4. Multi-Agent Systems, Time Geography, and Microsimulations

Magnus Boman and Einar Holm

1. Introduction

We seek to unify two paradigms: that of microsimulations (used heavily in the social sciences) and that of multi-agent systems (used heavily in computer science and to an increasing extent also in the social sciences). We illustrate the attempted unification chiefly by means of time geography, which can be seen as a third paradigm. Here, the concept of space is explicitly modelled, which is not always the case in the other two paradigms.

1.1 The Concept of an Agent

An *agent* is an autonomous pro-active entity, the actions of which depend on its internal state. The autonomy of the agent refers to the fact that its existence does not necessarily rely on the existence of any other object, such as a particular resource, or another agent. The pro-activeness of the agent gives it the possibility of acting without being told to or prompted to. The internal state is logically represented as a state in a finite automaton, the description of which is part of the agent.

We will concern ourselves chiefly with *simulated agents*, i.e., software representations of agents. Whenever we concern ourselves with *embodied agents* (i.e., humans, physical robots, or any other kind of non-simulated agent), we will explicitly say so. A completed series of runs with agents as its primitives is called an *agent-based simulation*. Agent-based simulations containing a distribution of simulated agents are referred to as *multi-agent systems (MAS)*, and completed series of runs are then *agent-based social simulations (ABSS)*. For such a simulation to be meaningful, the agents must have means to communicate. Only then can social structures emerge, and the designer may study and monitor co-operation, competition, group formation, self-organization, and other structural properties of the simulation. Likewise, if the purpose of the simulation is computational, such as the optimization of a goal function, an agent approach outperforms other methods only if there is inter-agent communication. Nevertheless, most simulations that purport to be agent simulations use *solipsistic agents*, agents that do not accept any input. The use of the term agent is then merely cosmetic: The traditional way of communicating in MAS is through messaging (Smith, 1980). Indeed, the agent approach has been criticized for the huge amount of message passing in situations of negotiation or other form of social adaptation.

There are three fundamental constraints in agent communication. Firstly, messaging may be constrained in space. For instance, if the agent distribution is spatial, messages might only travel over a limited Euclidian distance, or agents might have the capacity to address only agents in their immediate neighborhood, e.g., their von Neumann neighborhood. Messaging may also be constrained in time. A multi-agent system can have time represented intrinsically, usually based on the computer system clock (synchronous model). Alternatively, the representation may be based on system events (asynchronous model). In a synchronous time system, agents may be allowed to send only a limited number of messages each cycle. In an asynchronous time system, agents may be allowed to address other agents only before or after certain events. Finally, messaging may be constrained by architecture. These constraints have to do with inability of the agents, of the underlying hardware, or of the network, to cope with message passing.

The semantics of the model can be very complex, and if the system is to be interpreted in the real world, the art and engineering of such interpretations is very difficult. This is a research area in need of much development, and hitherto many models have been presented that are more difficult to understand than the real world they represent.

If a multi-agent system is intended to represent parts of reality, the ABSS can be a model of those parts of reality, subject to limitations of the representation, languages used, and the universe of discourse (see, e.g., Boman *et al.*, 1997). Some ABSS can represent social phenomena, a fact that has led social scientists to MAS use (cf. Verhagen, 2000). In socio-economic systems, statistical mechanics is used to an ever-increasing extent. The analogy between the explanation of how collections of atoms can exhibit correlated behavior and the explanation of how various group behaviors may arise in societies of interacting individuals is popular (see, e.g., Durlauf, 1999). It is not evident, however, that statistical mechanics in practice gives the most appropriate representation of agent systems with considerably more complex properties and interaction than atoms, and we will return to this issue below. The increasing use of MAS for electronic trade will presumably increase their usage for explanatory purposes in the future (LeBaron, 2000).

When modeling social systems, in particular with microsimulation, the agent is usually a representation of a human. Sometimes, certain aggregates of individuals (e.g., families, firms, municipalities, neighborhoods, clubs, and associations) are modeled as encapsulated objects and are then dubbed agents. Such an aggregate may be modeled with some decision and action capacity beyond that of its member individuals, and labeled accordingly, such as "a decision making unit." A family might appear only as a passive property of some individuals, or as a relation between individuals. When such an individual dies, the family to which it belonged basically just becomes smaller. Often, however, specific methods and properties are given to the family (such as moving) that can only be triggered by the family entity and not by its member individuals in splendid isolation. Each individual might be part of or belong to several other aggregate agents, with a partial action capacity of their own. The quest for emergence is to have these appear without being predefined. This calls for clear definitions and careful maintenance of individual and aggregated agents, and their interrelations.

1.2 The Paradigm of Modern Multi-Agent Systems Research

In the 1980s, MAS research branched out from distributed artificial intelligence (Bond & Gasser, 1988). While the latter concerned itself with distributed problem solving with a global system task, MAS approaches tackled local system tasks, i.e., agent tasks, and let global solutions emerge. Contrast for example the distributed solution of the problem of maximizing a global utility function, and the centralized solution of the problem of amalgamating the solutions of a number of local utility maximizers. A further difference between the two approaches is that in distributed problem solving, processes typically cooperate, while in the MAS approach agents may cooperate but may also compete. The paradigm was from the outset separated into research on languages, theories, and architectures.

1.2.1 Agent Languages

Language issues include agent communication languages, i.e., standardized forms of inter-agent communication, but also protocol standards, and the development of new programming languages suitable for agent programming. In particular, an engineering approach to MAS (represented by, e.g., Genesereth & Ketchpel, 1994) describes agent-oriented programming as an extension of object-oriented programming, the main added features being that messages in MAS have fixed meaning, and the agents have dedicated communication protocols. An alternative cognitive science approach to MAS (represented by, e.g., Castelfranchi, 1998) takes more of an interdisciplinary stance. Inspired by philosophers commenting on representational artificial intelligence issues, such as Dennett (1978) and Bratman (1987), and on language issues in particular, chiefly Searle (1969), this approach takes the notion of states in an agent as placeholders of mental states in humans. This stance leads to problem solving in agents being modeled through the so-called BDI-model (for Belief, Desire, and Intention; see, e.g., Rao & Georgeff, 1995, for a brief survey). It is also programmed with the intent of emulating human problem solving, e.g., in the early Procedural Reasoning System (Georgeff & Lansky, 1987), in keeping with early artificial intelligence research (Newell & Simon, 1961). Even in this setting, the suggestion of speech act theory as a standard for agent communication languages is remarkable: All international standardization attempts (the two largest ones being KQML/KIF and FIPA, see http://www.fipa.org) have been based on speech acts. Habermas (1981) is to be found among the many critics of this theory, which strongly constrains agent messaging.

