, & Dornhaus, 2004).

Some of the shortcomings of system dynamics and discrete event simulation as well as other methods for modeling concurrent processes can be overcome by the **multi agent simulation** paradigm. The essential idea of agent-based modeling and simulation (ABMS) is that complex phenomena (such as economic systems and business organizations) can best be represented as systems of relatively simple autonomous agents that follow comparatively simple rules of interaction. These agents are capable of making independent decisions and interactions with the rest of the system. Therefore, multi agent simulation uses multi agent systems to represent the structure of simulation models. A multi agent system is composed of multiple interacting agents capable of achieving their goals, which are beyond their individual abilities, through mutual cooperation.

Multi agent simulation consists of simulated agents that “live” in a simulated—*artificial environment*, and in simulated—*virtual time*. Environment can play an important role as it frames the agents’ behaviors and interactions. The difference between multi agent simulation and multi agent systems is that agent environment within multi agent systems is “sensed” by the agent as it is, while agent environment in multi agent simulation is artificially created as a part of the simulation model, thus allowing for much more control over the developed system.

There are several advantages of multi-agent simulation in comparison to system dynamics. System dynamics is restricted only to the macro level, making it incapable of answering questions concerning the relationships between different granulites of the observed system (such as relationships between the microeconomic activities and the macroeconomic aggregates) in a simplified way. ABMS, on the other hand, allows introduction of different layers of observations: individual level, population level and a number of customized intermediate levels. Another drawback of system dynamics is the assumption of homogeneity of entities and space, so that individualism and heterogeneity cannot be represented. However, agents may be capable of adoptive behavior and flexible interaction with other entities. They may change their environment and perceive those changes afterward. This kind of flexible feedback loops is not possible using system dynamics or any other simulation approach.

Multi agent simulation deals with systems with similar characteristics as discrete-event simulation does. Discrete-event simulation can be represented as directed graphs called queuing networks. These graphs can have two types of nodes: servers with or without a queue. Servers are used for processing jobs that pass through the graph. If a server is busy, other jobs must wait in line for the server to complete its task. Even though all queues have their own queuing discipline, no job entity may leave the queue due to its own decision. If the job has branching routes, probability-based decisions are made, because all job entities are the same, without internal structure that could allow them to make their own routing decisions. Besides, discrete-event simulation models do not allow for variable system structure (number of servers, paths and interactions are fixed) while in a multi agent simulation model variable system, structure can be achieved via intelligent job agent processing. Agents provide heterogeneity, where classical modeling approaches were based on homogeneity of behavior.