MULTI-AGENT BASED SIMULATION (MABS)

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Background reading for participants at the ECF Venice workshop on agent based modelling for sustainable development. If you wish to quote or make any further use of this material, please contact Dr Pascal Perez, pascal.perez@anu.edu.au

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Introduction

When asked about Multi-Agent Systems (MAS), I'm used to say that they are equivalent to our famous Unidentified Flying Objects (UFO): everybody knows about them, but nobody can tell exactly what they are! Confusion starts with the terminology itself, entangled in a web of closely related terms: agent-based modeling, multi-agent simulation, individual-based modeling, and some more. Obviously, this profusion denotes the existence of a flourishing, young and exuberant field of research.

The history of MAS is to be written but we can locate its birth in the rich breeding ground of the interdisciplinary movement. In the USA, Distributed Artificial Intelligence developed in computer science, separately from the world of physics where the concept of Artificial Life was first initiated. In Europe, on the other hand, the emergence of the MAS community arose from the coming together of researchers from different disciplines, namely: ecology, sociology, economics and computer science (Bousquet et al., 1999).

Any given scientific course needs axioms and theorems in order to comply with our rational and deductive reasoning. Thus, I lay myself open to criticism by proposing the intentionally weak, but consensual, following definitions (Ferber, 1999):

Definition of a Multi-Agent System:

" *A MAS is a system composed with the following elements:*

1. An environment (E), often possessing explicit metrics.

2. A set of passive, located objects (O). These objects can be located, created, destroyed or modified by the agents.

3. A set of active agents (A). Agents are particular objects that constitute the active entities of the system.

4. A set of relationships (R) linking objects and/or agents together.

5. A set of operators (Op) allowing the agents to perceive, create, use, manipulate or modify the objects."

Definition of an agent:

"*An agent is a physical or virtual entity that demonstrates the following abilities:*

1. Autonomous actions within its environment.

2. Communication with other agents.

3. Limited perception of its environment.

4. Bounded representation of its environment (if any).

5. Decision making process based on satisfying goals and incoming information."

A Multi-Agent Based Simulation (MABS) is the result of the implementation of an operational model (computer-based), designed from a conceptual representation of an observed system. Thus, the formalization process transforms 'theoretical agents' coming from the MAS-based system analysis into intermediate 'conceptual agents' and finally into 'computer agents'.

The development of MABS is closely related to the problem of complexity (multiple scales and organization levels, multiple agents and viewpoints, recursive interactions) and the related search for simple representations of the real world through modeling. In particular, what we usually call Complex Adaptive Systems (CAS) are inherently unpredictable as a whole. "*Their futures are not determined. Their global behaviors emerge from their local interactions in complex, historically contingent and unpredictable ways*" (Bradbury, 2000).

Nowadays, flagship research about complexity arises from various integrated analysis of human ecosystems, i.e., systems where human activities prevail and endlessly modify the environment (agricultural landscapes, urban systems, share markets). Though, one should notice that the very first hints about complex phenomena and doubts about our scientific certitudes came from quantum physics (unpredictability), thermodynamics (non-equilibrium phase transition) and even paleontology (punctuated equilibrium). D.Batten (2000) demonstrates how human ecosystems are inherently complex and adaptive, due to the ability of human beings to switch from rational deductive reasoning to inductive pattern recognition, in order to solve (with more or less success) any given problem. Beside, our ability to communicate and learn from others creates the conditions for a co-evolutionary process where positive feedback loops follow negative ones, punctuation dispels equilibrium, chaos threatens order, and chance gives a hand to necessity.

Why the method is useful

Distributed problem solving constitutes the largest field of application for the Multi-Agent Systems. Medical diagnosis, pattern recognition, network control, distributed task conception benefit from the interactivity and adaptability of MAS-based solutions. But these applications are seldom concerned with the implementation of MABS.

Computer simulation has become an essential tool in life, earth and social sciences. Theoretical models, often based on differential equations or matrix of transitions, tend to explore or predict natural phenomena. Their implementation is achieved through numerical simulation. In the case of human ecosystems, Dynamic Modeling has brought tremendous insight into recursive relationships and stability of the studied systems. But this system-wide approach suffers several flaws (Gilbert and Troitzsch, 1999):

1. *Global analysis*. The mathematical model describes global phenomena occurring at the system level. Thus, variables and parameters are located at the same macro-level of analysis. For instance, it is impossible to relate population characteristics with the behavior of its individuals (micro-level).

2. *Opacity of the parameters*. Sometimes, the system of differential equations needs global parameters, difficult to estimate from observation or simply unrealistic. The famous Lotka-Volterra's model gives a good example: In an impressive shortcut from fecundity theories, one parameter corresponds to 'the efficiency of food transformation into offspring'.

