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Agent-Based Modelling[1]

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1. Introduction

Agent-based modelling (ABM) is the computational study of social agents as evolving systems of autonomous interacting agents. ABM is a tool for the study of social systems from the complex adaptive system perspective. From this perspective, the researcher is interested in how macro phenomena are emerging from micro level behaviour among a heterogeneous set of interacting agents (Holland, 1992). By using ABM as computational laboratories, one may test in a systematic way different hypotheses related to attributes of the agents, their behavioural rules, and the types of interactions, and their effect on macro level stylized facts of the system.

Since the early 1990s ABM has increasingly been used in most of the social sciences. I shall focus on the applications of ABM related to ecological economics (Janssen, 2002, 2005; Janssen and Ostrom, 2005). ABM of ecological economic systems can be defined as systems that are populated with heterogeneous population of agents, who determine their interactions with other agents and with their environment, on the basis of internalized social norms and mental models, internal behavioural rules and cognitive abilities, formal and informal institutional rules that affect how agents interact, individual and social learning, etc.

2. Motivations for Agent-based Modelling

Some readers may question why we need complex approaches such as ABM. Are equation-based models not sufficient? Other readers may argue that ABM is not new. My response to these queries is that it all depends on the type of questions one is interested in. For many problems, equation-based models are excellent tools to study the problem of concern. However, for a problem like coordination or strategic interaction, multiple agents need to be distinguished.

Traditional game theory has been very successful in addressing strategic interaction by a small number (mainly two) (types of) players, using equation-

[1] This is a shortened version of Janssen (2005).

based models. Unfortunately, traditional game theory is rather restrictive: Agents are required to have high cognitive abilities, the rules of the game are fixed, and the structure of the interactions is on a rigid lattice or fully random. But from empirical studies it is known that humans are boundedly rational, the rules of the game change, and social interactions have complex social structures (e.g., Gigerenzer and Selten, 2001; Janssen and Ostrom, in press). It is no surprise that ABM has been widely applied to games since the early 1980s (e.g., Axelrod, 1984).

Indeed, models of individual units were developed long ago, such as statistical mechanics and micro-simulations. But these methods assume no interaction, or random interaction, between the agents. A key element in ABM is the possibility of complex structures of social interactions. In some systems, the macroscale properties are sensitive to the structure of interactions between agents and social networks. In equation-based models, the agents are frequently, implicitly, assumed to be well mixed, the mean-field assumption, and thus these approaches miss the opportunity to investigate the sensitivities of the structure of interactions.

Finally, within integrated modelling of ecological economic systems, one of the key problems is how to match the scale of social and ecological dynamics (Levin, 1992; Gibson et al., 2000). By the use of agents, we derive tools that make it possible to integrate processes and interactions at different levels of scale, for agent-agent and agent-environment interactions.

3. ABM Methodology

Most ABMs applied within ecological economics consist of two elements: cellular automata and agents. I will now discuss briefly both elements.

Cellular Automata

Originally, the cellular automata (CA) approach was introduced by John von Neumann and Stanislaw Ulam at the end of the 1940s. Since the early 1970s, CA have been used by many disciplines to study complex dynamic behaviour of systems. The essential properties of a CA are:

- a regular *n*-dimensional lattice (*n* is in most cases of one or two dimensions), where each *cell* of this lattice has a discrete state,
- a dynamical behaviour, described by so called *rules*. These rules describe the state of a cell for the next time step, depending on the states of the cells in the *neighbourhood* of the cell.

The basic element of a CA is the *cell* that is represented by *states.* In the simplest case, each cell can have the binary states 1 or 0. In more complex simulations, the cells can have more different states. These cells are arranged in a lattice. The most common CAs are built in one or two dimensions. The cells can change state by transition rules, which determine the state of the cells for the next time step. In cellular automata, a rule defines the state of a cell in dependence of the *neighbourhood* of the cell.

With regard to our interest for ecological economics, the application of CA can be rather straightforward. In fact, CA can be used to produce a dynamic

Geographical Information System (GIS). The lattice represents a map of a certain area, with each possible state of a cell representing a possible land use. Due to physical restrictions, cells on some locations may be restricted to a limited number of states; for example, a secondary forest cannot turn back into a primary forest. Transition rules determine when a certain land use of a cell changes into another land use. Cell changes can be influenced by local rules; for example, if the cell is a forest-cell, and if one of the neighbour cells is on fire, then the cell turns to fire. However, global rules are also possible, since land use changes can be influenced by demand for certain land on a higher level of scale. For example, demand for extra agricultural land can be translated as changing those cells to agriculture that are the most suitable.

A drawback of using CA for representing social agents is its simplicity. For example, social networks are more complex than the local neighbours on a lattice. The number of possible states in which a social agent can be might be too large to be efficiently represented as a CA. Within land use models, landowners may own multiple cells and make decisions on the land use of their cells. Thus a cell-based rule that ignores parcel boundaries is inadequate. The study of agents has been a topic of research for a long time in computer science, which has developed its own tools and frameworks.