1.2.2 Agent Theories

Reflex agents do not reason, but act in a stimulus-response fashion. *Deliberative agents* reason, usually under constraints. Because deliberation takes time, there is a trade-off between capability and efficiency of MAS. The MAS designer can, for instance, choose between having many agents that reason very little, so-called *swarms*, and fewer agents that reason a great deal, so-called *intelligent agents*. There is also the possibility of designing intelligent agents that reason only when time permits. Such bounded intelligence is akin to Simon’s bounded rationality, and can be highly useful in practice. The agents can then be programmed using anytime algorithms (Dean & Boddy, 1988): they quickly guess or approximate a solution, which is then refined for as many rounds as permitted. If such algorithms are too demanding to write, the crude alternative is to let the agents jump between an intelligent state (in which they reason) and a non-intelligent state. Defining when to jump, and indeed defining the time bounds for an anytime algorithm, is a prime example of a meta-design problem for MAS. Another meta-design problem is how to make the agents perform means-ends analysis, necessary for matching their capability with goal-seeking behavior. In short, deliberation yields declarative knowledge allowing for prioritization among goals, while means-ends reasoning is required for the procedural knowledge: how to achieve the goals.

Cognitive science is concerned only with intelligent agents. In particular, the emulation of human behavior is a pivotal design principle. The agent states are likened to human mental states, and the agent reasoning and knowledge base are discussed and manipulated using mentalistic notions, such as beliefs, desires, and intentions. In the Procedural Reasoning System (Georgeff & Lansky, 1987), for instance, desires are implemented as plans, part of a plan library. Any sequence of plans executed in order to reach a goal constitutes an intention of the agent. The semantics are usually described using modal logics (see, e.g., Woolridge, 2000), many of which are esoteric by the standards of theoretical philosophy, and all of which have high computational complexity (Fagin *et al.*, 1995). The latter problem is chiefly due to the large number of primitive modal operators, usually equal to the number of agents in the

MAS times the number of modalities. This and many other problems concerning cognitive theories of agents are inherited from the symbolic approach to artificial intelligence (Winograd & Flores, 1986). In particular, the problem with using plan libraries is that each plan requires continuous maintenance. Plan revision and belief revision have become research areas in their own right, and the depth of the maintenance problem has led to alternative approaches to intelligent agents in MAS.

A totally different approach is the so-called *reactive* approach to agent design (Agre & Chapman, 1987). Brooks (1990) argued that the symbolic representation of knowledge and reasoning is not a requirement for intelligent behavior. Instead Brooks suggested equipping agents with various capabilities, and stated that intelligence is an emergent property of interaction in a MAS of such agents. While he focused on embodied agents and built several robots to illustrate his theories himself, his neo-behaviorist design architectures and ideas also quickly penetrated the theory of systems of simulated agents (see, e.g., Steels, 1990).

In a classic paper by Rosenschein and Kaelbling (1986) on how the cognitive and reactive approaches can be combined it was argued that symbolic representation may be adequate at the meta-design level, while such representation should be "compiled away" to produce efficient behavior at run-time. Their work also helped introduce *situated automata* (declarative specifications of behavior) and their "compiled" version *digital machines* (procedural executables) to the agent community (Kaelbling & Rosenschein, 1990). Together with *cellular automata* (Langton, 1986), these building blocks are used to study perhaps the hardest and so far among the least successful of all agent problem areas: learning.

1.2.3 Agent Architectures

An agent architecture usually presumes hardware, such as computer architecture, as well as software, such as operating systems. The computer architecture in practice often amounts to a local network (closed or semi-closed system), but may incorporate portions of the Internet (open system). In peer-to-peer MAS, agents address each other directly. In client/server MAS, which include all MAS involving agents roaming the Internet since the Internet uses TCP/IP—a client/server protocol, messages are routed through a server. Typically, each agent is then a client, and there is only one server.

On top of the computer architecture reside the two design principles for MAS architectures, often called the deliberative and the reactive principle (cf. Maes, 1991). The most widespread architecture obeys the reactive principle: Brooks' (1986) *subsumption architecture* is extremely simple. In reactive architectures (Agre & Chapman, 1987) the number of agents is very high, and reasoning amounts to little more than stimulus-response. In deliberative architectures, the number of agents is low and the reasoning capability of each agent is considerable. This distinction also applies to many microsimulation models, most of them being entirely reactive while some, in particular time geography inspired models, also contain deliberative elements. There are also hybrid architectures, but perhaps most successful have been the mixed architectures, where deliberation is exploited only when time (or some other constrained resource) permits.

1.3 The Paradigm of Social Science Microsimulation

The MAS development described so far mainly pertains to methodological findings within computer science. However, some ABSS have something interesting to say about observable phenomena outside the model, especially in relation to the emergence of new structures, objects, and institutions. There is also a substantial amount of earlier and contemporary modeling in the social sciences that is based on representations of interacting individual actors. Strangely, those social science traditions seem to have co-developed without much mutual contact. One noteworthy exception is Gilbert and Troitzsch (1999), who give a comprehensive overview of simulation modeling approaches, including MAS applied to social science. They also recognize microsimulation as the main early effort. The overview limps in that all three characteristics given (viz., only prediction, no explanation; no interaction between individuals; and intentions disregarded) might apply to some of the early efforts but certainly not to later developments like CORSIM and SVERIGE described below. A few older and later MAS-related social science developments will therefore be described below with a focus on microsimulation and time geography.