3. *Absence of action*. Mathematical models consider actions through their consequences at the global level or through their probability of occurrence. But it is nearly impossible to take into account the co-evolutionary process of collective

behavior. As a consequence, unsuspected emerging phenomena can't be detected through this global approach.

4. *Qualitative deficiency*. Mathematical models are inherently unable to take into account qualitative information coming from the real system. This is particularly damaging when considering human ecosystems.

MABS correspond to a totally alternative vision by offering the opportunity to simulate individual behavior and collective interactions. The global patterns at the system level are just resulting from the micro-level activities. Indeed, MABS are very efficient for simulating artificial worlds where interactions are essential. These worlds can be used as 'virtual laboratories' in order to reproduce controlled experiments. One can look at MABS as analogical models similar to these scale models used to perform tests in aeronautics.

Finally, I'd like to illustrate all these concepts with the *Plot Auction* example (Figure 1). Let's imagine 10 farmers located on a 10x10 mesh (100 plots). Each farmer is randomly allocated with 10 plots at the beginning of the game. The productivity of one plot is a linear function of the distance to the farm. Thus, each farmer will try to improve his income by exchanging plots with his neighbors. The first situation includes an auctioneer who centralizes the offers and demands from all the farmers and then distributes the plots according to the best productivity values. In this case, the auctioneer is able to reach the optimal solution very easily. A second situation let the farmers negociate without auctioneer and split into two groups of acquaintances (5+5). Communication is not allowed between groups, but within a group farmers know all the plots under offer (synchronous messages). In this case, the farmers can reach a set of unstable sub-optimal solutions. In the third situation, the farmers have to take a decision to lease or not as soon as they receive an offer (asynchronous messages). In this case, the plot pattern displays an infinite chaotic behavior.

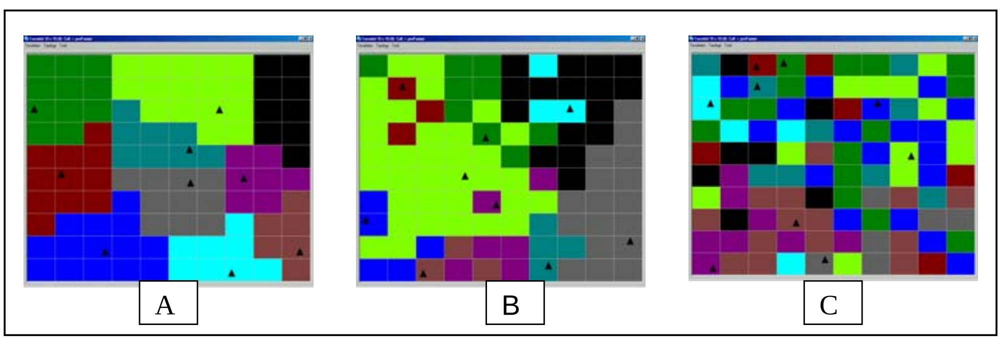

Figure 1 Plot Auction. 10 farmers exchange their plots through auctions according to three different rules: (A) a central auctioneer manages the offers, (B) two groups of farmers negotiate synchronously, (C) two groups of farmers negotiate asynchronously. Results after 10 runs.

What does it mean? In the first case, a central control with an holistic knowledge is able to find a solution to this rather simple problem. In the second case, individual agents, with a bounded perception of their environment, are able to find a sustainable solution through a 'trial and failure' process. In the third case, agents with a nearly autistic perception of their environment are stuck in a world of chaos. I guess you'd already got the message: human ecosystems are made of an ever-changing mix of these three situations.

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The theory behind the technique

Ferber (1999) proposed a theoretical framework for the Multi-Agent Systems; he called *Kenetic*. This framework offers a set of rules and definitions about the agents, the interactions and the organizations encountered within MAS. Unfortunately, this approach was mainly developed for the applications concerned with distributed problem solving. The use of MABS, especially when applied to human ecosystem simulations can hardly fit in the engineering views of Kenetic.

Sometimes, this lack of theoretical formalism creates some kind of fuzziness during the implementation of a MABS model. Like any other modeling approach, MABS have to go through a three-stage process: Theoretical phase, Conceptual phase and Technical phase. The diversity of the MABS applications comes from the fact that the multi-agent concepts are used at different stages of the creation process (Drogoul et al., 2003):

Theoretical stage: the thematicians have to decide whether the observed system (target) has anything to do with the MAS concepts. If they consider that micro-level behavior and interactions are essential to understand and explain the system, then they have to decide which part of the system is concerned and which level of granularity they need. They gather all the available information (qualitative and quantitative) and build 'real agents' as close as possible to their representation of the system.

Conceptual stage: The modelers join the thematicians in order to organize the agents into a conceptual system. This is an essential part of the creation where the structure of the agents, of the communications, of the global organization is decided. Spatial distribution, time dependency and multi-agent concepts are essential parts of the conception. Class and sequence diagrams are created at this stage (Figure 2). The 'real agents' become 'conceptual agents'.

