On Multi-Agent Based Simulation

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1 Introduction

Agent-Based Computational Economics (ACE) and Agent Based Simulation (ABS) are two relatively young fields of research that lie on the boundary of social science, computer science and the cognitive sciences (AI and cognitive psychology). Originally these fields find their origin in computational physics, where multi-agent systems (MAS) are used to study models with heterogeneous agent populations. As AI researchers were looking for new applications for their artificial agent models, these could be readily found within the confines of the social sciences, in particular in economics and game theory, that are already strongly founded in analytical and computational methods. For example John von Neumann was a strong proponent of the idea of replacing Homo Oeconomicus with so called Homo Algoritmicus, focussing more on the process of rationality rather than on the outcome. The proponents of agent-based simulation are therefore sometimes referred to as Simulationists since the research is mainly centered around simulation studies, instead of mathematical analysis. At the boundaries where the orthodox deductive-analytical research program and the simulation approach touch on issues that have usually solely been studied within the orthodox research program, the first nowadays finds more competition from the second during formal and informal meetings than perhaps a decade ago. Although this may cause heated debates among researchers, it may turn out that there is much to learn on both sides of the divide as the boundaries between the two approaches begin to fade and a new synthesis is formed between the more rigorous mathematical analysis of orthodox neoclassical economics and the more

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flexible simulation approach of agent-based simulation. This survey is meant as a bridge to cross that divide.

2 Levels of explanation

A common critique on models that deal with explaining so called *stylized facts* is that the models do not describe what actually happens at the micro-level. Instead, they are stories told in order to match the empirically observed facts. These models are on a level of explanation that is at the macro-level, and can therefore be said to belong to the phenomenological approach of modelling social phenomena. A reason why such modelling at the macro-level is convenient is because it is concise and parsimonious. Another reason is that the complexity involved in dealing with multi-agent models of a more game theoretic nature, with strategic interaction between the agents, is often daunting.

The ABS approach is tilted more towards studying models in which the level of explanation is at the microscopic level. Researchers in the agent based social simulation (ABSS) community hold the view that modelling in the social sciences should take a descriptive stand and that it should therefore entail positivistic elements, i.e. it is a behavioristic approach to modelling social phenomena.

Agent based social simulation looks at agent behavior at a decentralized level, at the level of the individual agent, in order to explain the dynamic behavior of the system at the macro-level. There are clear trade-offs between model complexity and the model's descriptive detail. Increasing the detail of a micro-model may lead to an increase in the model's complexity, but not to an increase in the model's explanatory power. And the increase in complexity may not scale linearly with increase in descriptive detail. The realistic modelling of agent behavior in agent based simulation models suffers from the critique that it may no longer be possible to analyze what is going on at the micro-level, precisely *because* the model is too detailed. The details of the model blur the results that can be obtained from it. The overview is lost.

3 Agent-based Computational Economics (ACE)

From the point of view of General Equilibrium Theory the literature on social simulation lacks mathematical rigor. But not all studies done by researchers who use agent based simulations are purely based on computer simulations. Often the simulation studies are testing certain theoretical hypothesis, or have been constructed to illustrate a certain phenomenon which can be of practical or theoretical interest, and which may be used to develop new theory or to extend already existing theories. Also, agent based social simulations may be used to gain insights into uncharted territory where no theoretical results are yet available, and may thus give rise to new hypotheses. But also here there are clear trade-offs between mathematical rigor and model complexity, since models that are relatively small can often still be analyzed by analytical methods while slightly more complicated models can become analytically intractable. It is in such cases that simulation can be very useful. A simulation model can be set up with a high degree of model modularity, modelling different mechanisms separately and then letting them interact to produce the global system results.

For an introduction to the ACE literature, we refer the reader to the survey paper Tesfatsion (2002) and to the ACE-website that is maintained by Leigh Tesfatsion for extensive resources on ACE methodology.[1] Another reference should be made to the 'Handbook of Computational Economics II: Agent-Based Computational Economics', edited by Judd and Tesfatsion (forthcoming 2006).

4 Agent Based Simulation (ABS)

A seminal and often cited contribution to the field of agent based simulation is Epstein and Axtell (1992) who remark in their introduction:

> 'Herbert Simon is fond of arguing that the social sciences are, in fact, the hard sciences. For one, many crucially important social processes are complex. They are not neatly decomposable into separate subprocesses – economic, demographic, cultural, spatial – whose isolated analysis can be aggregated to give an adequate analysis of the social process as a whole. And yet, this is exactly how social science is organized, into more or less insular departments and journals of economics, demography, political science, and so forth ....
> The social sciences are also hard because certain kinds of controlled experimentation are hard. In particular, it is difficult to test hypothesis concerning the relationship of individual behaviors to macroscopic regularities, hypotheses of the form: If individuals behave in thus and such a way – that is, follow certain specific rules – then society as a whole will exhibit some particular property. *How does the heterogeneous microworld of individual behaviors generate the global macroscopic regularities of the society?*
> Another fundamental concern of most social scientist is that the rational actor – a perfectly informed individual with infinite computing capacity who maximizes a fixed (non-evolving) exogenous utility function – bears little relation to a human being. Yet, there has been no natural methodology for relaxing these assumptions about the individual.
> Relatedly, it is standard practice in the social sciences to suppress real-world agent heterogeneity in model-building. This is done either explicitly, as in representative agent models in macroeconomics Kirman (1992), or implicitly, as when highly aggregate models are used to represent social processes. While such models can offer powerful insights, they 'filter out' all consequences of heterogeneity. Few