In a MAS, the behavioral content of the agents and the attributes of their environment are pure fantasy. They are not expected to replicate observables or even to let them be recognizable. The aim is rather to achieve a certain functionality of a kind that might be observed, but also of a kind that might never even be conceived in human systems. Social science inspired models with individual actors are, on the other hand, almost always thought of as a direct surrogate for individuals within a certain society. The aim is to vary the conditions in the surrogate in order to reach conclusions that are also applicable, relevant, or at least interesting, outside the model. Such experiments would then partly replace the need for painful and expensive efforts to implement new policy directly – efforts often doomed to failure. This kind of "decision support" modeling is often implicitly based on the naïve epistemological assumption that the model directly represents reality, whereas it is often claimed that any model only is or should be a model of a theory (cf. Huberman & Glance, 1993). An ontological compromise stance might be to regard some objects (individuals) in such models as actually representing something existing outside the model, independent of observers and theory, but to consider the objects' methods and other implemented causal structures as an imagination-based theory that nonetheless might be supported by empirical generalizations.

1.4 Aim and Disposition

We argue that social scientists (including economists) as well as researchers in the natural sciences would benefit from having basic skills in multi-agent simulation techniques. No arguments are needed for the converse, but some pitfalls for multi-agent system designers are nevertheless listed below. A synthesis of the two paradigms is indeed underway, and our aim is to pinpoint the remaining obstacles and propose means to remove them. We will be led by the words of Thomas Kuhn (1970:44): "…if the coherence of the research tradition is to be understood in terms of rules, some specification of common ground in the corresponding area is needed. As a result, the search for a body of rules competent to constitute a given normal research tradition becomes a source of continual and deep frustration. Recognizing that frustration, however, makes it possible to diagnose its source."

In the case of MAS, some of the novelty comes from the increase in computational capacity, but even more important is the increased accessibility of such capacity. Just as a decision maker today has a powerful computer on her desk, decreasing her dependence on engineers, the MAS modeler has a myriad of tools, modeling languages, and textbooks available off-the-shelf. The increased accessibility not only vouches for more practitioners, it also makes MAS modeling more fun. The open-endedness comes to MAS in part from the inherent inter-disciplinarity of the activity. The domains studied include biology, chemistry, organization theory, sociology, geography – the list can be made very long. In many of the fields listed, researchers have discovered the viability and flexibility of MAS, as well as some of its weaknesses. This has led to intense activity with dozens of international workshops and conferences each year.[1]

Likewise in the case of social science microsimulations, the impact of the increased accessibility to computational capacity has been important, although it has not triggered a similar rapid expansion of the field. Since most social science models are heavily data driven, it is at least as important a fact that the increased computational capacity has enabled rapid management and analysis of large databases intimately connected to the modeling efforts. The development of a plethora of useful packages for statistical and spatial analysis is also important.

For large-scale applications, the computational capacity recently reached a level offering fundamentally new working conditions. Earlier, much effort went into programming smart file transfer schemes, which slowed down execution speed tremendously and complicated modeling algorithms and made the models less transparent, with more administrative overhead. It is still necessary to "squeeze" the representation of agent objects so that each bit is used and significant, and it is still necessary to avoid or get around fancy but ill-designed operating system services (like Microsoft's threading mechanism and garbage collection, where the supported style of programming seems to target toy applications constrained to the number of objects that can fit the screen simultaneously when visualized). In the SVERIGE model (cf. sections 2.5.4 and 4 below) it is now possible to represent 10 million fairly detailed agents with many properties and interactive behaviors entirely in core memory on a standard computer. That model now runs a simulated year in 90 seconds.

The following section will provide the basis for our attempt at synthesis. In section 3, we discuss and criticize the critique of MAS and ABSS methodology. After that, we turn to our subjective and perhaps optimistic view of the current situation, using our collected past experience of the two paradigms. We then focus on the systems analytical components of our work, in keeping with the overall theme. The introduction to this volume also provides the excuse for a somewhat unfair bias towards Swedish efforts here. Finally, we offer our conclusions.

2. Social Phenomena

2.1 Social Phenomena in Multi-Agent Systems

In ABSS social phenomena can pertain to two different things. First, the ABSS can be claimed to adequately represent social phenomena observable in reality. Second, the agents in the MAS can be part of social phenomena. A proviso in the latter case is *situatedness*: that the agents are connected to the environment, and not just to a model of the environment.[2] The agents might for instance cluster into groups in accordance with their preferences for a particular resource, such as food, encoded in their respective internal states. Under some

[1] With three annual workshops running in Europe, the U.S., and the Pacific rim (MAAMAW, the DAI workshop, and MACC, respectively) already in the mid-1980s, the community did not see its first international conference until 1995 (Lesser, 1995).

[2] In many of the cases we consider, the model is the environment, in some sense. It is also interesting to note that the fascination with the concept of situatedness in artificial intelligence and early multi-agent systems theory came in part from Giddens' (1984) theory of structuration, and in particular from his concept of situated practices. The adoption of this term is a prime example of a "notion theft" of the new paradigm, of which we will see more below.

circumstances, a social phenomenon (where "social" here refers to the environment contained in the MAS) might emerge. Clustering and possibly teamwork might be considered behaviors emerging from the fact that all agents are drawn to areas in a spatial landscape where some resource is plentiful, and hence the basic conditions for teamwork, viz. geographical proximity and social interaction capability, are met (see, e.g., Boman, 1999). The bottom-up nature of ABSS is in general considered to provide nourishment for emergent phenomena (Epstein & Axtell, 1996). Some such phenomena only evolve over repeated runs. In evolutionary multi-agent systems, agents must be adaptive, i.e., be capable of mutation, of revising their patterns of interaction, even of learning in a weak sense.