Technical stage: The computer engineers join the group and decide which type of language, platform, and structure would fit best the conceptual model. Obviously, there is a strong link between Object-Oriented-Programming (OOP) and MABS, as agents can be seen as super-objects. Identically, the hierarchical structure of most of the OOP languages suits perfectly the nested structure of the MABS. The 'conceptual agents' become 'computer agents'.

From this breakdown, one can perceive the reasons of the fuzziness attributed to MABS. Some colleagues are using MAS concepts at the Conceptual level only, even if it was not worth it from a theoretical viewpoint. Relying heavily on the spatial distribution facilities, these *super-GIS-like* models find their final justification into the use of OOP during the technical stage.

Finally, some detractors dub the MABS approach and argue that any kind of OOP model is 'some kind' of a multi-agent based model. Jennings et al. (1998) list three important ways in which agents can be distinguished from objects:

1. Although objects have the ability to control their own internal state (private methods), they are not able to exhibit control over their behavior. This means that if a method is available for other objects to invoke, they can do so whenever they want. On the reverse, agents can deny access to an encapsulated method.

2. A standard object does not encompass the notion of flexible (reactive, proactive, social) and autonomous behavior. This is one of the most recognized features of agent-based models.

3. The third distinction is that agents are each considered to have their own thread of control, whilst a standard object-oriented model has a single thread of control.

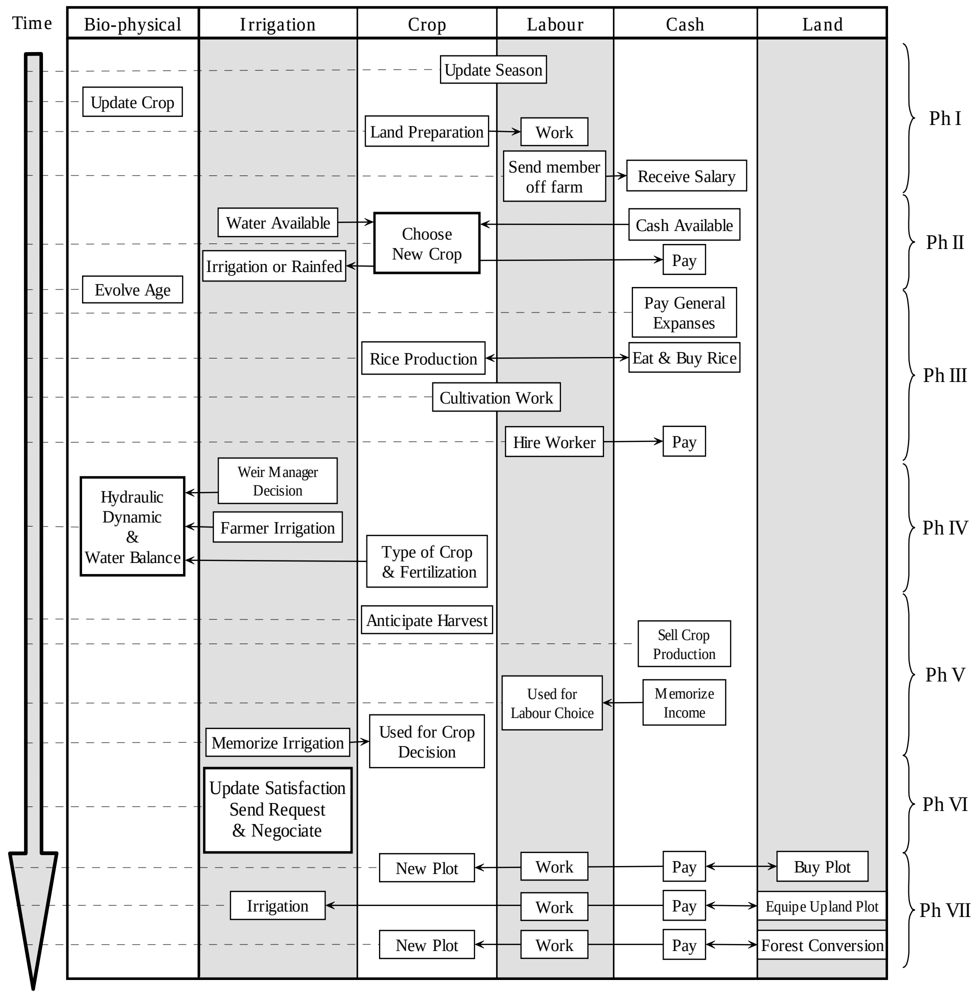

Fig. 3. Modelling sequences flowchart.

Figure 2 Sequence diagram from the CatchScape model. The flowchart describes the activities of the agent ‘Farmer’ during a simulation (Becu et al., 2001).

