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Modeling the Forest or Modeling the Trees

A Comparison of System Dynamics and Agent-Based Simulation

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Abstract:

System Dynamics and Agent-based Simulation are two approaches that use computer simulation for investigating non-linear social and socio-economic systems with a focus on the understanding and qualitative prediction of a system's behavior. Although the two schools have a broad overlap in research topics they have been relatively unnoticed by each other so far. This paper contributes to the cross-study of System Dynamics and Agent-Based Simulation. It uncovers and contrasts the primary conceptual predispositions underlying the two approaches. Moreover, ideas about how the approaches could be integrated are presented.

Key words: System Dynamics, Agent-based Simulation

Introduction

Computer simulation itself is still a relative young field; in the social sciences however, the use of computer simulation can be considered a well-established domain of research (Conte et al., 1998). Two main purposes of computer simulation are foresight and insight. According to Troitzsch (1997) prediction (foresight) can again be divided into qualitative prediction – prediction of behavior modes – and quantitative prediction – prediction of the state the system reaches at a specific point in time. There are predominately two simulation schools that use computer simulation for investigating non-linear social and socio-economic systems with a focus on the more quantitative goals – the understanding and qualitative prediction of a system's behavior; they are System Dynamics and Agent-based Simulation. Although the two schools have a broad overlap in research topics they have been relatively unnoticed by each other so far (Phelan 1999), a cross-study of the two disciplines is overdue (Scholl, 2001). Meadows and Robinson (1985, p. 17) explain what new insights such cross-studying can bring about: "every modeling discipline depends on unique underlying assumptions; that is, each modeling method is itself based on a model of how modeling should be done." The authors continue that these assumptions are constantly used but rarely examined by the modeling community, which is why they are called paradigms. “Different modeling paradigms cause their practitioners to define different problems, follow different procedures, and use different criteria to evaluate the results” (Meadows and Robinson, 1985, p. 20).

A cross-study of System Dynamics and Agent-based Simulation gives both communities the opportunity to learn about each other’s modeling paradigm, question own assumptions, see problems from a different viewpoint and probably identify potentials of integration that can overcome some of the pitfalls a single approach might have in certain areas.

The main purpose of this paper is to uncover and compare the primary conceptual predispositions underlying System Dynamics and the Agent-based Simulation approach. In the first section a literature review separately examines the two fields. They are then compared in the second section. The paper concludes with some ideas about conceptual integration potentials.

System Dynamics: modeling the forest

System Dynamics is an approach that applies concepts from engineering servomechanism theory to social sciences (Richardson, 1991). It was developed in the 1950s at the MIT, primarily by Jay W. Forrester who is himself an electrical engineer working in the field of servomechanism. In his 1958 article “Industrial Dynamics, a Major Breakthrough for Decision Makers” Forrester outlines the new approach – at that time called Industrial Dynamics – using a practical example: he models a four-tier downstream supply chain and analyses the effects of capacity constraints, different inventory and order handling policies, as well as advertising and supply chain size on demand amplification – a phenomenon that today is called the Bullwhip- or Forrester-Effect.

Forrester defines the new field as: “Industrial Dynamics is the study of information-feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise” (Forrester, 1961, p. 13). Since that time the method has been applied to a wide variety of social systems, the probably most popular being described in the book “Limits to growth” (Meadows et al., 1972).

There are three main reasons why the identification of the concepts and assumptions underlying System Dynamics is rather straightforward. Firstly, the approach was mainly developed by one person, J.W. Forrester. Secondly, in his early books, “Industrial Dynamics” (Forrester, 1961) and “Principles of Systems” (Forrester, 1968) he gives a detailed description of both, the theoretical concepts and definitions, as well as the practical application of the approach; the conceptual fundament is thus set in the very beginnings. And finally, succeeding work – most of which has been pragmatic, meaning application-oriented (Meadows and Robinson, 1985) – builds on Forrester’s work without changing the general concepts and definitions. The System Dynamics community therefore holds a relative homogenous view about the fundamentals underlying the approach. A comparison of Meadows and Robinson (1985) and Saleh (2000) who both aim at identifying the basic concepts of the System Dynamics approach supports this statement. The two works basically differ in the hierarchical organization of the individual concepts, not in the concepts themselves.

