Perspectives and Challenges of Agent-Based Simulation as a Tool for Economics and Other Social Sciences

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ABSTRACT

This paper argues that the agent-based simulation approach is just the one appropriate to the social sciences (including economics). Although there were many predecessor approaches, which tried to build formal models of social systems, all of them fell short of the peculiar features of the objects of all social sciences: complex systems consisting of numerous autonomous actors who interact with each other, who take on different roles at the same time, who are conscious of their interactions and roles and who can communicate with the help of symbolic languages even about the counterfactual.

These human actors are unlike physical particles although their behaviour might sometimes be quite similar to the behaviour of physical particles when humans occur in very large numbers (but they are most interesting when they form only small networks). Real human actors would not concede that their behaviour is stochastic, they will always assert that their actions are deliberate (but at the same time these actions are not entirely predictable). Human actors are not entirely rational although their behaviour might sometimes seem as if they were (but they are most interesting when their rationality is only bounded and when their payoff is multidimensional).

Social systems seem to be the most adaptive systems that we know about, and this is why we could perhaps use them as patterns for artificial adaptive systems — and if we knew enough about the modes of operations of human social systems, social sciences could even contribute to agent-based modelling in other fields.

General Terms

Social systems simulation

Keywords

Agents, simulation, complex system, social system, level hierarchy, role

1. INTRODUCTION

As social and economic systems are among the most complex systems in our world, this paper will mainly deal with

applications of simulation in general and agent-based simulation in particular in economics and the social sciences. Thus it might be in order to cast a brief look back on the predecessors and origins of agent-based simulation in these sciences from the time when some first interdisciplinary researchers used, or rather should have used, multi-agent systems. Multi-agent systems proper could only be implemented after the early 1980s, but much earlier, namely in the 1960s some political scientists built models that can be described as forerunners of multi-agent systems.

They developed ingredients that nowadays are a defining part of agents in multi-agent systems, such as fact and rule bases [2] in which early "agents" stored information that they communicated among each other, although they lacked the defining feature of autonomy. But afterwards for a long time social and economic simulations did not often address the fact that in social and economic systems there are actors who are endowed with a very high degree of autonomy and with the capability to deliberate. Although not for all purposes of the sciences dealing with these systems, autonomy and deliberation are necessary ingredients of theory and models, one would not content oneself with humans being modeled as deterministic or stochastic automata but prefer models that reflect some typically human capability. And one would not content oneself with models that deal only with the macro level of a society. As early as in the nineteenth century, Emile Durckheim [16] proposed "sociological phenomena [that] penetrate into us by force or at the very least by bearing down more or less heavily upon us", thus anticipating what Coleman [10, p. 10] introduced as the well-known "Coleman boat" (see Figure 1), a representation describing the process of human actions (co-) determined by their social environment and at the same time changing this environment, such that social change is not just a change of the macro state of a society (or organisation, or group) but at the same time always a change in the micro state of most or all of the individual beings.

Figure 1: Downward and upward causation and the link between the micro and the macro level as described by Coleman
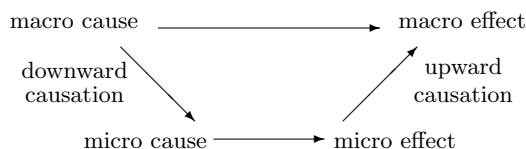
Coleman's diagram of upward and downward causation coincides with a concept of exactly two societal levels (micro and macro) — which for many socio-economic models might seem too simple (cf. [55]), which makes it necessary to elaborate on the concept of levels and to discuss alternatives.

Peter Hedström's similar diagram [29] is about the idea of supervenience which in a way replaces the idea of upward and downward causation and also the idea of emergence, but the question may be left open whether there is a difference between emergence and supervenience (the semantic difference between the two latin verbs "supervenire" and "emergere" is not very great as both mean something like "come forth").