Agents

The architecture of agents in ABM has been much influenced by work on multi-agent systems in Artificial Intelligence (AI). Multi-agent systems research studies the behaviour of adaptive autonomous agents in the physical world (robots) or in cyberspace (software agents). Wooldridge (2002) argues that intelligent agents are able to act flexibly and autonomously. By flexibility we mean that agents are goal-directed (satisfying or maximizing their utility), reactive (responding to changes in the environment) and capable of interacting with other agents. One of the difficulties is in balancing reactive and goal-directed behaviour. Developing models with agents who have only reactive behaviour is relatively simple, and individual-based ecological modelling addresses problems by simulating non-human agents as reactive objects (e.g., DeAngelis and Gross, 1992).

However, humans combine reactive and goal-directed behaviour. Conventional economics assumes the selfish rational actor to describe individual behaviour. Although this agent model provides a good description of human behaviour in highly competitive markets, as is confirmed in experimental studies, it is not satisfactory for the description of behaviour in various decision situations of importance for ecological economics (Gintis, 2000). For decision situations such as economic valuation and collective action, motivation, fairness and preferences play an important role, and the characteristics may vary within the population of human agents. Furthermore, decision problems related to environmental management are often so complex that it is not likely that one has full information and understanding of the problem and is able to evaluate all possible options. Models of bounded rationality have been used as an alternative in economics (Simon, 1955). Furthermore, using concepts from psychology, we are able to include dimensions of economic agents such as emotions, motivations, and perceptions. A problem is that loosening the tight framework of the selfish rational actor leads to many possible frameworks. Within behavioural economics, there is mainly attention to models of learning that explain observed behaviour in experiments (Camerer, 2003). Others focus on fast and frugal heuristics, of how individuals make a choice in simple problems under time pressure (Gigerenzer et al., 1999).

A scheme of a simple model of two agents interacting with each other and their environment is given in Figure 1, which provides the simplest description of ABM applied to ecological economics. Agents derive information from the environment that informs the perception they have about the state of the environment. Based on the goals and attributes of the agents they make decisions on actions to perform and these actions affect the environment. The agents can interact indirectly, for example by affecting the common resource, or directly by communication. This communication might be used to exchange information about possible strategies, knowledge about the resource and agreements how to solve collective action problems.

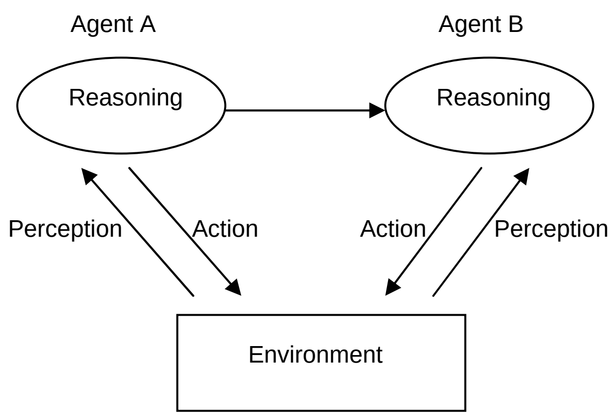

Figure 1: A Scheme of Cognitive Interactions between Two Agents and their Environment

4. Agent-Based Modelling in Ecological Economics

I shall now describe the main areas within ecological economics where ABM has been applied and provide some of the key references.

Evolution of Cooperation

Laboratory experiments and case study analysis show that people have the capacity to organize themselves to achieve cooperative arrangements when humans share common resources (Ostrom, 1990, Ostrom et al., 1994). But there are many unknowns in the model of the individual, the role of communication, sanctioning and ability of groups to craft new rules. ABM can contribute to a better understanding of the factors that stimulate such self-governance. The irrigation system of Bali is an example of the use of ABM to understand self-governance (Lansing, 1991; Lansing and Kremer, 1994). Another relevant paper is Janssen and Ostrom (in press), who study the conditions that are needed for a population of agents to voluntarily restrict their own behaviour, to avoid the collapse of a resource in the longer term. They show that when agents are able to evolve mutual trust relationships, a proposed rule on restricted use of the resource will be accepted, since they trust that others will, in general, also follow the rules.

There is a substantial literature on the use of ABM on the management of common-pool resources. Bousquet et al. (1998, 2001, 2002) developed a modelling platform, CORMAS, dedicated to the study of common-pool resources by ABM, and performed many applications. In their application they work together with the local stakeholders, often in Africa and Asia, to develop ABM for practical natural resource management problems. Deadman (1999) compared his ABM with experimental data of common-pool resource experiments and Jager et al. (2000) tested how different theories of decision making affect the state of the common resource.