2.2 Agent-Based Computation

In MAS, agents can also be used for computational purposes. Axtell (2000) distinguishes three levels of use for agents, of increasing complexity and interest:

1. Agent models as classical simulation;
2. Agents as complementary to mathematical theorizing; and
3. Agent computing as a substitute for analysis.

When discussing the first level, Axtell (2000:6) poses a question of the highest relevance also to our study: "Imagine that some social process is under study, and that it is possible to write down one or more mathematical relationships that fully describe the process. Furthermore, imagine that the resulting model may be solved explicitly, either symbolically or numerically. Then what role is there for an agent-based computational model of the process?" In his answer, Axtell points to the value of building symbolic models (agent models being the case in point) and comparing these to numerical models. That this area is understudied is quite clear, and it is in great need of this kind of alignment studies (cf. Axtell *et al.*, 1996; Axelrod, 1997a, 1997b; App. A). While the general requirements for such studies are starting to be discussed in transdisciplinary terms, case studies are still rare. Carpenter (2002) provides an interesting case in which equilibria in bargaining situations are computed in two ways. Firstly by differential equations, and then by decentralized agents that adopt bargaining strategies via a simple learning rule. In spite of the game-theoretic environment he uses, Carpenter's results are generalizable to a large class of problems. The most obvious extension is to predator-prey problems inspired by or referring to biological food chains, where differential equations can be compared to the many agent-based computation environments. The learning rules are here usually simple, and the differential equations are usually the well-established Lotka-Volterra.

Another kind of alignment model is provided by Möhring and Troitzsch (2001). They replicate 30-year-old simulations of the development of a lake, subject to eutrophication (e.g., due to fertilization). Möhring and Troitzsch do not stop there, however, but go on to modernize Jay M. Anderson's original model and make it a multi-agent model. The aim is to make the model part of a management information system with decision support and automated features, as illustrated by the ponderous sentence (*ibid*.:13.2): "…in our model, farmers and local governments still are only provided with a limited actor architecture using state variables, with equations and rule based actions (state transition functions), and a simple interaction mechanism, restricted to actors of different types, directly using attribute values of objects of other types (which means for instance that the government reacts on the actual amount of oxygen, biomass, and detritus of the lake, instead of being notified with a message sent from the lake to the government)."

Everybody does not go for alignment, however. Van Parunak *et al.* (1998) consider a supply network case in equation-based (EBM) vs. agent-based modeling (ABM), but implicitly argue for incommensurability (*ibid*.:10): "EBM begins with a set of equations that express relationships among observables. The evaluation of these equations produces the evolution of the observables over time. … The modeler may recognize that these relationships result from the interlocking behaviors of the individuals, but those behaviors have no explicit representation in EBM. ABM begins, not with equations that relate observables to one another, but with behaviors through which individuals interact with one another. … The modeler begins by representing the behaviors of each individual, then turns them loose to interact. Direct relationships among the observables are an output of the process, not its input." This pertains more to Axtell's second level, at which agent-based computations do not rival as much as complement numerical computations: what can be learned from numerical experiments with equations for which we do not have a closed form, can sometimes be learned (faster) from agent-based experiments. Axtell (2000) gives several examples in the equilibrium computation domain. Depending on the complexity of the problem, and other factors, agents also substitute rather than complement, taking us to Axtell's third and final level.

2.3 Multi-Agent System Complexity and Some of Its Pitfalls

For comparisons between numerical and agent-based symbolic computation to be feasible, the equations must not be hard. Integer programming is an example of a class of equation-based problems that is of high but just tolerable complexity when it comes to the execution of agent-based computations within reasonable limits. This is in sharp contrast to the complex macro-level patterns observable already in ABSS with a relatively simple set-up. All forms of stable patterns and structures, such as agent group formations in which migration halts, arise from nonlinear interactivity among the individual agents. To lose the possibility of alignment with numerical or even analytical solutions can be a pitfall of agent-based computation: if new results can be achieved only in the presence of emergent phenomena due to stochastic elements, irreproducibility may be a fact.

In economics, the search for Walrasian equilibria (see, e.g., Mas-Colell *et al.*, 1995) has been aided by the introduction of market-oriented programming (Wellman, 1993). Here, an automated auctioneer is in control of updating prices and other values, and the general equilibrium price is the main emergent property. Program trading is a growing field suitable for agent-based models and computations, and during the last five years much effort has gone into protocol and market design. In market-oriented programming, the auctioneer reacts in real time. It is usually not driven by events, however, but by a synchronous clock. The Trading Agent Competition (TAC; see http://www.sics.se/tac) is a good example. In TAC, agents represent travel coordinators, whose goal is to arrange travel packages for eight clients. These travel packages consist of flights, hotel rooms, and tickets to entertainment events, all of which the agents trade in electronic auctions. The first two competitions (in 2000 and 2001) ran on the Michigan Internet AuctionBot server (Wurman *et al.*, 1998). Agents communicate with the AuctionBot via a TCP-based application programming interface, supporting the development of trading agents in a variety of programming languages, the most popular of which so far is C++, followed by Java.[3]

[3] Just to get some idea of the level of ambition: our agent RiskPro (which finished seventh in TAC 2000) consisted of 7000 lines and 20 classes of Java code (Boman, 2001). About 3000 of these lines were devoted to communication with the AuctionBot server.

Complexity is also a factor in the interpretation of results, and not just with respect to computational complexity. If a numerical and an agent-based symbolic computation diverge, the reasons for the diversion must be distinguishable at the meta-level, by the designer of the experiment. Hence, unacceptably high complexity of the experimental set-up is another pitfall. Finally, the patterns generated in ABSS can be seductive. Interesting mathematical properties of a simulation run can make the designer forget the "rubbish in, rubbish out" principle and fall into the *inductionist trap*: a situation where the designer cannot distinguish between significant and non-significant output of the simulation, due to myopia or other self-induced handicap.

2.4 Agent Complexity and Some of Its Pitfalls

The following list gives some example properties of artificial agents on a scale of increasing complexity. A crude distinction between microsimulation models constructed so far and MAS models would be that the former exploit less complexity in the representation of individuals than the latter. Roughly, individuals described as in the first half of the list would cover the vast majority of social science based modeling of agents, whereas the latter half somehow covers at least the ambition in most of computer science based MAS.