Thus a concept of levels will always be a part of any modeling of complex systems (but see [45]). With "level" a set of things of the same "natural kind" is understood, and two subsequent levels $L_i < L_j$ are sets of things for which the following holds[8]:

$$L_i < L_j =_{df} (\forall x)[x \in L_j \Rightarrow (\exists y)(y \in L_i \land y \in \mathcal{C}_{L_j}(x))] \quad (1)$$

which means that the things called x on the macro level L_j are composed of entities on the micro level which we call y. In both Coleman's and Hedström's diagrams the micro level is the level of individual human beings while the macro level is the level of society, but both diagrams are of course simplifications, as any upward and downward causation does not necessarily occur between the individual and the society as a whole but can and will be intermediated by entities of one or more meso levels.

In a recent discussion about levels of complex systems Ryan [45] debunks the idea of levels. His alternative is to replace them with what he calls scopes and resolutions. Unlike levels, resolutions are not defined as sets of entities of the same natural kind, but as spatial or temporal distinctions, such that they can encompass entities belonging to different natural kinds. On the other hand, Ryan's concept of scope and resolution is perhaps less appropriate for socio-economic systems, as will be seen later in this paper. Here it might be sufficient to mention that Ryan restricts himself to interesting, but not very complex models of socio-economic phenomena such as the tragedy of the commons and the prisoners' dilemma [45, p. 17], where he distinguishes between "local and global structure", but with only two levels, resolutions, scopes or scales (to add still another related concept also mention by Ryan) it does not really seem necessary to make a difference between these four concepts. Only when we have to deal with a deeper nesting this difference seems to make a difference. The game-theoretic examples mentioned by Ryan, as many other game-theoretic underpinnings of agent-based models, still seem too simple as to truly reflect what keeps societies going — given for instance the trivial observations that humans can usually change the rules of a game and its pay-off matrix.

The role simulation plays in the context of complex systems (as these are viewed from the perspective of the multi-agent systems community) can be described as the role of a method that helps to construct "would-be worlds" [9] and artificial systems with the help of which the behaviour of real systems can be understood better. When Casti states that and "how simulation is changing the frontiers of science" he obviously has in mind that simulation is a tool to develop "a proper theory of complex systems that will be the capstone to this transition from the material to the informational." [9, p. 215] His idea that "the components of almost all complex systems" are "a medium-sized number of intelligent, adaptive agents interacting on the basis of local information" necessitates a new formalism that currently cannot be provided by mathematical calculus. The mathematics of stochastic nonlinear partial differential equations is capable of dealing with a large number of not very intelligent agents interacting on the basis of global information — as the synergetics approach [26, 58] and sociophysics [32, 31] have impressively shown. But in the case of medium-sized numbers of agents, the approximations and simplifications used to find closed solutions (for instance, of the master equation) will not always be appropriate.

Although Casti's "intelligent, adaptive agents" might also move in a "social field" [39] and be driven by "social forces" [33], both concepts cannot capture the cognitive abilities of human beings, as these, unlike particles in physics, move autonomously in a social field and can evade a social force. Thus, for instance in a situation of pedestrians in a shopping center (as it is modeled in [33, p. 631]) humans decide autonomously whether they obey the "social force" exerted on them by the crowd, or the "social force" exerted by their children or by the shop windows — these two latter forces are by no means physical forces and cannot be modeled as such, as they are usually exerted by speech acts or other symbols that have to be consciously processed before they can take an effect on the recipient of the symbolic message. Admittedly, often "people are confronted with standard situations and react 'automatically' rather than taking complicated decisions, e.g. if they have to evade others" [33, p 625], but more often than not they do make complicated decisions — of which the former are only "shortcuts" [3]. Another assumption that will not always hold is "the vectorial additivity of the separate force terms reflecting different environmental influences" — again, this assumption is doubtful and must perhaps be replaced with the assumption that only the strongest "force" is selectively perceived (perhaps only with a particularly high probability) and obeyed by a pedestrian (to keep to the example). Thus the selectivity of Casti's "intelligent, adaptive agents" (the term does not only refer to human beings, but to other living things as well) has the consequence that emergence in complex physical systems (such as lasers) is quite different from emergence in living and, particularly, cognitive systems. This describes the role of simulation in the context of the complex systems in Casti's sense as quite different from the role it plays in general complex systems.