[1]The ACE-website can be found at: http://www.econ.iastat.edu/tesfatsi/ace.htm

social scientists would deny that these consequences can be crucially important, but there has been no natural methodology for systematically studying highly heterogeneous populations.
Finally, it is fair to say that, by and large, social science, especially game theory and general equilibrium theory, has been preoccupied with static equilibria, and has essentially ignored time dynamics. Again, while granting the point, many social scientists would claim that there has been no natural methodology for studying non-equilibrium dynamics in social systems.' (Epstein and Axtell (1992), p.2)

This quote gives a very concise summary of all the main features of agent-based simulation: the interdisciplinary nature of the research, doing experiments, bounded rationality of agents, heterogeneity and dynamics. The approaches of Agent-based Computational Economics (ACE) and Agent Based Simulation (ABS) are a response to the apparent lack in the social sciences of models that study non-equilibrium dynamics in societies with boundedly rational and artificial agents. Below we discuss the differences and similarities between these two simulation methodologies.

5 Multi-Agent Based Simulation (MABS)

Within the simulation community there are two basically very different fields of research: Multi-Agent Systems (MAS) and Agent-Based Social Simulation (ABSS). MAS has been largely influenced by AI and logic-based approaches in the cognitive sciences and can be described as follows:

> 'Intelligent agent- and mechanism design and the development of optimization techniques that meet specific software engineering needs, possibly resulting in agent-based software applications.' (Moss, 2000)

And ABSS on the other hand can be described as follows:

> 'The computer simulation of social phenomena at the intersection of the social, mathematical and computer sciences.'

Within social simulation, the overshadowing influence of economics and game theory has mostly lead to mathematically based models, and relatively less influence was exerted from contributions of other social sciences:

> 'The hegemony of these fairly specific areas of the social sciences on MAS is essentially due to attention paid by economists and game-theorists to the study of the evolution of cooperation from local interactions among self-interested agents, also the quintessential problem of MAS scientists.' (Conte, 1998)

A number of different *leitmotifs* can be given for doing agent based social simulation. Foundational agent based social simulation is aimed at developing general social theories. Representational agent based social simulation by and large does not indulge in such theoretical questions, but rather focuses on solving practical issues, such as software engineering. Within the MABS community one of the leitmotifs for doing simulation modelling is the relationship between agent design (micro-level) and system performance (macro-level).

Recently, through the collaboration of researchers, the two respective fields of MAS and ABSS have been forged together to form a new field which is now appropriately called Multi-Agent Based Simulation, or MABS. The interest in such collaboration comes from both sides:

> 'The agent based social simulation community has long been interested in interaction among software agents both as representations of human and social actors and to formalize elements of agent design for multi agent software systems.' (Moss 2000)

And from the MAS side:

> 'The role played by economics has prevented the MAS field itself from taking advantage of the whole range of theories, models, and conceptual instruments that abound in the social sciences and that have received a great impulse thanks to the spread of computer simulation.' (Conte 1998)

However, despite their evident affinities there still exists a gap between MAS and ABSS (Conte 1998):

1. the two fields in question have suffered and still suffer from an inadequate interface;
2. Their cross-fertilization would encourage research in both fields and at the same time stimulate research arising at the intersection between them.

5.1 Model validation

An important issue for MABS modelling is the validation of simulation models:

> 'The whole issue of the conditions in which agent behavior will lead to observed or intended system results is a thread running through the fabric of agent based social simulation. In general these conditions are tied up with issues of validation. For social simulation modelling, validation turns on observed correspondences between agent behavior and the behavior of the social actors those agents represent and also between the macro behavior of the model system and the observed behavior of social institutions and the evidence of social processes.' (Moss 2000)

The issue of validation depends on the point of view of the modeler, namely whether he or she has in mind a predictive or a descriptive model (Moss 2000):

- Validation as prediction (associated to the Santa Fe Institute):
  A simulation model is validated if its predictions about macro-level outcomes are correct in a statistical sense. This is taking into account the phenomenon referred to as *universality*, which is that the same macro behavior can result from a variety of different micro-level specifications. This reduces the importance of exactly specifying the individual agents considerably. A model has been validated predictively if the stylized facts at the macro-level match.

- Validation as description (associated to the European special interest group on agent-based social simulation): For social simulation modelling, a simulation model is validated if it describes phenomena and actual social processes that can be associated with the individual agents, such as beliefs, desires and trust. A model has been validated descriptively if it provides a correct representation of the data generating process.