Assumptions required

Four assumptions, coming from the Complex Adaptive Systems theory, are accepted, rather then requested, by the Multi-Agent Based Simulation:

Emergence: this is the key concept coming from CAS and entirely accepted by MABS. According to Gilbert and Troizsch (1999): “*a phenomena is emergent if it requires new categories to describe it, which are not required to describe the behavior of the underlying components*”. Thus, interacting agents instanciate emerging patterns at the system level.

Path dependency: due to the highly non-linear relationships between autonomous agents, any given outcome from a simulation depends on the initial conditions. Furthermore, a converging solution at the system level can be achieved through an infinite number of combinations at the micro-level.

Non-equilibrium: the systems represented through MABS display an ever-changing dynamic equilibrium, driving back and forward the system between chaotic to ordered states. 'On the edge of chaos', the system is very sensitive to any perturbation from the individual agents (Batten, 2000).

Adaptation: the evolution of the system is driven by the evolution of the agents. The agents adapt to their environment and modify it in a recursive way. If the agents represent human beings, the adaptation relies mainly on the individual and collective learning processes. MABS formalization of the learning processes depends on the social and psychological theories used by the modeler. Jager and Janssen (2003) have proposed the *Consumat theory* to handle the problem of implementing individual learning into MABS. They define four learning behavior according to the agent's levels of uncertainty and satisfaction (figure 3).

The overall effect of these four assumptions is that a co-evolutionary process between the agents and the environment characterizes the system.

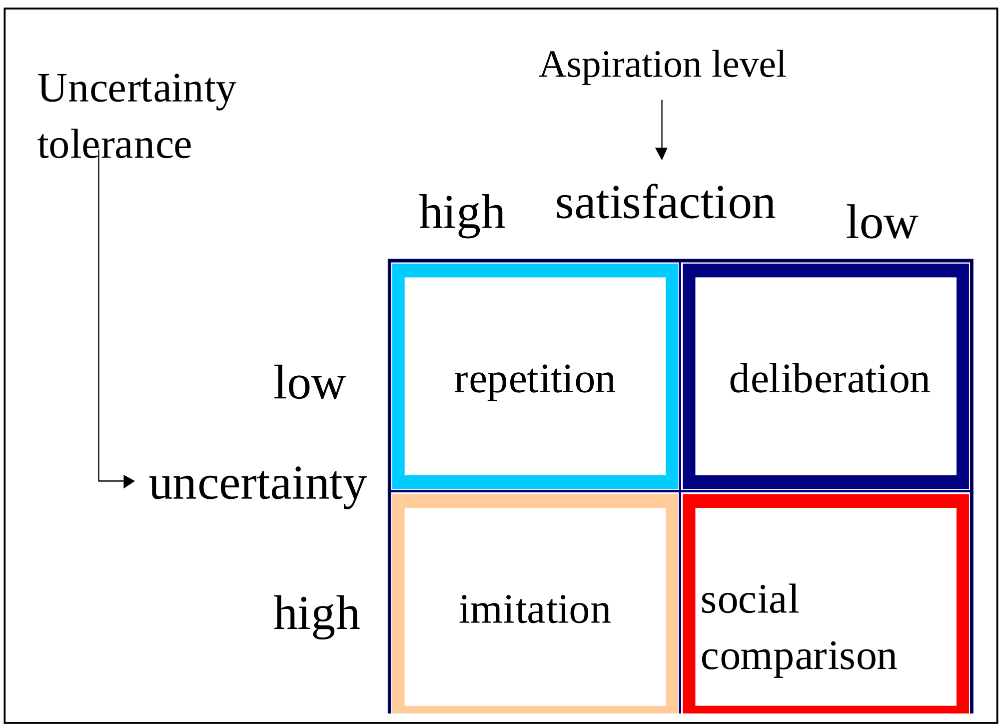

Figure 3 Consumat theory. Learning methods of an agent, based on its uncertainty and satisfaction levels (Jager and Janssen, 2003)

Mathematic calculations involved

From a purely MAS perspective, if the system can be entirely described through emerging processes and if a large number of agents are created, the tasks required from each agent is minimal and so its mathematical formalism. Agents often manipulate more symbols then equations and the decisional tree remains the most popular way of structuring agent's activities (figure 4).