In System Dynamics real-world processes are represented in terms of stocks (for example stocks of material or knowledge), flows between these stocks, and information that determines the value of the flows (Forrester, 1968). The primary assumption is that the internal causal structure of a system determines its dynamic tendencies (Meadows and Robinson, 1985); it is not single decisions or external disturbances that are responsible for a system's behavior, but the structure within which decisions are made – the policies (Richardson, 1991). Abstracting from single events and concentrating on policies instead, System Dynamics takes an aggregate view (Forrester, 1961). The reasons for using continuous simulation can be found in this aggregate viewpoint as well as in the focus on structure in general (Forrester, 1961; Richardson, 1991). The mathematical description of a continuous simulation model is a system of integral equations (Forrester, 1968).

The overall structure of a system is organized hierarchically as depicted in Figure 1 (Forrester, 1968; Maier, 1994). Within a closed boundary – closed meaning that all elements relevant for generating a system's characteristic pattern of behavior have to be modeled endogenously – a system is composed of interacting feedback loops. It is the concept of feedback, where output is again used as an input, that makes a system capable of generating behavior endogenously. Every feedback loop consists of two fundamental types of variables: Levels, representing the state of the system and rates, incorporating the elements of a decision process and by that resulting in action that changes the state of the system. Two fundamental types of feedback loops exist: negative loops in general showing goal-seeking behavior and positive feedback loops having the tendency to reinforce their input leading to exponential growth or decay.

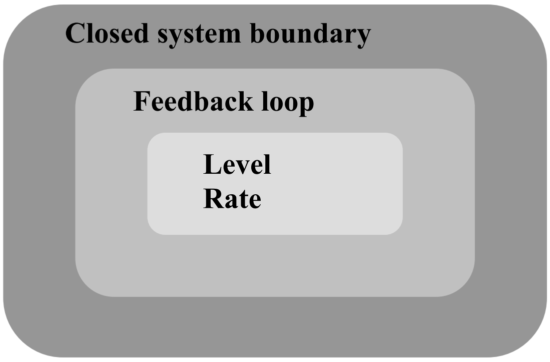

Figure 1: Metastructure in System Dynamics

The basic structure of a decision process, modeled as an information-feedback loop, is depicted in Figure 2. Sterman (2000) distinguishes between the physical and institutional structure of a system and the decision rules of the participating agents, between decision making and action taking. The physical and institutional structure contains the measurement and reporting processes and produces the information cues that are then passed on to the decision maker. The decision maker interprets the available information cues by applying his/her decision rules (the policies). The output of a decision process, the decision, results in action which then alters the state of the system leading to a change of the information cues.

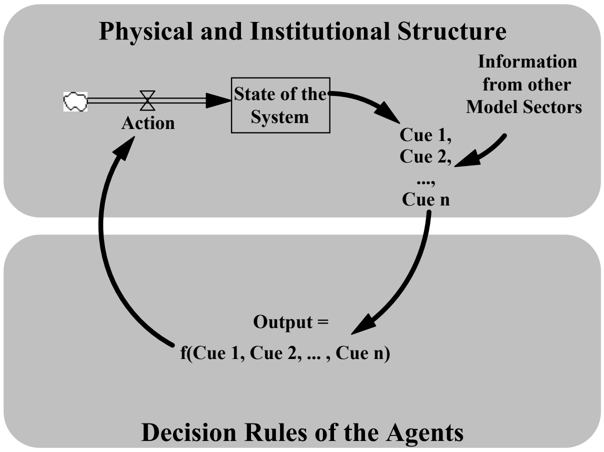

Figure 2: Basic structure of a decision process (Sterman, 2000)

Only rarely information used for decision making is complete, unbiased and actual. The behavior of an information-feedback system is highly sensitive to the kind of information used to make decisions and the accuracy of that information (Saleh, 2000, p. 10). The addition of a time delay to a negative feedback loop, for example, can change the behavior of that model from goal-seeking to oscillating. Delay structures can thus be considered another essential concept of System Dynamics (Forrester, 1961).