- Aggregate representation of classes of individuals
- Individual representation
- Individuals with a few static attributes
- Individuals with many dynamic attributes
- Explicit relations to other individuals (like mother)
- Intention and condition (will and can)
- Explicit separation of information
- Short term memory for perception, cognition, decision and action
- Adaptive behavior (cooperation, competition)

- Long term memory from different domains (success and failure)
- Long term memory for social relations
- Value and performance driven goal setting
- Strategic behavior
- Achieve strategic goals by changing immediate and close constraints
- Continuous feedback from environment, change goal often
- Self-organization
- Emergent behavior

As mentioned in the introduction, our aim here is to discuss simulated agents with complex behavior and environment as mainly portrayed in the latter part of the list above: agents under emerging social structures, co-operation, competition, group formation, and self-organization.

2.5 Microsimulation

Early microsimulation efforts were almost entirely a reaction to the shortcomings of aggregate and disaggregate economic and demographic models of society, a type of modeling that still rules in economics, regional science, demography, and social science in general. The whole purpose of such models is to represent observables and facilitate policy experiments, sometimes with the help of theory and theoretical concepts; and if the model fails in prediction (as they normally do), there is no other excuse for its construction. Compared to MAS, this effort leans much more heavily on data collection, representation, estimation, and validation in an empirical setting, as well as on substantial social science theory and findings.

It is instructive to try to characterize the mindset or dominant cognitive picture held by scholars of the two paradigms. For many microsimulation modelers, the model probably is envisioned as something like a database containing many records ("rows"), each representing one individual with many observed attributes ("columns"). The purpose of the simulation is to extend that database into the future by updating, year after year, the attributes of each person as accurately as possible. The test is the model's ability to replicate observed history, or to maximize some function of futures, e.g., to outperform an index on a stock market. The use is to produce alternative, contra-factual or future histories based on some changed condition. For a MAS modeler (cf., e.g., Bertels & Boman, 2001) biological evolution is one inspiration, but the modeler invents the model whereafter the model by itself creates different artificial species interacting and evolving in computer memory while occasionally producing new functionality and complexity with properties sometimes also recognizable outside the model.

The social scientists' much heavier emphasis on substance, replication, and policy relevance also partly explains their lower ambitions regarding the intricacy and degree of autonomy of the represented agents. It is hard to combine those ambitions within one model, project, tradition or even lifetime but nevertheless that is our vision.

2.5.1 Micro-Analytic Modeling[4]

One early source of ideas behind the "micro-analytic modeling approach" are the theories of economist Guy Orcutt, as presented in his article entitled "A new type of socio-economic system" (Orcutt, 1957). Together with Greenberger, Korbel, and Rivlin, he also developed a running model, presented in a book issued in 1961, in which the results of these efforts were presented (Orcutt *et al.*, 1961). From this starting point, many micro-analytic models have been designed and executed.

Those early micro-analytic models primarily dealt with the U.S. economy, as an alternative to traditional macroeconomic modeling approaches like the macro time series approach associated with Tinbergen (1939), the interindustry approach initially developed by Leontief (1951), and the transition matrix approach elaborated by Stone (1966). One of Orcutt's arguments for an alternative individual-based representation was that the problem of testing hypotheses in models which are formulated in terms of one-of-a-kind entities, such as regional population or unemployment, is substantial (Orcutt, 1986). It is difficult to test macro models based on low frequent macro time series. Such efforts are subject to technical problems such as multicollinearity, autocorrelation, and feedbacks (Orcutt & Cochrane, 1949; Nakamura *et al.*, 1976). In addition, it is not possible to evaluate the effects of policy changes on the decision-making units, such as individuals, firms, and households, in macro models.

[4] The first part of this overview draws largely on the corresponding sections of Holm et al. (2000) and Clarke and Holm (1987).

The basic feature of the micro-analytic approach is the identification and representation of individual actors with some dynamic, adaptive behavior producing individualized response to endogenous and exogenous stimuli. The focus shifts from sectors of the economy to the individual decision-making units. Knowledge about individual behavior, other actors and decision-making units is integrated in the model and the consequences of many individuals' behavior or responses to external influence are explored (Krupp, 1986).

2.5.2 Data Requirement

Microsimulation models can incorporate individual behavior and micro processes in the models and use theories of individual behavior. The heterogeneity of information can be fully represented in the model and maintained during simulation. The output can easily be aggregated to levels suitable for answering theoretical and applied questions. Such models obviously require appropriate data. Information about attributes of the decision-making units (agents) is needed, preferably beyond one single cross-section. Such longitudinal data is needed for estimating transition probabilities reflecting behavioral hypotheses. This kind of data is rarely available. Often therefore, alternatives, such as surveys/samples and synthetic data, are utilized. Today, however, for most practical purposes, an earlier obstacle, the heavy demands on computer capacity, is removed.

Early micro models were often static, without explicit dynamic, temporal behavioral responses, just comparing an *ex post* to an *ex ante* distribution with the dynamics replaced by an "equilibrium" response algorithm at the individual level. Such models are often designed for, and useful for answering questions about, short-term effects on income distribution induced by changes within the welfare systems. However, only in dynamic models is it possible to represent indirect effects and the evolutionary trajectories of all agents and their properties.

2.5.3 Stochasticity

Microsimulation models often contain both deterministic and stochastic relations. Deterministic relations obviously produce the same result in every simulation with identical initial conditions. They mirror unavoidable rules or strong logical or structural constraints, e.g., tax liabilities or subsidies (if the agent survives one year, it unavoidably becomes one year older). However, in most cases response behavior is partially unknown due to lack of knowledge or because it is intrinsically undeterminable (free will, genuine uncertainty, etc.). In practice, the error term of the regression equation representing the behavior in question can often be used as an estimate of the undeterminable part of this behavior. It is essential – and this is at the heart of microsimulation – that this error is internalized and maintained in the simulation. Thereby full heterogeneity is preserved despite the drivers being only partially known. The unknown part of the cause is then replaced with a random number generator in the simulation. In such a stochastic model, the outcome of each simulation is different. Replicating the model execution many times with different random seeds gives information about the overall prediction error. The impact of parameter changes can be directly compared with this unavoidable random variation.