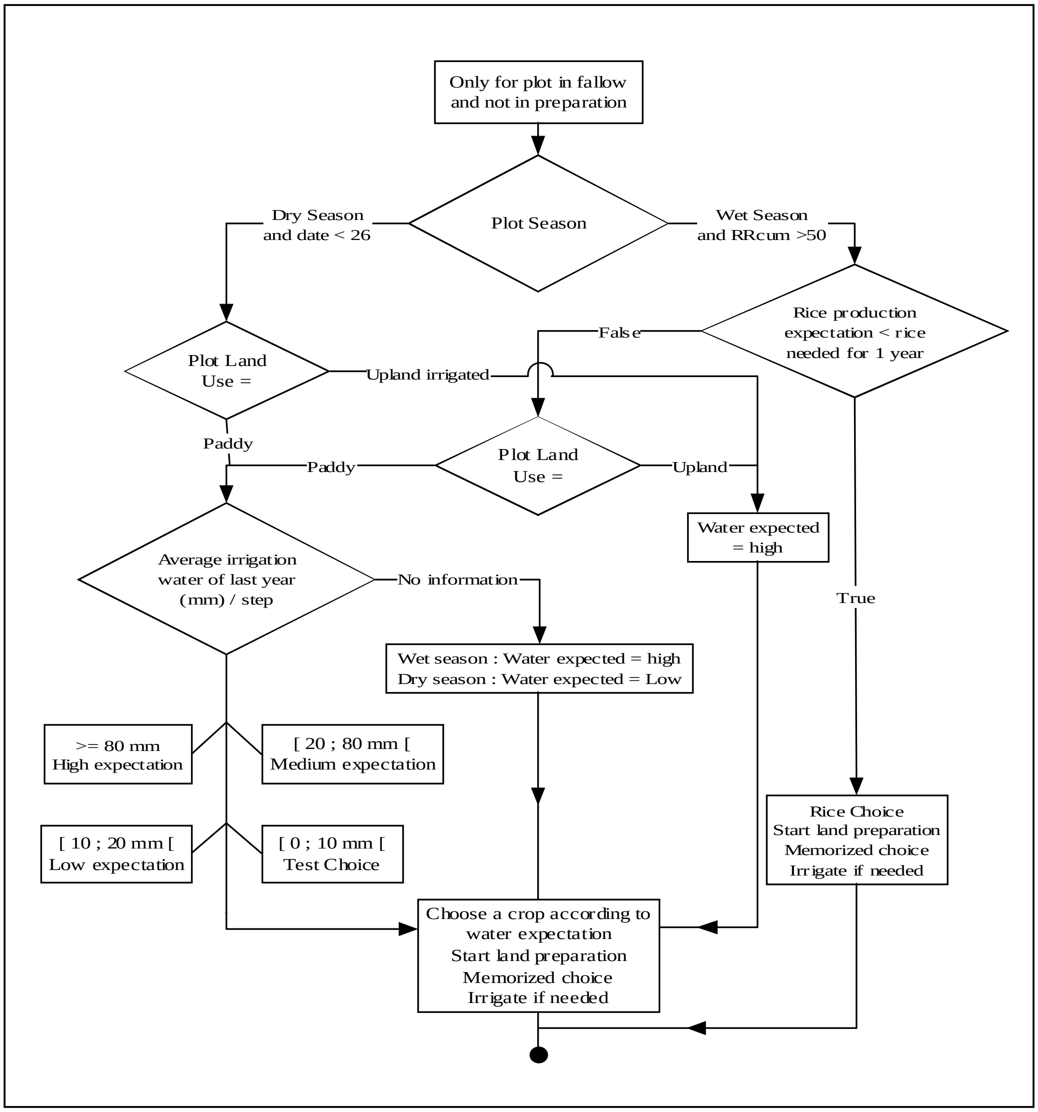

Figure 4 Example of a decisional tree used in the CatchScape model (Becu et al., 2001).

There is not incompatibility between MABS and other scientific modeling approaches. MABS only proposes a new type of organization to look at a given system. Any existing model consistent with the level of desaggregation (or granularity) of the agents can be implemented as a specific method.

Often, when the complexity of the mathematical methods used by a type of agent becomes too abstruse, it is time to think about a sub-level of granularity. Hence the agent may be disaggregated into simpler interacting agents. Otherwise, it could be useful to search for a simpler mathematical formalism.

The drawback of this apparent simplicity is that MABS needs very specific languages in order to restitute the profusion and gradation of interaction and communication between agents. For example, agents may “believe”, “trust” or “engage”.

Data and data relationships

The question of the data requirements takes us back to creation process, composed of theoretical, conceptual and technical stages. The first stage helps the thematicians to express a problem to be explored with the MABS. The more complex the system is, the more precise the initial question should be. The question inevitably shapes the level of granularity of the analysis and, consequently, the type of agents needed.

The agent’s behavior is governed by a list of attributes and methods that can be activated and modified during the simulation. Thus, the input data concern mainly:

1. the initial values of the attributes,

2. their estimated range of variation,

3. the kind of actions the agent should reproduce.

Obviously, the modeller will come up with a mixed set of quantitative and qualitative data. At the conceptual stage, the modeller and the thematicians have to decide which level of precision they need for the different processes involved in the system. The choice depends directly from the quality of the available data and the weight of the process compared with all the other ones in the system. One can say that this fragile balance has more to do with an art then science. For this reason, the term of *soft-modeling* is sometimes applied to MABS.