Definitions of "complexity" and "complex system" are manifold and they refer to different aspects of what these terms might mean. For the purpose given here, the following characteristics may suffice: Complexity deals with a dynamic network of many agents acting and reacting to what other agents are doing. The number of different kinds of interactions may be arbitrarily high (not restricted to the forces of physics), and the state space of agents may have a large number of dimensions.

2. PREDECESSORS AND ALTERNATIVES

This section will only give some hints at the similarities and differences between agent-based simulation in multi-agent systems and some of the earlier approaches to simu-

lation: continuous and discrete, event-oriented and oriented at equidistant time steps, microsimulation and system dynamics, cellular automata, genetic algorithms and learning algorithms. Many of these earlier approaches were developed for applications in biology, ecology, production planning and other management issues as well as in economics and the social sciences, and at the same time physicists exported some of their mathematical and computer based methods to disciplines such as economics and sociology, forming interdisciplinary approaches nowadays known as econophysics and sociophysics. Socionics, on the other hand, is a field where multi-agent systems, simulation and classical theory building methodologies of empirical social science come together in order to inspire computing.

Among the early forerunners of multi-agent systems in the social sciences perhaps two can be named where processes of voter attitude changes are modeled and simulated in an agent-based manner as both of them represented voters, candidates, media channels with structured variables in programming languages, as in [1] or in the Simulmatics project supporting John F. Kennedy's election campaign [52]. And these models dealt with communication acts among citizens, between citizens and candidates as well as between citizens and media channels, and they modelled their behaviour and actions in a rule-based manner.

Epstein's and Axtell's Sugarscape [18] and Schelling's segregation model [46, 47] are more recent examples of models of populations of agents interacting with each other and with their environment. In discussing these bottom-up approaches — and most simulation approaches to complex systems are of the bottom-up type — one has to take into account that the bottom-up approach is not always useful, see the discussion in [50, 49], where the argumentation is that a bottom-up approach that meticulously mimics the movement of each single molecule would have been misleading to explain the flow of heat in a gas. But this argumentation neglects that the averaging of the impulses of molecules could only be successful as all these molecules obeyed the same laws and were by no means selective with respect to several different forces by which they were driven — as there was only one force. Biological and social systems underlie the effects of several forces and are often not only reactive but proactive, have goals, sometimes conflicting, such that the mathematical reduction often proposed by physicists and game theorists would not lead to success in cases where the interactions between the micro level entities are manifold.

If one compares the capabilities of these agents to one of the standard agent definitions [60] one finds that Schelling's agents are autonomous, reactive, perhaps even proactive, but their social ability is rather restricted: although they interact in a way with their neighbours, this interaction is not mediated by any kind of language or message passing. These agents have only very simple beliefs (their perception of the neighbouring eight cells) and only one intention, namely to stay in a cell where the number of neighbours of the same colour exceeds an exogenously given threshold. In spite of the extreme simplicity (which Schelling's model shares with the game of life as well as with many game-theoretical models), the model displays some emergent behaviour. But these emergent phenomena are of a relatively simple kind — if one accepts that "temperature is an emergent property of the motion of atoms" [25, p. 11], then, of course, the game-of-life patterns and the ghettos in Schelling's model are emergent

phenomena as well. Without formalising the notion of an emergent phenomenon in this chapter, it can be described as a phenomenon that "requires new categories to describe it which are not required to describe the the behaviour of the underlying components." [25, p. 11] In this sense, the property of gliders and oscillators to be able to glide or to oscillate obviously is an emergent property, as the ability to move is not a property of the game-of-life cells at all.

Their artificial world called sugarscape is populated with agents who make their living on two complementary types of products (sugar and spice), both of which they need for surviving, but at individually different proportions. Both products grow on the surface of a cellular automaton and can be harvested, stored, traded and consumed. In the different versions of the model reported in [18] and several extensions published by other authors (see for example [37, 17, 19, 20]), agents are not only autonomous and reactive, but also proactive as they have goals they try to achieve, and they have some social abilities as they exchange goods and information. In [37] they explore their environment actively (moving around satisfies their curiosity) and store information about the cells they saw within their range of vision, about the resources and other agents in all these cells; part of this information is forgotten or invalid after some time. The agents even form primitively structured groups whose chieftains collect information from their tribe members and redistribute it to them, and in [19, 20] agents can mark a cell that they currently occupy and sanction agents trespassing a marked cell — from which a possession norm emerges. Agent societies in [20] without the possession meme were less sustainable than those with the possession meme, and, similarly, in [37] agent societies where chieftains redistribute information among their tribes are more sustainable than agent societies without the exchange of information.