Agent-based Simulation: modeling the trees

The second paradigm to be analyzed is Agent-based Simulation. Jennings et al. (1998) trace the concept of software agents back to three different areas of research: (i) artificial intelligence, (ii) object-oriented programming and concurrent object-based systems and (iii) human-computer interface design. The agent concept itself cuts across many different disciplines, but the use of agents for designing simulation models is mainly applied in the fields of complexity science (Phelan, 2001) and game theory (Axelrod, 1997).

In Agent-based Simulation universally accepted definitions lack for some key concepts (Jennings et al., 1998) what makes the identification of the basic concepts and assumptions underlying the discipline more difficult than in the case of System Dynamics. Even for the concept of a software agent the answer to the question, which properties an entity has to feature in order to deserve to be called “agent” is not clear-cut: definitions range from a mere subroutine to a conscious entity (Rocha, 1999). As many of the agent-properties found in literature are developed to a greater or lesser extent – depending on the purpose the agent is designed for – it is probably more appropriate not to differentiate between agents and non-agents, but to speak of a continuum of agency. The more agent characteristics an entity possesses and the more developed those are, the higher the degree of agency it has. Table 1 gives an overview of agent properties that can be found in the literature (the list is not exhaustive).

Properties	Description	Literature
Proactiveness, Purposefulness	Ability to take the initiative in order to achieve goals	Hayes-Roth (1995) Wooldridge and Jennings (1995) Ferber (1989) Klügl (2001) Nwana (1996) Jennings et al. (1998) Franklin and Graesser (1997) Maes (1995) Smith et al. (1994) Murch and Johnson (2000)
Situatedness	Agent is embedded in its environment and senses and acts on it	Franklin and Graesser (1997) Russel and Norvig (2003) Hayes-Roth (1995) Ferber (1989) Klügl (2001) Ferber (1989) Goldspink (2000) Jennings et al. (1998) Maes (1995)
Reactiveness, Responsiveness	Ability to react in a timely fashion to changes in the environment	Wooldridge and Jennings (1995) Goldspink (2000) Nwana (1996) Klügl (2001) Jennings et al. (1998) Murch and Johnson (2000)
Autonomy	Ability to control own actions and internal state	Wooldridge and Jennings (1995) Maes (1995) Nwana (1996) Klügl (2001) Jennings et al. (1998) Murch and Johnson (2000)
Social Ability	Ability to interaction and communication with other agents, sometimes even awareness of other agents	Wooldridge and Jennings (1995) Ferber (1989) Nwana (1996) Klügl (2001) Jennings et al. (1998) Murch and Johnson (2000)
Anthromorphity	Having human-like attributes, e.g. beliefs and intentions	Wooldridge and Jennings (1995) Klügl (2001) Murch and Johnson (2000)
Learning	Ability to increase performance over time based on previous experience	Hayes-Roth (1995) Nwana (1996) Murch and Johnson (2000)
Continuity	Temporally continuous running process	Hayes-Roth (1995) Murch and Johnson (2000)
Mobility	Ability to move around in the simulated physical space, sometimes even between different machines	Nwana (1996) Murch and Johnson (2000)
Specific Purpose	Designed to accomplish well-defined tasks	Smith et al. (1994) Maes (1995)

Table 1: Properties of agents

An agent-based system, is “one in which the key abstraction used is that of an agent” (according to the “definition” in table 1) (Jennings and Wooldridge, 1998, p. 5). The agents are modeled as to represent natural entities in the system under consideration, for example human beings, animals, or institutions (Edmonds, 2000). An agent-based simulation model mostly consists of more than one agent, why it is often called a Multi-Agent System. According to Jennings et al. (1998, p. 17) Multi-Agent Systems have four characteristics: “

- each agent has incomplete information, or capabilities for solving … [a given] problem, thus each agent has a limited viewpoint;
- there is no global system control;
- data is decentralized; and
- computation is asynchronous.”