Key outputs and interpretation

Multi-Agent Based Simulations are path dependent. Tracking back the pathways becomes very quickly challenging as the complexity of the system rises. MABS users give-up, somehow, the prospect of a deterministic comprehension of the simulated processes. The first objective of MABS should be to explore the system rather trying to anticipate any outcome according to identified initial conditions. From this perspective, MABS complies with the principle of Artificial Life: “*life as it might be rather then life as it is*” (Langton, 1988 cited in Bousquet, 2001).

Partial validation of the results can be done at the system or the agent levels. But, apart from very simple and very well documented problems, this validation can’t certify that the pathway taken was entirely consistent. Simply because there is no procedure of validation that can deal with such an amount of information and, more realistically, because it is impossible to gather the relevant field observations.

Any art is subjective. Thus, the only way to ‘validate’ a piece of art is to rely on the subjective judgement of your peers. The same concept can be applied to MABS through the social validation of the organisation and the outcomes of the simulations. Interesting attempts have been conducted (figure 5), with experts and local stakeholders discussing the validity of a MABS model and coupling the modeling with role-games (Bousquet et al., 2002).

Figure 5 Local stakeholders discussing the outcomes of simulations in Senegal (photo: F. Bousquet).

Limitations of the method or reservations about the method

From a knowledge and software engineering viewpoint, MABS suffers several limitations listed by Oliveira et al. (1999):

"*1. Domain specification problem. How can we formulate in a non-ambiguous way the problem at hand?*

2. Communication problem. What are the most suitable protocols enabling sophisticated interaction between agents?

3. Computational problem. Can we design and implement a system in a way that avoids computational overload?

4. Verification problem. What formal and practical approaches will allow us to verify, diagnose and easily correct MAS applications?"

One can add to this list the implicitly non-predictive character of multi-agent based simulations. This is specially the case with human ecosystems where human behavior can't be predicted beyond a limited domain of environmental changes.

How could the method be enhanced ?

In terms of data acquisition, the main problem for MABS comes from its ability to encapsulate qualitative information. Often, this information is coming from local stakeholders in a very clumsy way. Therefore, MABS scientists are working more closely with knowledge engineering (KE) specialists, in order to set up replicable methods for eliciting mental models (Bousquet et al., 2002). Bridges between KE and MABS concepts have already been created (Table1).

In terms of computer formalism, several teams are working on a purely Agent-Oriented-Programming language. Such a product would definitely solve the problem of computer engineers having to adapt OOP methods and tools to MAS oriented conceptual frameworks (Drogoul et al., 2003).

Hybrid models try to couple MABS with complementary methods coming from different theories: genetic algorithms, neural networks, system dynamics.

Table 1 Table of correspondance between knowledge engineering (KE) and MABS concepts.

Knowledge object	Description of knowledge objects	MABS formalism
Concepts (physical object, idea, person, organization)	Concepts are described by its relationships to other concepts and by its attributes and values	Class
Instances	Instantiated class	Instance
Processes (task, activity)	Sets of actions performed to satisfy a goal or a set of objectives. They are described using other knowledge objects, such as inputs, outputs, resources, roles and decision points	Operations
Attributes and values	Describe the properties of other knowledge objects. Attributes are generic properties, qualities or features of a class of concept Values are specific qualities of a concept and are associated to a specific attribute	Class attribute and Instance attribute's value
Rules	Statements like the form "If … then"	Methods
Relationships	Relationships between concepts or tasks The relation type may be a classification or a composition	Association, Aggregation or Inheritance

Judging the success of the method

Jager and Janssen (2003) judiciously quote Reynolds, father of the famous Boid's flock:

"*success and validity of these simulations is difficult to measure objectively. They do seem to agree well with certain criteria and some statistical proportions of natural flocks and schools […]. Perhaps, more significantly, may people who view these animated flocks immediately recognize them as a representation of a natural flock.*"

We are back to the cross-breeding between scientific and social validation presented earlier. In the case of human ecosystems, the MABS exercise has to be closely related to field activities and should be used in an interactive companion simulation approach. Missing this opportunity would reduce the exercise to a mere video game development.

Tools for operationalising the method

The number of platforms dedicated to MABS is increasing continuously. Some tend to be generic (SWARM, MADKIT), others are domain dependent like CORMAS (ecosystems) or NETLOGO (education). It is a source of confusion and deception for the potentially new users of MABS. On the other side, Dynamic modeling (for example) is relying nowadays on largely distributed VENSIM or STELLA softwares. Let's say that MABS is still very young and that tomorrows champions are already in preparation.

Marietto et al. (2003) conducted a comparative analysis of three platforms against a set of development and analysis criteria (Table 2).