Cultural transmission, absent in Schelling's and Hegselmann's [30] segregation and migration models, seems only to be possible if agents have at least some memory (as in the tags in [18], the memes in [19, 20] and the memory in [37]). Thus cultural transmission necessitates the storage of information about the environment, i.e. agents must be able to develop models of their environment in their memories, and they must be able to pass part of these models to other agents. "No social mind can become appropriately organized except via interaction with the products of the organization of other minds, and the shared physical environment" [35, p. 160]

3. UNFOLDING, NESTING, COUPLING: RECONSTRUCTING COMPLEXITY

Multi-agent systems also lend themselves to coupling models of different types and to unfold models in a top-down way, starting with a macro model of the top level (see eq. 1) of the system and then breaking it off, replacing part of the rules of the macro system with autonomous software entities representing real-world elements of the modelled overall system, as for instance exemplified in [6]. With this technique we can start with a macro view on a complex real-world system. Whereas the "complexity" of many models derived from some of the existing system theories is restricted to complexity of the interactions between state variables of the system as such [22], we usually observe that systems are decomposable into interacting system elements

which in turn might be systems of another "natural kind" [8]. On all the levels of such a nested system, agents can be used for representation, although not on all levels the respective agents would need to have all the features that are commonly attributed to them [60] — autonomy, reactivity, proactivity, social ability. Moreover, in such a view, not only the complexity of the domain can be mapped into a simulation model, but also the complexity of time — different time scales for the different levels of a nested system — as for every kind of agents different mechanisms of representing time can be used.

In a way, "agents cover all the world" [7] in that multiagent systems can be used for all simulation purposes, as agents can always be programmed in a way that they behave as continuous or discrete models, can be activated according to event scheduling or synchronously or in a round-robin manner, can use rule bases as well as stochastic state transitions, and all these kinds of agents can even be nested into each other, thus supporting a wider range of applications than any of the classical simulation approaches. This leads to a third aspect of complexity (after the complexity of domains and the complexity of time): agent-based models can encompass several different approaches, from a technical and implementation point of view, but also from the disciplines making use of simulation (for instance, disciplines such as ecology, economics, sociology and political science can combine their contributions into a deeply structured simulation model [42], and the same holds for neurophysiology, cognitive psychology, social psychology and sociology in other conceivable examples).

3.1 Different roles in different environments

First of all, one has to observe that real world entities can be components of several different systems at the same time — perhaps a fourth type of complexity. This is most obvious for humans who typically belong to a family, to a peer group, school form, enterprise department, military unit at the same time. All these systems are of different "natural kinds", to keep to Bunge's system theory [8]. Although the micro level is the same for all these kinds of systems (and consists of human individuals) the set of (bonding) relations or interactions between these men and women is different between a family and a military unit: not all relations that hold in a family would also hold in a military unit, for instance, be the (bonding) relation of nursing ($\langle a, b \rangle \in R_i \Rightarrow a \triangleright b$, meaning a nurses b) such that it is not very reasonable to think of the different kinds of social systems mentioned above (as forming a unified (meso) level of social subsystems between the individual (micro) level and the macro level of society).

In the end this means that the concept of level defined in 1 is not very helpful, but for other reasons then those mentioned in [45], and Ryan's scope and resolution would not help either to cope with the problem of individuals belonging to different kinds of systems at the same time. Agent-based simulations, however, can easily model all these relations.

Only very few papers on simulation models have ever made use of the versatility of the agent-based approach in a way that took into account that real-world humans can belong to several systems at the same time. In systems of different kinds, agents perform different roles, and even in the same system (e.g. a team [48]), a member can perform different roles at different times. In [14], agents can perform the role of a leader or a follower, in [37] they can additionally perform the role of a single.