In such a system it is the interaction between the individual, often heterogeneous agents that creates the overall behavior; in other words, the macro-level system behavior is a result of the micro-level behavior of the agents (Schillo et al., 2000) – giving the agent-based simulation approach also the name *bottom-up simulation* (Axelrod, 1997; Richardson, 2003).

The behavior of an agent is defined by its internal state, its schema which is “a cognitive structure that determines what action the agent takes at time t, given its perception of the environment” (Anderson, 1999, p. 219). An agent’s schema can evolve over time what allows it to adapt to its environment. From a modeling perspective, this adaptation can be achieved by the use of feedback and learning algorithms (Phelan, 2001). Often schemata are modeled as sets of simple generative rules. Nevertheless, complex patterns can arise from the interaction of the agents.

A comparison of the approaches

Table 2 extracts the major differences between System Dynamics and the Agent-based Simulation approach from the literature section. For the identification of the differences it also draws upon work done by Dong-Hwan Kim and Juhn Jae-Ho (1997), Pourdehnad et al. (2002), and Schieritz and Größler (2003). The following section will be used to elaborate on these differences.

	System Dynamics	Agent-based Simulation
Basic building block	Feedback loop	Agent
Unit of analysis	Structure	Rules
Level of modeling	Macro	Micro
Perspective	Top-down	Bottom-up
Adaptation	Change of dominant structure	Change of structure
Handling of time	Continuous	Discrete
Mathematical formulation	Integral equations	Logic
Origin of dynamics	Levels	Events

Table 2: System Dynamics versus Agent-based Simulation

Basic building block: feedback loop versus agent

A System Dynamics model consists of interacting feedback loops. This feedback structure leads to endogenously generated behavior, the kind of behavior a System Dynamist is mainly interested in. The feedback loop can therefore be considered the basic building block of a System Dynamics model (Forrester, 1968).

In Agent-based Simulation the basic building block is the agent (Jennings et al., 1998). A model consists of multiple agents and their environment. Often even the environment is modeled as one or more agents, of course featuring different properties than the actors. Every agent is given a set of rules according to which it interacts with other agents; this interaction then generates the overall system behavior.

Basic unit of analysis: structure versus rules

The behavior of a System Dynamics model is determined by its structure. The structure itself has to be defined before starting the simulation, it is fix. It is the structure in which System Dynamists try to find leverage points for changing the behavior of the system in a deliberate direction.

In Agent-based Simulation the focus lies on agents' rules. An agent's rules determine its interactions with other agents what then determines the macro system behavior. Rules often are flexible, that is they can change in the course of the simulation. The policies of a System Dynamics model also represent rules of how decisions are made. Compared to Agent-based Simulation however, they are modeled structurally.

Level of modeling: macro versus micro

The type of simulation used in System Dynamic belongs to the group of macro simulation approaches. The term *macro simulation* can be somewhat misleading, it does not imply that System Dynamics can only be used for macro-economic, or more general, macro-social problems. System Dynamics – depending on the problem under consideration – can also be applied to the level of individual actors, being the micro level of a social system (Schillo et al., 2000). Davidsson (2000, p. 97) explains the differences of micro and macro simulation as follows: "…in macro simulations, the set of individuals is viewed as a structure that can be characterized by a number of variables, whereas in micro simulations the structure is viewed as emergent from the interactions between the individuals". In System Dynamics, a system is modeled from an aggregate view, representing the characteristics of objects or the objects themselves via average properties. This is a direct result of the modeling technique used: the level variables are accumulations of the flows; therefore, single objects flowing through the system can not be identified.