2.5.4 Microsimulation Models

In a survey by Merz (1991) it was shown that 57 major dynamic and static microsimulation models had been developed and implemented between 1960 and 1990. They covered the following topics: wealth accumulation and distribution, labor force participation, pension reform, family formation, distributional effects of tax transfer policies, urban housing markets, distributional impact of energy policies, national health insurance, state unemployment insurance, land-use forecasting, residential energy demand, housing allowance, labor supply, shortening of working hours, distributional impacts of child allowance changes, market and non-market activities, shadow economy, effects of tax regulations on industrial firms, and more. Leaving the static models aside, a few examples of dynamic microsimulation models will be presented below.

Orcutt's pioneering work from the beginning of the 1960s is the root of one of the most significant contributions within the field – DYNASIM, Dynamic Simulation of Income Model (Orcutt *et al.*, 1976). DYNASIM is a genuinely dynamic model that simulates the economic and social behavior of American households over time. Fifteen events or characteristics are simulated (e.g., birth, death, marriage, education, labor force participation, wage rate, job change). For each of the fifteen events a large number of determinants are included in the transition probability computation. For example, the probability of job change is taken as a function of age, race, sex, education, tenure, and sector of employment. Additionally DYNASIM includes a relatively simple macro-economic model of the U.S. economy to determine factors such as the overall unemployment and wage rates which can be fed into the micro-level operating rules. The need for system closure in this fashion is a common feature in microsimulation models (Clarke & Wilson, 1986).

Some of the main ideas and experiences of the DYNASIM project have been furthered by a research team at Cornell University led by Steven Caldwell. The CORSIM-model has been developed in a number of steps and version 3.0 completed in August 1995 consists of 700 distinct equations representing 25 equation-based processes (Caldwell & Keister, 1996). The latest, recently released version (4) is even more comprehensive (Shaw, 2000). Besides demography, CORSIM is designed to analyze welfare reform scenarios, dental conditions, future census counts, assets and social security, pension policies, state of residence, state-to-state migration processes, and family wealth.

At the Spatial Modeling Center (SMC) located in Kiruna, Sweden, the spatial micro-simulation model SVERIGE has been constructed, partly inspired by CORSIM but adding geography and the use of large longitudinal data sets. Agents, assumed to represent individual human beings, live their lives, perform basic actions, creating and disconnecting relations in cooperation and competition like their observed counterparts. In SVERIGE, individuals are born, enter and leave primary school, secondary school and university, move away from home, get a professional education, get work and income, change income, leave work, mate on a local "partner market," marry, divorce, immigrate and emigrate, migrate domestically and locally to specific 100 meter squares, give birth, and die. Each of the nine million individuals in the full model faces those choices and events at least annually.[5] In models to come, individuals also compete for a specific localized education, job and dwelling, get sick, get social benefits including unemployment support, old-age, and early retirement pension. They also pay taxes, travel and select mode of transport, produce carbon dioxide, etc. Other agents are also active, such as firms, schools, housing agencies, and local municipalities.

One idea behind building a spatial microsimulation model like SVERIGE is to create an artificial laboratory enabling systematic experiments with conditions and policy options that otherwise are hard to perform in the real population. From this point of view any implemented governmental or municipal policy can be regarded as an "experiment" in real time, space, resources and people involved. Such full-scale trials often fail, but since only one out of all possible histories happens and becomes observable we seldom have any knowledge about the

[5] The present model version (Turbo) runs at a minute and a half per year, on a one GHz machine with one GB of primary memory.

unobservable contra-factual development. We rarely get to know what would have happened with another policy, but under otherwise the same initial conditions. Hence, politicians in charge can claim anything they want, e.g., that the alternative would have been even worse, or that no policy change or a different policy would have been better for achieving the same goals. If just a tiny fraction of those "real experiments" could first have been performed and evaluated in a model maybe some expensive mistakes could have been avoided. Some example applications of the SVERIGE model are presented in Holm and Sander (2001).

Another contribution to the flora of microsimulation models is the Dynamic Population Microsimulation Model (DYNAMOD), developed by the Australian National Centre for Social and Economic Modelling (Antcliff, 1993). The ageing process of DYNAMOD is not the commonly used annual transition probabilities method, but survival functions. Individuals are assumed to have various possible futures with predicted times until relevant events occur. In this way annual transitional probabilities are replaced by an estimation of the probability of "surviving" in the current state in the future. The survival function is estimated through the use of a piecewise exponential hazard regression. When an event occurs a new set of predicted durations are calculated. All events that come about are stored in memory and will censor all other events which vary with that change of status.

Most applied microsimulation models, like DYNASIM and CORSIM, have basically been time driven, i.e., all attributes are updated synchronously. An alternative method is to use survival functions, as presented above. The realization time for different events (such as leaving home, marriage, entry into labor force, cohabitation, premarital pregnancy) depends on the individual's age, sex, and other circumstances. New events, however, will change the realization time for future events. The ideas behind event driven simulation are related to survival functions. When adopting event driven simulation, discrete points in time, in which something important occurs, are identified. By means of previous events new points in time can gradually be scheduled. For example, a couple who are living together may get a child after nine months – a child who might be a girl; thirteen years after the delivery the girl reaches fertile age and after another thirty-two years the menstrual cycle stops (Holm *et al.*, 1989).