Diffusion Processes

Diffusion processes are important for understanding what determines the spread of innovations in a population. Such innovations might be the use of a new environmentally friendly product, a technology to reduce waste, or norms about green consumption. Diffusion processes often replicate the observed stylized fact of an S-shaped curve of cumulated adopters of the innovation. In fact, the increasing number of adopters is in essence the diffusion process. The growth of new products is a complex process, which typically consists of a large body of agents interacting with each other over a long period of time. Traditional analytical models described diffusion processes at the market level, but in recent years ABM has become used as an alternative model. (e.g., Weisbuch, 2000).

Applications of ABM to diffusion problems within ecological economics are rare. An interesting example is Berger (2001), who studied the diffusion of agricultural technologies based on the concept of different types of adopters (early and late) applied to an agricultural region in Chile. Another application is of Deffuant et al. (2002) who simulate adoption of organic farming practices as a consequence of governmental policy, for an agricultural region in France. In a more theoretical study, Janssen and Jager (2002) study the diffusion of green products in a coevolution of consumers and firms, where firms try to make products that fit the demand of the consumers, and consumers have to make a choice between a limited number of products.

Within the field of evolutionary economics (e.g., Nelson and Winter, 1982), simulation models are used to simulate innovation, diffusion and learning of firms and organizations. An interesting application of ABM for ecological economics related to industrial organizations might be the area of industrial ecology where different types of agents process material and energy flows in their economic activities (Axtell et al., 2002).

Mental Models and Learning

If agents do not have perfect knowledge of the complex ecological system, how does their mental model of the system affect their actions, and how can they learn to derive a more accurate mental representation? This problem refers to the general problem in ABM, that agents do not have perfect knowledge of the system and make their decisions based on the perception they have on the problem. These perceptions do not have to include correct representations of reality and may vary among agents.

A number of ABMs in the field of ecological economics have addressed this problem. Janssen and de Vries (1998) developed an ABM where agents have different mental models of the climate change problem. They simulate a learning process where agents may adjust their mental models when they are surprised by observations, and make adjustments in their decisions according to their new perception of the problem. This approach has also been applied to lake management (Carpenter et al., 1999), and rangeland management (Janssen et al., 2000).

Carpenter et al. (1999) developed a simulation model with different types of agents to explore the dynamics of social-ecological systems. The ecosystem is a lake subject to phosphorus pollution, which flows from agriculture to upland soils, to surface waters, where it cycles between water and sediments. The ecosystem is multistable, and moves among domains of attraction depending on the history of pollutant inputs. The alternative states yield different economic benefits. Agents form expectations about ecosystem dynamics, markets, and/or the actions of managers, and choose levels of pollutant inputs accordingly. Agents have heterogeneous beliefs and/or access to information and their aggregate behaviour determines the total rate of pollutant input. As the ecosystem changes, agents update their beliefs and expectations about the world they co-create, and modify their actions accordingly. Carpenter et al. (1999) analyze a wide range of scenarios and observe irregular oscillations among ecosystem states and patterns of agent behaviour, which resemble some features of the adaptive cycle of Holling (1986).

Land Use and Land Cover Change

ABM for land-use and land-cover change combine a cellular model representing the landscape of interest, with an ABM that represents decision-making entities (Parker et al., 2003). Due to the digitalization of land use/cover data (i.e., remotely sensed imagery) and the development of Geographic Information Systems (GIS), cellular maps can be derived for analysis, and since the 1980s, cellular automata have became used to model land use/cover over time. Human decision-making was implicitly taken into account in the transition rules, but not expressed explicitly. Sometimes the cells represent the unit of decision-making but, in most applications, the unit of decision making and the cell do not match. The desire to include more comprehensive decision rules, and the mismatch between spatial units and units of decision making, led to the use of ABM for land use and land cover change. By including agents, one can explicitly express ownership, or the property about which an agent can make decisions. An agent can make decisions on the land use in a number of cells, for example by allocating cells for deriving a portfolio of crops.

Applications on land use and land cover change include impact of innovations and policy on agricultural practices (Balmann, 1997; Berger, 2001; Deffuant et al., 2002), reforestation and deforestation (Hoffman et al. 2002) and urban sprawl

(Torrens and Benenson, 2004). Gimbett et al. (2002) and Parker et al. (2003) provide recent reviews of this area.

Participatory Approaches
In the spirit of adaptive management (Holling, 1978), various researchers have developed their ABMs together with the stakeholders of the problem under concern. Bousquet et al. (2002) have developed an approach, which they call 'companion modelling', that uses role games to acquire knowledge, build an ABM, validate the ABM and use it in the decision making process (see also Barrateau, 2003). As for the participatory modelling approach, such as is practiced in systems dynamics (e.g., Costanza and Ruth, 1998), they use the model as a tool in the mediation process with stakeholders. Within the system dynamic model, agents are represented at an aggregate level, and the use of ABM makes it possible to include a broader set of interactive autonomous agents. These autonomous agents may respond to the decisions of the stakeholders in the participatory process in unexpected ways.

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