Using Davidsson's definition Agent-based Simulation belongs to the micro simulation approaches, as it concentrates on modeling populations by modeling the behavior of the heterogeneous individuals and enable them to interact. The modeler does not determine the characteristics of a population in advance, but they evolve in the course of the simulation. By that, Agent-based Simulation establishes a link between the micro and the macro level of a model, whereas System Dynamics establishes a link between system structure and system behavior.

Perspective: top-down versus bottom-up

As explained in the last two paragraphs, aggregation is imposed by the modeler in System Dynamics, but occurs as a bottom-up process in Agent-based Simulation. This bottom-up process is often seen as the source of a phenomenon called emergence. According to Gilbert (1995, p. 15) "emergence occurs when interactions among objects at one level give rise to different type of objects at another level. More precisely, a phenomenon is emergent if it requires new categories to describe it that are not required to describe the behavior of the underlying components".

If a System Dynamics study is to analyze an emergent phenomenon it would capture this phenomenon by modeling its properties, its structure. That is, the emergent phenomenon itself is modeled. In an Agent-based model, however, it evolves in the course of the simulation.

Adaptation: change of dominant structure versus change of structure

The process of adaptation takes an important role in both approaches. According to Holland (1975) adaptation is the modification of structure with the goal to better perform in a given environment. In a System Dynamics model the structure has to be determined before starting the simulation; it cannot be modified in the course of the simulation. Therefore, System Dynamics models are not capable of adaptation in the sense Holland uses it. However, by defining a weaker sense of adaptation, meaning no change in structure, but shifts in loop dominance generated by nonlinearities (Forrester, 1987), adaptation can be achieved by a System Dynamics model. According to Richardson (2000) "nonlinearities enable continuous models to adapt and change over time".

Agent-Based models on the other hand have the possibility to adapt in the strong sense. The change in structure can for instance be achieved by the use of evolutionary or genetic algorithms. A genetic algorithm makes a subsequent generation of agents evolve from its ancestors. This development is mainly achieved by two processes: cross-over and mutation (Holland, 1975). Cross-over occurs, when the genes of a new agent consist of a mix of its parents' genes, mutation is the accidental change of genes.

Handling of Time: continuous versus discrete

System Dynamics focuses on a continuous representation of real-world systems. Forrester (1961) advocates a continuous point of viewpoint for several reasons. Firstly, he argues for a "continuous point of view" (Richardson, 1991, p. 152) in general when he claims that "even major executive decisions represent a rather continuous process" (Forrester, 1961, p. 65), especially when the focus lies on the general framework of the decision. Secondly, the process of aggregation leads to a more continuous overall behavior than the consideration of single events. Finally, Forrester argues that the dynamics of a continuous-flow model are easier to understand and should therefore be the starting point of the modeling efforts. This does not imply that discontinuities are not compatible with the idea of System Dynamics (Forrester, 1961) it is just that its focus is on the continuities in socioeconomic systems (Richardson, 1991).

In the Agent-based Simulation literature no clear proposition is made about the handling of time. But, in general a discrete view is applied (Dong-Hwan und Jae-Ho, 1997). This partly results from Holland's (1975) definition of adaptation, as structural changes require some degree of discreteness. The genetic algorithm proposed by Holland for achieving this adaptation is inherently discrete through its two central concepts: cross-over and mutation.

Mathematical formulation: integral equations versus logic

The structure of a feedback loop consists of two fundamental types of variables: levels and rates (Forrester, 1968). Levels are the accumulations of rates of flow, which themselves are the output of the decision rules and represent action. The process of accumulation is mathematically expressed by integrating the net difference between inflow and outflow over time (Forrester, 1968). The state of a system at any specific point in time is solely described by the level variables. Levels are necessary for a system's dynamics, as they "permit the inflow rates to differ … from the outflow rates" (Forrester, 1968, p. 86). Mathematically, a System Dynamics Model is "a system of coupled, non-linear first-order integral equations" (Saleh, 2000, p. 13).