[48, p. 313] discusses the "assignment of roles to team members" as "of critical importance to team success". Teams are here defined as in [36] as a special kind of "group whose members share a common goal and a common task ... The most critical distinction between teams and groups [sc. at large] is the degree of differentiation of roles relevant to the task and the degree of member interdependence." Thus for modeling and simulating teams, it is necessary to endow team members with a problem solving capacity, a symbol system and a knowledge base. [48], extending Soar [38] to Team Soar, emphasise that "each member in Team-Soar develops two problem spaces: a *team problem space* and a *member problem space*", as each members tries to achieve both the common goals and the member goal (which they just describe as "make a good recommendation to the leader", but the individual goals could, of course, be manifold, and in modeling and simulating project teams, members could even work for different projects at the same time). For the evolution of such teams, see [12].

Geller and Moss, too, make use of the concept of roles when they [23, p. 115–116] describe the "complex interpersonal network of political, social, economic, military and cultural relations" in Afghan society. This network, called a *qawm*, consists of a number of different actor types. In reality (though not in their model), individual actors may "incorporate a variety of roles", and, moreover, members of different *qawms* compete among each others (and perhaps there might be even individuals who belong to more than one *qawm* at a time. The knowledge that agents (as representatives of real-world individuals) have in [23] is packed in so-called endorsements. "Endorsements are symbolic representations of different items of evidence, the questions on which they bear, and the relations between them. Endorsements can operate on each other and hence lead to the retraction of conclusions previously reached, but since there is no formal accounting of final conclusions, the process is seen as a procedural implementation of non-monotonic patterns of reasoning rather than as a logic." [51, p. 626], referring to [54].

Another approach to modelling agents that "engage in several relations simultaneously" was recently published in [4]. The authors here represent agents on different planes in a cube, where on each plane the inter-agent network is displayed. Technically speaking, the agents move between planes, and this movement between planes represents the change in focus an agent has on its respective relations. The idea behind is that "an agent can belong to social relations, but possibly not simultaneously" [4, p. 492]. Although this idea can be criticised from a real-world perspective (where, e.g. husband H's relation with his wife W is simultaneous with his relation to his boss B, and both B and W influence H at the same time when they ask him a favour each, and these two favours are conflicting), the authors' approach is a step forward, and they extend the original approach a few pages later where "agents will have to face several contexts constantly, either simultaneously, or at rhythms imposed by the different settings." [4, p. 494]. This concept might be combined with the endorsement concept used by [23], as — at least in the case of "rhythms" — the agents would not deliberate with respect to the current state of their environment, but on what they remember about the different settings.

3.2 Interactions

Interaction between agents is usually modeled in different modes. On the one hand, and this the simpler case, agents just read from other agents' memories. This is easily programmed, but not very naturalistic when agents represent human beings, as these communicate via messages, most of them verbal, but also using facial expression or gesticulation, but these messages need not necessarily express the real opinions or attitudes that these humans have in their minds. Thus software agents in simulation of socio-economic processes should also be able to exchange messages that hide or counterfeit their internal state. For the exchange of messages, an environment (see below) is most often necessary (at least in the real world, but for message passing in the simulated world one would have blackboards for one-to-all messages or mail systems for one-to-one or one-to-few messages), but what is even more necessary is that agents have something like a language or some other symbol system for communicating. This can be done with the help of the pheromone metaphor [15], but only for relatively simple types of messages, but rather with agent languages. These symbol systems have to refer to the components of the agents' environments and to the actions agents can perform.