2.5.5 Time Geographic Simulation

Microsimulation models have less often been used in spatial modeling (Clarke, 1996). However, an early dynamic, spatial simulation model at the micro level was made by Hägerstrand in 1953 in his innovation diffusion model. This model included several of the basic features characterizing contemporary spatial microsimulation models and also many multi-agent systems, although at that time it had to be executed by hand calculations. Some of the features included were:

- actions are induced by the behavior of individual actors (persons, households, firms) with a diversified or homogeneous behavior;
- actors, resources, constraints, and events are located in space, influencing the subsequent course of events;
- actions and events are influenced by the individual properties of actors, by conditions in the time-space environments and by the actions of other actors;
- the course of events is influenced by a random component.

With time geography, the influence of micro-level interaction in time-space between individual actors, resources and constraints is also introduced in the simulation. However, the development of spatial micro theories still is a major challenge to geographers and regional scientists.

Hägerstrand's time geography (1975a; 1975b; 1995) gives an important and still only partly explored theoretical basis for developments in spatial microsimulation. Time geography provides a conceptual framework for the micro-level analysis of spatial dynamics, based on a representation of actors, resources and other objects located in a micro-level time-space. This perspective emphasizes the importance of the location *and* duration of single events, intended actions, activities, projects, and constraints. It focuses on the actions of the individual, and how they are determined in specific micro-situations and time-space contexts.

The traditional time-geographical model includes a conceptual and graphical representation of physical conditions for human activities and has mainly functioned as a tool for description. Hägerstrand also formulated a theoretical base, in the form of basic rules, representing the fundamental limits to interaction in time and space between individuals and between individuals and their environment: people can only be at one place at a time, activities take time to perform and they need space, space is limited, mobility in space takes time, etc. These obvious and self-evident determinants of human actions are usually neglected in social and economic theories.

Hägerstrand draws attention to time-geographical constraints that affect people's opportunities to carry out acts and planned projects. He distinguishes between three types of constraints: (a) capacity constraints (when the individual does not have the physical, economic or social means to realize certain acts), (b) coupling constraints (the potential activities are constrained since individuals cannot be engaged in various activities or projects or be at different locations simultaneously) and (c) steering constraints (rules, laws, etc., created with the intention of limiting or giving increased access to time-space). These constraints are points of departure for a further potential development of a time-space micro theory including the influence of power (steering constraints), social relations (coupling constraints) and resource distribution (capacity constraints) on everyday lives and on individuals' life courses.

One of Hägerstrand's ideas is that activities are not only conditioned by physical but also by social constraints preventing agents from performing certain activities and enabling others. Time geography provides an alternative perspective on agents and collectives since it emphasizes the importance of concurrent micro-level representation of agents and their relations to other agents. Time geography has introduced a conceptual framework for analyzing social micro-level interaction in time-space. The major task, however, of formulating a comprehensive time-geographical theory of human agency, is still to be achieved.

A major shortcoming of time geography has been the difficulty of modeling and developing a theory of human action which goes beyond the effects of delimiting constraints. It is easier to explain why "impossible" alternatives are rejected, more difficult to specify a theoretical explanation of human decisions, choices and performed actions, to anticipate which of several possible alternatives will be chosen in given situations and thus to model individuals' actions in time and space.

An interactive and dynamic time-geographical population model (HÖMSKE) was made by Holm *et al.* (1989). Within that model individuals have relations to other individuals and to "stations," such as residence and work place, in their environment. Agent actions are preceded by information, search, and decision process, e.g., regarding how work, school, and partner are chosen. Individuals are interactive and if one agent is affected by another agent's intention the decision process is extended to a joint decision in which, e.g., the acceptance of a new job in another region is affected by the conditions and preferences of all family members.

When agents interact in time-space, a web of trajectories arises. The freedom of action for a specific agent is constrained by the actions of others and by the time-space. The prescribed causal structure behind the decision process within the HÖMSKE model is channeled through three “modal domains,” including what people *can* do, what they *want* to do, and what they *ought* to do. The IRPUD model of urban transportation and land-use presented by Wegener and Spiekermann (1996) has been complemented with developed a related theoretical framework, including the concepts of choice, transitions, actors, preferences, and constraints. An ambitious recent paper by O’Donoghue (2001) surveys 29 dynamic microsimulation models, four of which are Swedish (MICROHUS, SESIM, SVERIGE, and Swedish Cohort Model).

3. Critique of Agent-Based Models

3.1 The Structuralist Stance

A more fundamental criticism of agent-based modeling and some other forms of microsimulation is often based on structuralist views in social science. In this case, MAS is just a new example, the criticism challenges a wider sphere of empirical, quantitative research focusing on individual behavior. The two classical sociologists Weber and Durkheim have come to personalize opposite views in this debate. Durkheim argues that society is something entirely different from its individuals and that its properties cannot be explained by reference to the properties of the individuals, while Weber is often cited as saying there is no society beyond the aggregate of its individuals.

In social science there is sometimes a confusion between aggregate and structure. Many scholars reject a pure individualistic approach on the grounds that it tends to methodological individualism, tends to hide external, obvious or hidden “structures” (like prevailing power relations between classes, sexes and regions, the heavy inertia of the former behavior of all other members of society) that condition the actions of the agent to a larger extent than its individual attributes and will power. The confusion lies in the fact that some influential structuralists seem to believe that aggregate indicators largely reveal the structure. The income distribution between individuals certainly reflects the impact of power relations and conditions beyond individual control, but that is not the full story. The individual economic result of the dynamics of interaction between agent and society is probably as much influenced by individual ability, achieved and inherited. And generally it is just a coincidence if the measured aggregate of some dimensions happens to reflect driving structures. One might as well claim that it is manifest only in the individual deviations from the aggregate average, and then again the individual representation is necessary in order to discover its empirical traces.

3.2 The Individualist Stance

In a recent review article, O’Sullivan and Hakley (2000) examine a large set of agent-based models (ABMs) applied in the life sciences, economics, planning, sociology, and archeology and conclude that this modeling approach “strongly tends towards an individualist view of the social world,” i.e., towards methodological individualism. They direct attention towards

> the inadequacy of an individualist model of society with reference to debates in social theory … [I]t is important that institutions and other social structures be explicitly included, or their omission be explained. … We conclude that if ABMs are to have greater value as tools of social science enquiry, then they must be informed by contemporary social theory (whether structurationalist, realist, or morphogenetic) which recognizes the dual nature of individuals and societies and their mutually constitutive roles. … The definite example of agent-based modeling technology is provided by the Santa Fe Institute's 'Swarm' simulation toolkit.