There is no universally accepted formalism for the mathematical description of Agent-based Simulation models. According to Inverno et al. (1997) most formalisms are logic-based, for example Fisher and Wooldridge (1996) suggest the use of temporal logic as a general framework for modeling Agent-based Systems. But, as Dong-Hwan und Jae-Ho (1997) state, the research methodologies in Agent-based Simulation are so diverse that no common modeling platform exists.

One fundamental difference between System Dynamics and Agent-based Simulation can be found in the transition from one state to the next: future behavior of a System Dynamics model solely depends on the current state; in an Agent-based Simulation model, however, agents can possess a stable memory that uncouples future behavior from the current dynamics. Joslyn and Rocha (2000) call such agents *dynamically incoherent*.

Source of dynamics: levels versus events

A central concept of the System Dynamics approach is the concept of accumulation (Saleh, 2000). Accumulation is achieved by integration that "uncouple[s] inflow rates from outflow rates and make[s] dynamic behavior possible. A system representation with no accumulators can show only static, equilibrium conditions." (Forrester 1989, p. 9) The system elements that represent accumulation processes are referred to as state variables or levels. They create inertia or delays and thus determine the timing of system behavior (Meadows, 1985). The significance of levels is emphasized by the fact that they are one of the two basic elements of a model (the other being flow variables that represent the inflow respectively the outflow rates). All sub-structures (e.g. delays, feedback-loops) contain levels.

The statements found in the System Dynamics literature regarding the significance of the accumulation process for the dynamic behavior of systems are universally valid. Without accumulation (whether discrete or continuous) no dynamics can exist, as nothing changes. However, the Agent-based Simulation approach does not emphasize the process of accumulation at all. A concept applied in Agent-based Simulation that can be used to oppose the level concept in System Dynamics is probably the idea of events. Events can be considered the source of dynamics as they trigger a change in system behavior. A variable that crosses a threshold can for example cause an agent to interact with other agents.

Modeling the forest versus modeling the trees

How would now a forest system generally look like when modeled using the System Dynamics respectively the Agent-based Simulation approach?

First of all, applying an Agent-based perspective one starts with identifying the different agents of the system under perspective, which in this case are the different types of trees (as well as the environment), provides them with the necessary properties and gives them rules to interact. The forest then is a phenomenon that emerges in the course of the simulation from the interactions of the trees with each other and with their environment. In a System Dynamics study, however, the forest properties are constituents of the model; the overall structure of the forest is modeled by a number of variables and their causal relationships. Thus, the emergent phenomenon itself, the forest, is modeled.

Moreover, an Agent-Based model would probably be spatial explicit leading to the fact that the consequences of decisions not only have a temporal, but also a spatial element. Let's assume the agent *fire* "decides" to break out at a specific position within the forest. The ability of the fire to spread then depends on the wood quality of the direct neighbors of the smutted tree. A System Dynamics model, by aggregating the different types of trees in level variables (one level for every type), does not possess spatial explicitness. Here, the ability of a fire to spread is calculated using the overall (meaning aggregated) wood quality of the forest; it determines the proportion of the forest to be destroyed.

The outbreak of a fire is also a good starting point for exemplifying differences in the handling of time and in the importance of events. In an Agent-based model such an outbreak is an event; it has a beginning and an end. The occurrence of fire can be modeled using a probability distribution; the duration then depends on the wood quality of the neighboring trees as discussed above. System Dynamics in contrast does not model the outbreak *per se*, but continuously a proportion of the forest is destroyed by the fire; that is, at any point in time the fire is present. What changes in the course of the simulation dependent on the overall wood quality is the proportion of wood destroyed.

Potentials of integration: modeling the forest and the trees?