Table 2 comparative analysis of three MABS platforms (Marietto et al. , 2003)

	CORMAS	MADKIT	SWARM
Scheduling technique	Discrete time	Discrete time or event-driveb	Event-driven
Agent launching method	As objects	As objects, applets or threads	As objects or threads
Message manager	Synchronous and asynchronous	Synchronous and asynchronous	Synchronous only
Organisational abstractions	Groups and aggregates	Agent-Group-Role structure	No groups
Multiple societies use	no	Group-like	As swarms
Behavioral events observer	Not formally	System agents	Not formally
Data analysis facilities	yes	no	Some libraries
Website	cormas.cirad.fr	www.madkit.org	www.swarm.org

Applications

What are the 5 key attributes that need to be present for this method ?

Initial question to answer with MABS
Justification of the level of granularity
Type of interactions between agents (task-based, communication)
Number of hierarchical levels
Type of validation

<u>Example 1</u>

Name: MANTA (1990)

Author: Drogoul A.

Team: Laforia, Univ ParisVI (France)

Domain: ethology

Description: ethologists studying ant colonies face many difficulties setting-up controlled experiments, specially when they want to study their initial phase of creation (abortion rate is very high). Thus the question was: Under which conditions a new colony might survive? Two levels of organization were chosen: the ants and the nest. The ants were designed as simple reactive agents and the communications are managed through stimuli propagation. With a minimum of external factors (light, humidity and food), the model was able to reproduce the initial stages of the edification of the colony. The identical agents were able to perform various tasks in order to maintain the nest, without any central control or perfect knowledge of their environment. Most of the results coming from MANTA were validated by ethological experiments.

Paper: Drogoul A., Ferber J. 1992. Multi-agent simulation as a tool for modeling societies: Application to social differentiation in ant colonies. In: Proceedings of MAAMAW'92.

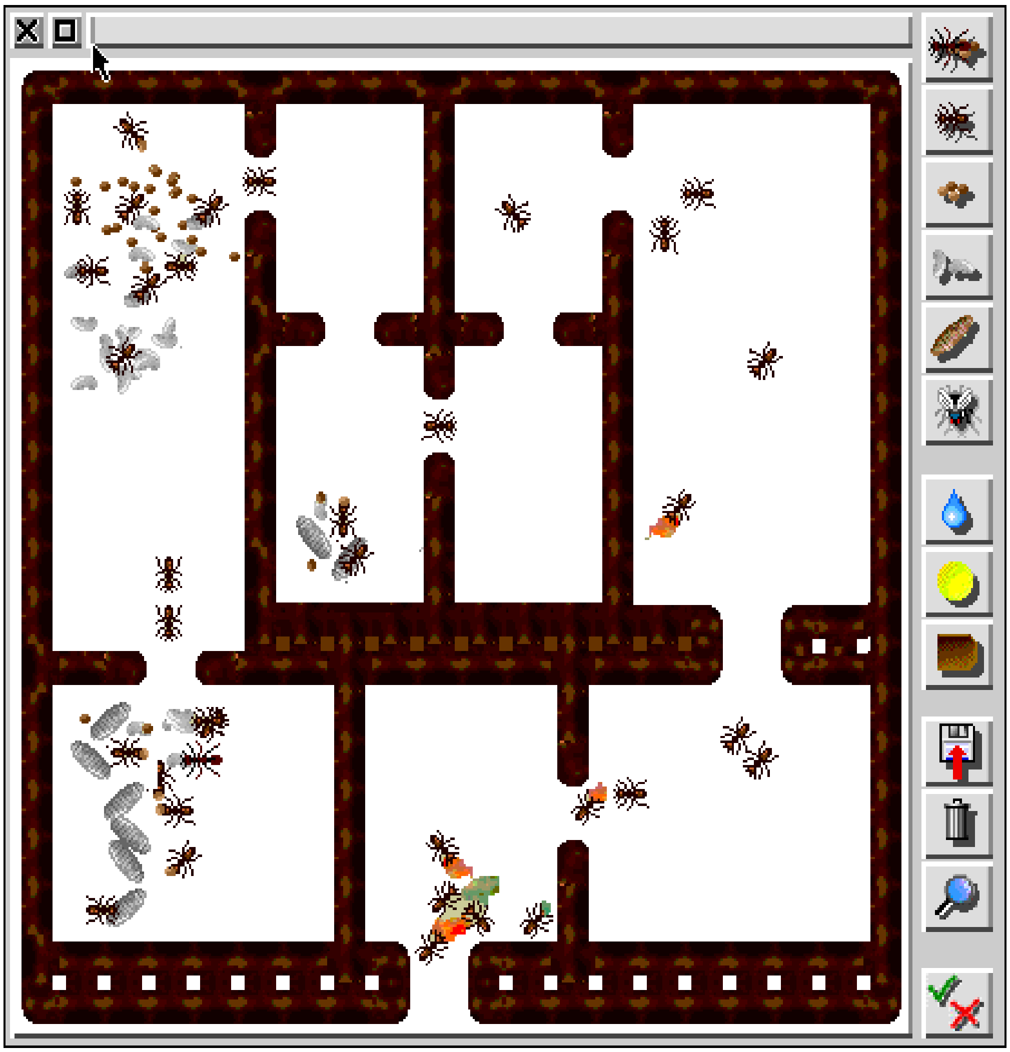

Figure 6 MANTA software. Main visual frame displaying the ant colony (Drogoul and Ferber, 1992)

Example 2

Name: CATCHSCAPE (2001)

Author: Becu N.