The notion of "validation as prediction" can be associated to MAS, while the notion of "validation as description" is associated to ABSS. The joining field of Multi-Agent Based Simulation (MABS) thus suffers from the problem of having two orthogonal validation criteria: to reproduce the stylized facts at the macro-level with models that are descriptively correct at the micro-level.

6 Computational Economics: How and Why?

In this section we try to answer the question why computational models have some methodological merit, why computational models *should* be used in economics, how they *could* be used, and how such models *are being* used in actual practice. Simulation models can be used in the following ways:

1. To restate already existing theories.
2. As a descriptive language to formulate new theories.
3. As a method for testing theoretical hypotheses.
4. For testing theory against reality.
5. As scenario analysis to investigate possible dynamic behavior of a system.
6. As a process for policy analysis to study 'What if?' questions.

Testing of existing theories and hypotheses entails the following: a theoretical model of interest is transformed into a computational model (computer program); the specific parameters deemed significant for the model's behavior are identified; the theory is tested by varying the parameters for separate runs of the computational model. Development of a new theory usually proceeds dialectically by the following iterative process: starting from a certain theoretical framework a model is constructed. This is followed by experimental testing of the model, revision and enlargement of the theoretical framework (generalization and/or correction), new experimental testing, adjustment of the theory, etc.

The benefits of the computational approach as opposed to the analytical-deductive approach are outlined by Klüver, Stoica and Smidt (2003). Firstly, the transformation of the usually informal theoretical models into a computational model requires operationalizing the basic mechanisms of the model and a higher level of precision of the theory's most important presuppositions and statements. Secondly, the transformation process itself may be informative for the construction of a computational model and may give insights into the original theoretical model that would else have remained hidden. And finally, the approach may show that the original model needs enlargement or correction if the computational model does *not* show behavior that was expected theoretically, or if it *does* show behavior that was *not* expected theoretically.

Thus the translation from theory to computational models forces the modeler to make explicit the mechanisms that would else have remained implicit, and this is one of the main advantages of the computational approach since it disciplines the modeler. Using simulations for testing and validating the computational models could be seen as performing an experiment:

> 'Because in the social sciences "real" experiments are in most cases not possible or only in a very restricted way, the use of computer simulations plays a decisive role: very often computer experiments have to play the part of real experiments in the laboratory sciences. By the way, that is also the case in those natural sciences where for similar reasons experiments are not (yet) possible, in particular in the 'historical' sciences like physical cosmology and evolutionary biology.' (KSS 2003, par. 5.7)

The main problem with the so called 'historical' sciences is that the historical processes being studied cannot be investigated experimentally. It is not possible to turn back the clock and start over with a different configuration of the universe, at least not as a field experiment. What is possible is to do simulation experiments, by running so called 'scenarios', also known as 'what if'-experimentation. The same holds *mutatis mutandis* for evolutionary biology. Also here it is not possible to reset the actual biosphere in order to repeat the evolutionary processes with a different choice of the initial conditions and then compare evolutionary outcomes. But we can do simulation experiments. Now the question forces itself: Is economics in this respect more akin to physical cosmology and evolutionary biology, or is it fundamentally different and is true experimentation possible after all?

7 A generative social science

Epstein and Axtell speak out the hope of developing a new theory in the social sciences and make a plea for a *generative social science*, where the term *generative* is used in a similar way as in Noam Chomsky's generative grammar:

> 'The grammar of a language must be generative in the sense that it must be a set of rules capable of "generating" all well-formed (i.e. grammatical) sentences of a language and none of the ill-formed ones.' (Casti 1989, p. 215, as quoted in Epstein and Axtell (1992), fn.177.)

For the generative social science of Epstein and Axtell this means that it must contain a set of rules capable of generating all *well-formed* artificial societies and none of the *ill-formed* artificial societies, where well-formed and ill-formed refer to the generative sufficiency of the simulation model to reproduce the stylized facts of real societies. Compare this to a criterion of Robert Lucas for what is a good economic model:

> 'A "theory" is not a collection of assertions about the behavior of the actual economy but rather an explicit set of instructions for building a parallel or analogue system – a mechanical, imitation economy. A "good" model, from this point of view, will not be exactly more "real" than a poor one, but will provide better simulations.' (Lucas 1980, p.697)

This does not mean that scientists who use MABS as a research methodology can build a theory by performing simulations alone:

> 'The ability to generate noiseless data is a powerful feature of artificial societies. In addition to this kind of empirical study, it is desirable to pursue formal analysis – outright theorems and proofs – where possible. While the exact evolution of *individual* agents and sites seems analytically intractable, certain probabilistic analyses are possible.' (Epstein and Axtell 1992, p.176)

Without a solid analysis of the problem no sensible simulations can be performed, and without the simulations it is often difficult to grasp the global dynamical features of the model. Therefore, the analytical and computational tools should be viewed as complements rather than as substitutes, and both approaches are indispensable in understanding the behavior of complex adaptive systems.

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