Despite the many differences between System Dynamics and Agent-based Simulation, there are also some obvious similarities: both focus on social systems with local, meaning decentralized, decision making. And, both have the same aim: the search for principles underlying the dynamics of complex systems (Phelan, 1999). An integration of the two concepts can be fruitful when it allows for the combination of properties that are otherwise proprietary to a single concept. This section intends to identify potential sources of synergy by looking at different approaches to integrate System Dynamics and Agent-based Simulation.

The idea of integrating the System Dynamics and the Agent-based Simulation approach is not new. Dong-Hwan und Jae-Ho (1997) call for the use of System Dynamics as a platform for Agent-based Simulation. The authors use array variables to model different agents in a System Dynamics environment. Using a system of price adjustment as an example, they find that the dynamics of an aggregate simulation model substantially differ from those of a multi-agent model. Akkermans (2001) also uses a System Dynamics environment for simulating adaptive – in the weak sense – agents. He models a supply network with every agent carrying a mental model of the performance of the agents it is interacting with and analyzes the stability of the network.

Milling (2002) builds a System Dynamics Model for the analysis of diffusion patterns. In order to model the occurrence of innovations in organizational settings he uses a genetic algorithm, a concept widely used in Agent-based Simulation to model learning and adaptation of agents over generations. Analyzing the dynamics of policy evolution in a software engineering setting, it is again the genetic algorithm and its inherent discreteness that lets Hines and House (2001) integrate System Dynamics and Agent-based Simulation. In the System Dynamics part the authors model a number of projects, each controlled by a manager. The managers themselves are modeled as individual agents, as every manager has his/her own policy for controlling his/her project (a policy includes the number of programmers on the project, the time to hire and the time to change schedule). After a project is completed, managers learn and innovate – modeled with the help of the genetic algorithm. They then apply their new policies to a new project. By combining the two approaches the authors allow for adaptation in Holland's sense within a System Dynamics model – part of the structure becomes modifiable.

Jager (2000) takes a similar approach: in his analysis of resource management of individual agents in a commons dilemma situation and its effect on the environment, he uses an agent-based approach for modeling the individuals, whereas the environment is modeled using System Dynamics. Jager (2000, p. 28) establishes his argumentation for this choice as follows: "…in modelling a macro-economic system it seems appropriate to use a system-dynamical modelling framework, whereas the modelling of processes that involve social interaction requires a multi-agent framework."

Schieritz and Größler's approach (2003) contrasts this statement. They combine System Dynamics and Agent-based Simulation in a supply chain setting. But contrary to Jager (2000), they use System Dynamics to model the internal structure of the agents, their *mental models* in System Dynamics terms or *schemata* in Agent-based Simulation terms. The supply chain structure evolves from the agents interaction which is a result of decisions they make based on their internal structure. The authors state that the idea of modeling an agent's internal structure with the help of System Dynamics was already implicitly suggested by the agent-based community, with Phelan (2001) claiming that an agent's rules are to be modeled using feedback and learning algorithm or Choi et al. (2001, p. 353) comparing schemata with "Senge's [1990] notion of mental models". Schieritz and Größler allow for structural insights in the agents' policies (structure-behavior-link on the micro level) while at the same time establishing a link between the micro and macro level of a supply chain and allowing for a flexible supply chain structure.

Summary

This paper aimed at comparing two approaches for the simulation of non-linear socio-economic systems: System Dynamics and Agent-based Simulation. Primary conceptual predispositions underlying the approaches have been contrasted and integration potentials have been identified. However, the integration of the two concepts does certainly not only implicate advantages. Model validation for instance is one field where every method itself developed a vast body of literature. It has yet to be answered whether this knowledge can also be applied to an integrated approach. However, despite of this and probably a lot of more problems that have to be solved, an integrated approach possibly has the potential to help decision makers develop the capacity of thinking at one and the same time of both, the forest *and* the trees.

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