3.3 Environment

Environment in multi-agent simulation plays a special role. As discussed in [7, 6, 42] it is possible to represent the environment or several distinguishable parts of the environment with an agent or several different kinds of agents, respectively. Representatives of the non-human environment in social simulations would be relatively simple agents without social and proactive capabilities. The representation of elements of the agents' environments by additional agents is partly justified by the fact that from the perspective of an individual agent, all other agents belong to its environment [59, p. 8]. On the other hand, as e.g. discussed in [44, p. 2] as "it provides the conditions for agents to exist" and, as one could add, to communicate (as for the communication, see section 4). But unlike real world agents, software agents can exist without an explicit representation of a real-world environment (they need, however, the environment of a computer, its operating system and its runtime environment, but these are not the correlate of any real-world environment). But only with a simulated environment they are able to interact in a realistic manner (reading other agents' memories directly does not seem very realistic, the *no telepathy)* assumption [35, p. 160]. This environment allows them to communicate, by digital pheromones [15] or by abstract force fields (see the discussion above), but also — and this should be the typical case in social simulations — symbolically, as it may contain blackboards and other means for sending messages. But at the same time it is also necessary to allow agents to take actions other than those that directly affect other agents of the same kind (e.g. harvesting, as in [18]) and thus to affect other agents indirectly. And perhaps agents need an environment as an object to communicate about and as an object for representation. In an early description of the NEW TIES project [24], there is a generic description of what a minimal environment for multi-agent social simulation should consist of. Beside a topography, an interesting requirement is that the environment should provide agents with "tokens", "distinguishable, moveable objects, some of which can be used as tools to speed up the production of food, but most of which have no intrinsic function, and can be employed by agents as location markers, symbols of value (e.g. 'money'), or for ritual purposes".

In many special applications, for instance in traffic simulation, the representation of the physical environment is inevitable, as it "embeds resources and services" and defines rules for the multi-agent system [59, p. 16–17] in so far as it allows and forbids the usage of particular routes at particular times. Thus traffic simulation systems typically consist of a topography and agents (including both stationary agents such as traffic lights and signs and dynamic agents such as cars, bikes and pedestrians) [40]. In some interesting cases, the topography might not be static at all: evacuation scenarios need an environment that can rapidly change (outburst of fire, spreading of smoke, all of which have to be modeled in terms of their physical dynamics).

4. ISSUES FOR FUTURE RESEARCH: THE EMERGENCE OF COMMUNICATION

4.1 Agent communication

Although agent communication languages have been developed for a long time (back to 1993), it is still an open question how agents in a simulation model could develop a communication means on their own and/or extend their communication tool to be able to refer to a changing environment (see the special issue of Autonomous Agents and Multi-Agent Systems, vol. 14 no. 1). In their introduction [13, p. 119] to the latter special issue, Dignum and van Eijk even state "a wide gap between being able to parse and generate messages that conform to the FIPA ACL standard and being able to perform meaningful conversations." Malsch and his colleagues also complain that "communication plays only a minor role in most work on social simulation and artificial social systems" [41].

The problem of inter-agent communication has at least two very different aspects — one is about agents that use a pre-defined language for their communication, while the other is about the evolution of language among agents that are not originally programmed to use some specific language.

As far as simulation is concerned, the first aspect deals with languages that are appropriate for the particular scenarios simulated. [21] center this aspect around the concept of commitment, as agent communication in general (but also in the special case of simulating social systems) is most often used for commitments (and humans chatting just to kill time are seldom simulated). The same objective is aimed at in the current EMIL project (Emergence in the Loop [3, 11]) which attempts at creating an agent society in which norms emerge as agents observe each other and draw conclusions about which behavioral feature is desirable and which is misdemeanour in the eyes of other agents — which, as in the case of language emergence, makes it necessary that agents can make abstractions and generalizations from what they observe in order that ambiguities are resolved.

The second aspect, evolution of language, starts from agents having no predefined language at all, but have goals that they cannot achieve by themselves, which makes it necessary for them to ask others for help. It is not entirely clear whether a grammar is actually necessary as a starting point

of the evolution of language. What seems to be necessary is the capability of agents to draw conclusions from regularities in other agents' behaviors. One behavior b_1 regularly accompanying another behaviour b_2 might lead to a rule in an observing agent enabling it to predict that another agent will soon display behavior b_2 after it used b_1 immediately before. One of the first example of this approach is the paper by Hutchins and Hazlehurst [35] who made a first step into the field of the emergence of a lexicon, but their agents were only able to agree on names of things (patterns — moon phases) they saw. In another paper they developed agents that were able to learn that moon phases were regularly connected to the turn of the tide [34]. This enabled the agents in this extended model to learn from others about the role of moon phases for the turn of the tide and endowed them even with a very simplistic grammar.