Team: CIRAD (France), ANU/RSPAS (Australia)

Domain: water management

Description: In northern Thailand water management in the small catchments becomes an increasingly conflicting problem. Climate variations overlap with growing water demands and socio-cultural issues in a very complex way. Thus the question was: Does upstream water management influence the sustainability of downstream farms? The granularity of the model was brought to the level of the household (social agent) and of the farmplot (spatial agent). Three levels of aggregation were chosen: the irrigation scheme, the village and the catchment. Farmers have to find the best cropping pattern according to the location of their plots and to the water availability. They can communicate with the weir managers, in charge of the water allocation. Results have shown that income distribution and farm sustainability present a much more complex pattern then a trivial upstream /downstream gradient. Agents adapt their expectations (water expectations and crop production) according to the past experiences. The social validation of the model is undergoing.

Paper: Becu, N., Perez, P., Walker, A., Barreteau, O. Catchscape: An integrated Multi-Agent model for simulating water management at the catchment scale. A northern Thailand case study. In Ghassemi F., Mc Aleer M., Oxley L., Scoccimaro M. (eds), Integrating models for natural resource management, across disciplines, issues and scales (MODSIM2001 congress, Canberra, 10-13 Dec. 2001). MSSANZ, CRES, Australian National University, Canberra, pp 1141-1146, 2001.

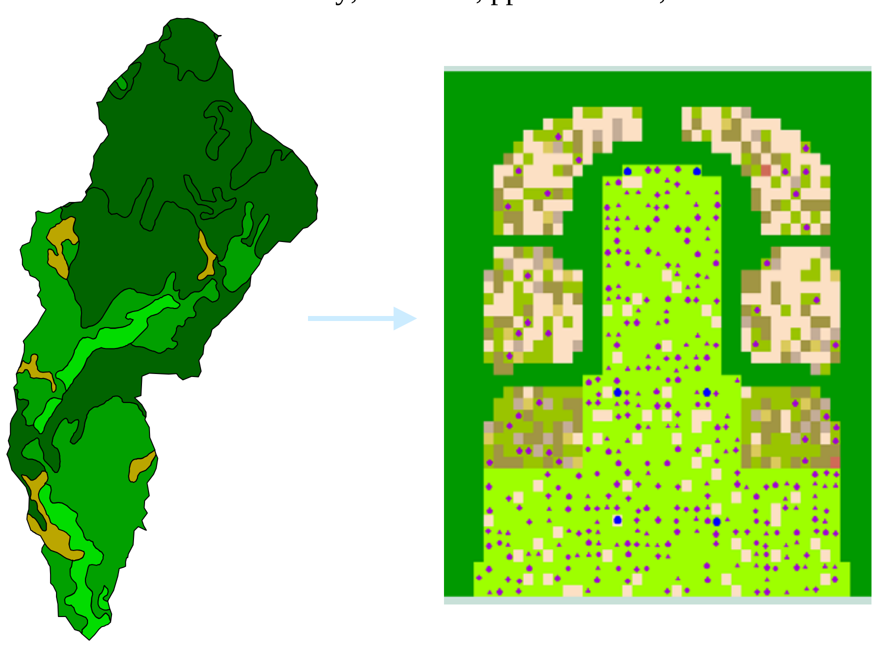

Figure 7 Moving from a GIS-based representation of the catchment to a MABS mesh. CatchScape model (Becu et al., 2001)

Sources of more information

Key publications

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Useful websites

http://www.santafe.edu/
http://cormas.cirad.fr/
http://cfpm.org/mabs2003/
http://www.tjurunga.com/
http://jasss.soc.surrey.ac.uk/JASSS.html

Key contacts

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APPENDIX 1

Timetable

Time	Description of session
9.00 – 10.30	MABS on the edge of chaos: a short introduction
10.30 – 11.00	Morning tea
11.00 – 12.30	MABS on the wind of change: know-how express.
12.30 – 13.15	Lunch
13.15 – 14.30	MABS for Dummies: discovering CORMAS.
14.30 – 15.15	MABS for Wizards: exploring CATCHSCAPE.
15.15 - 15.30	Afternoon tea
15.30 – 16.30	Reflection of method