O'Sullivan's and Hakley's basic claim is that the bias towards individualist perspectives is associated "with a focus on one-way emergence of social phenomena from the aggregate activity of individuals." It is important to come to grips with this argument. It can be maintained that this is a problem only if the modeler in so doing omits the impact from *other* social structures which instead, or in conjunction with the modeled ones, condition the modeled behavior. Otherwise this is precisely what one seeks to achieve with the model, viz. to make social structures (including things like inequity, imperialism, and socialism) endogenously emerge from postulated assumptions about the functioning of individuals, about other already emerged institutions, and their environment. It is hard to see any harm in that ambition, rather the opposite, as long as no cheating is involved. The criticism seems therefore a little overstated.

4. Convergence

The basic argument for a micro/time geographic approach to social phenomena goes something like this: Aggregation prior to analysis and modeling of trajectories over the state space of individuals *with* several attributes distorts not only individual but also aggregate results. Largely, this argument also holds as one of the reasons for developing entirely artificial MAS. The way in which individual trajectories interact with and constrain each other is often completely blurred if they are not described, analyzed, and modeled individually.

The connection between MAS and time geography (TG) seems to be somewhat closer than between traditional microsimulation (MS) and the other two paradigms that we consider. All three methodologies emphasize individual representation and computational solution. Many microsimulation models, however, apply a fairly "aggregated" and disconnected (from environment and other agencies) representation of individual behavior, in that certain individual characteristics largely determine individual action. In TG also the interaction with other agents and the environment is fundamental. ABM adds the ambition to include adaptive behavior, self-organization, and emergence. One the other hand, MS are developed with high estimation and validation ambitions, close to observables that facilitate empirical tests; TG, much less so, and MAS/ABM (deliberately) not at all.

If it is the case that higher resolution in physical space, in attribute space, in interaction, environmental conditions and constraints, memory representation, cognition depth, and self organization is so much better, judged by its potential to achieve new general knowledge, that it more than counterbalances the lack of operational test, then why stop with a highly developed TG/MAS? There is at least one artificial phenomenon in society that exploits much greater depths in most of these dimensions and that is pure or biographical fiction. It is not unlikely that the total body of novels, biographies, etc. ever produced in text and in movies has had a much greater impact as decision support than the total body of social science reports. So why attempt science and models? First, there is more systematic knowledge available about social behavior than is contained in the personal prejudices of any writer or other person, sometimes containing rather counterintuitive statements. Second, although the local consistency and depth in explanation found in novels may not be possible to match, the same does not hold for the secondary characters and all other characters in the novel. They pop up and go as required by the storyline of the main character. That is their only purpose. Nothing says that they, in turn, are locally consistent or even possible in the same way as the main character, since they are invented only to support his/her story. Therefore, the degrees of freedom to act for the fictitious main character are much greater than is the case for any real person he/she so faithfully seems to mimic, i.e., the behavior is not (necessarily) consistent with the social environment and therefore not possible to generalize to society. In the same way, it is impossible to scale up in-depth TG/MAS to a level where consistency within a large system is maintained. They seem to be bound to give small-scale examples imprisoned within arbitrary borders to a completely over-simplified surrounding system constructed by simple assumptions. Analogously, political action is often justified *post facto* by referring to *policy stories* that border between fact and fiction and attempt to create rational arguments out of unorganized affairs, by putting actions in context (i.e., by pulling them inside the frame of the story).

One of the virtues of the SVERIGE model is that it reaches beyond the limitation of a sample by applying a one-to-one mapping of the inhabitants in all of Sweden. This is important since, even with the crude representation in that model, agents still are different and completely individual. Such a representation facilitates a more accurate modeling of competition and cooperation than is otherwise possible. The partner market, labor market, housing market, and education market are so inherently scale-dependent that almost anything less than full-scale representation considerably truncates the choice set and forces the model to produce biased and inconsistent results due to the combinatorics of “normal” behavior. One of the most essential structural changes in Sweden (and probably elsewhere) is that the number of people that an average person can reach within daily commuting range has increased from less than 5,000 in 1800 to around half a million today. This development has facilitated a division of labor, education, housing, service provision, etc., which is actually utilized by real people and which constitutes a basic property of the contemporary society about which we claim to have things to say with the help of our models.

One possible use of the SVERIGE model is to have it provide a consistent, dynamic system environment for new, in-depth TG/MAS models of particular ideas, places, functionalities, etc. Such models could explore the potential of basic constructs for creating complex behavior and institutions in tractable small niches, while maintaining accurate impact on, and responses from, the environment. That would considerably extend the theoretical and practical potential of TG/MAS modeling. A practical resource for that kind of constructs developed by the Spatial Modeling Center (SMC) in parallel with its SVERIGE model is an event-driven simulator, EVSIM, essentially containing the functionality of the Simulation Package in Simula, but now implemented in C++.

5. Conclusion

We have argued that time geography provides a perspective that helps unify the two paradigms of (a) multi-agent systems, as developed within computer science, and (b) microsimulations, as developed within the social sciences. By identifying and defining these two paradigms, and by reasoning about the central concepts of each of them, we have taken a first step in amalgamating them. We have attempted to take a general systems approach in order to avoid myopia and jargon limitations, and hopefully avoid being too narrow in scope (an approach different from, e.g., Gimblett, 2002).

Our claim is that developments based on a synthesis of the three paradigms offer a rich potential for substantial advance of systems analysis methodology. It gives a new angle to classical problems like how to achieve consistency with the world outside a defined core system boundary, how to simultaneously represent processes on very different spatial and temporal scales, how to enable agents to concurrently obey internal and external rules, and how to integrate observable and postulated behavior while preserving achievability of endogenous emergence.

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