The NEW TIES project [24], ambitious as it is, aims at creating an artificial society that develops its own culture and will also need to define agent capabilities that allow them to develop something like a language although it is still questionable whether the experimenters will be able to understand what their artificial agents talk about. As compared to all earlier attempts at having artificial agents develop a language, the NEW TIES project is confronted with the problem of large numbers [24, 7.1], both of language learners and of language objects (many agents have to agree on names for many kinds of things and their properties).

A similar objective is aimed at in the current EMIL project (Emergence in the Loop [3, 11]) which attempts at creating an agent society in which norms emerge as agents observe each other and draw conclusions about which behavioural features are desirable and which are misdemeanour in the eyes of other agents — which, as in the case of language emergence, makes it necessary that agents can make abstractions and generalisations from what they observe in order that ambiguities are resolved. But even in this case it seems to be necessary to define which kinds of actions can be taken by agents in order that other agents can know what to evaluate as desirable or undesirable actions — software agents are not embodied in any realistic sense of the word, thus they must be given something like a virtual embodiment which defines which events and actions are possible in their virtual worlds. The current prototypical implementations of EMIL models [56] include an agent society whose members contribute to a large text corpus resembling a wikipedia. The language used is entirely fictitious, but has sufficient features to make it resemble natural language, and the actions include writing, copying, adding to existent texts, checking spelling and style and searching for plagiarisms. Without a definition of possible actions that agents can perform nothing will happen in these simulation models, and before any norms can emerge in such an agent society, at least some rules must exist according to which agents plan and perform their actions, but on the other hand, if all possible actions and their prerequisites were predefined, no emergence would be possible. The architecture of these agents [3] contains a normative frame which keeps track of all information relevant to norms and several engines to recognise a norm or not, to adopt it or not, to plan actions and to decide whether to abide by or violate a norm as well as to defend a norm by sanctions taken against others.

4.2 Concluding remarks

The use of multi-agent systems for simulating social and economic phenomena is not much older than about 15 years (if one neglects the early ancestors of this kind of approaches). Nevertheless it has made rapid progress during its short lifetime and used a wide range of methods and tools. And with some justification it has claimed to show "how the exercise of modeling and formalising of analytical constructs did not perforce have to condemn social analysis to reductionism and excessive abstraction, i.e. to the impossibility of grasping the fundamental ingredients of the social phenomenon" [53, p. 13, my translation].

Economists and, even more so, sociologists using multi-agent simulation for their purposes often even claim that they could contribute to the further development of computer science while developing simulations of socio-economic systems which in turn are self-adaptive. Thus there is a claim that the development of self-adapting software could use the insights of social science to construct something such as more co-operative, secure agent societies, for instance on the web. Socionics [43, section 1.1] "start[ed] a serious evaluation of sociological conceptions and theories for computer systems", thus "leaving the path of 'folks-sociology'" of which it was not clear whether its protagonists used notions such as agents forming "'societies', 'teams', 'groups', 'an organization'" and "behave 'socially', ... help each other, ... are selfish" only "for the limited purpose of simplifying the complex technical background of a distributed system" or whether they took these terms seriously. The founders of the socionics approach claimed that sociological paradigms such as "social roles, cultural values, norms and conventions, social movements and institutions, power and dominance distribution" should be useful paradigms to teach computer scientists build "powerful technologies" endowed with "adaptability, robustness, scalability and reflexivity". Hales and Edmonds [28] also mention "socially-inspired computing", reasoning that human social systems have "the ability ... to preserve structures ... and adapt to changing environments and needs" — even to a higher degree than biological systems that have already been used as a template for "design patterns such as diffusion, replication, chemotaxis, stigmergy, and reaction-diffusion" in distributed systems engineering [5]. But still there seems to be a long way to go until socially-inspired computing in a way that well understood social processes of norm emergence, trust formation and negotiation can be used as design patterns in distributed systems engineering — anyway, it might be "an idea whose time has come" [27].

5. ACKNOWLEDGMENTS

A more detailed description of the thoughts indicated in this paper appeared as [57].

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