Multi Agent Based Simulation: Beyond Social Simulation

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Abstract. Multi Agent Based Simulation (MABS) has been used mostly in purely social contexts. However, compared to other approaches, e.g., traditional discrete event simulation, object-oriented simulation and dynamic micro simulation, MABS has a number of interesting properties which makes it useful also for other domains. For instance, it supports structure preserving modeling of the simulated reality, simulation of pro-active behavior, parallel computations, and very dynamic simulation scenarios. It is argued that MABS is a useful technique for simulating scenarios also in more technical domains. In particular, this hold for the simulation of technical systems that are distributed and involve complex interaction between humans and machines. To illustrate the advantages of MABS, an application concerning the monitoring and control of intelligent buildings is described.

1 Introduction

Multi Agent Based Simulation (MABS) differs from other kinds of computer-based simulation in that (some of) the simulated entities are modeled and implemented in terms of agents. As MABS, and other *micro* simulation techniques, explicitly attempts to model specific behaviors of specific *individuals*, it may be contrasted to *macro* simulation techniques that are typically based on mathematical models where the characteristics of a *population* are averaged together and the model attempts to simulate changes in these averaged characteristics for the whole population. Thus, in macro simulations, the set of individuals is viewed as a structure that can be characterized by a number of variables, whereas in micro simulations the structure is viewed as emergent from the interactions between the individuals. Parunak et al. [19] recently compared these approaches and pointed out their relative strengths and weaknesses. They concluded that "…agent-based modeling is most appropriate for domains characterized by a high degree of localization and distribution and dominated by discrete decision. Equation-based modeling is most naturally applied to systems that can be modeled centrally, and in which the dynamics are dominated by physical laws rather than information processing."

We will here extend the work of Parunak et al. and argue for the applicability of MABS in other domains than it is commonly used, and while doing this compare it to some traditional simulation paradigms.

2 Multi Agent Based Simulation

MABS should not be seen as a completely new and original simulation paradigm. As we will see in this section, it is influenced by and partially builds upon some existing paradigms, such as, *parallel and distributed discrete event simulation* [16], *object oriented simulation* [23], as well as *dynamic micro simulation* [11,9].

2.1 MABS vs. Object Oriented Simulation

Since there is no commonly agreed definition of the term "agent", it is difficult to precisely define what constitutes MABS and how it should be contrasted to Object Oriented Simulation (OOS). What is referred to as an agent in the context of MABS covers a spectrum ranging from ordinary objects to full agents. For instance, we may characterize the entities in a simulation according to the following (not completely independent) dimensions:

- *pro-activeness*, ranging from purely reactive entities (cf. objects) to pro-active fully autonomous entities,
- *communication language*, ranging from having no communication at all between entities, via simple signals, e.g. procedure calls, to full agent communication languages, such as KQML [8],
- *spatial explicitness*, ranging from having no notion of space at all, to letting each entity be assigned a location in the simulated physical geometrical space,
- *mobility*, ranging from all entities being stationary to each entity being able to move around in the simulated physical space (however, not necessarily between different machines),
- *adaptivity*, ranging from completely static entities to entities that learn autonomously, and
- *modeling concepts*, ranging from using only traditional modeling concepts to using mentalistic concepts, such as beliefs, desires, and intentions.

Thus, there is no clear distinction between MABS and OOS, rather it may be viewed as a continuum; the further you go in each of these dimensions, the more MABS-like is the simulation. In an OOS, on the other hand, the simulated entities are typically purely reactive, not using any communication language, stationary, static, and not modeled using mentalistic concepts. How far you go in each of these dimensions is of course highly dependent on what entities are being simulated and the context in which they act. For instance, if a human playing soccer is being simulated, it is probably necessary to go quite far in all dimensions, whereas if a unicellular animal in a test tube is being simulated only a few dimensions are relevant.

2.2 MABS vs. Traditional Discrete Event Simulation

In principle, almost every simulation model can be seen as a specification of a system in terms of *states* and *events*. Discrete Event Simulation (DES) makes use of this fact by basing simulations on the events that take place in the simulated system and then recognize the effects that these events have on the state of the system. In continuous event simulations, state changes occur continuously in time, whereas they in DES occur instantaneously at a specific point in time. However, since it is possible to convert continuous models into discrete ones (by just considering the start and the end moments of the events), we will here only consider DES.

There are two types of DES, *time driven*, were the simulated time is advanced in constant time steps, and *event driven*, were the time is advanced based on when the next event takes place. The central structure in a traditional event driven DES is a time ordered *event list* were (time stamped) events are stored. A simulation engine drives the simulation by continuously taking the first event out of this list, setting the simulated time to the value of the time stamp of the event, and then simulate the effects on the system state (sometimes by inserting new events in the event list) caused by this event. Thus, since time segments where no event takes place are not regarded, event driven DES has the advantage of being more efficient, i.e., less time is needed to complete a simulation, than time driven DES. On the other hand, since time is incremented at a constant pace, e.g., in real time, during a simulation in time driven DES, this is typically a better option if the simulation involves human interaction (or even just monitoring) at run time, e.g., in training situations.

If we compare MABS to traditional DES we find that it has several advantages. Just like OOS, it supports structure preserving modeling and implementation of the simulated reality. That is, there is a close match between the entities of the reality, the entities of the model, and the entities of the simulation software. This simplifies both the design and the implementation of the software, and typically results in well-structured software. In addition, we argue that MABS has the following important advantages compared to more traditional DES techniques:

- It supports modeling and implementation of pro-active behavior, which is important when simulating humans (and animals) who are able to take initiatives and act without external stimuli. In short, it is often more natural to model and implement humans as agents than objects.
- It supports distributed computation in a very natural way. Since each agent is typically implemented as a separate piece of software corresponding to a process (or a thread), it is straight-forward to let different agents run on different machines. This allows for better performance and scalability.
- Since each agent typically is implemented as a separate process and is able to communicate with any other agent using a common language, it is possible to add or remove agents during a simulation without interruption. And, as a consequence of this and the structure preserving mapping between the simulation software and the reality, it is even possible to swap an agent for the corresponding simulated entity, e.g., a real person during a simulation. This enables extremely dynamical simulation scenarios.

- It is possible to program (or at least specify) the simulation model and software on a very high level, e.g., in terms of beliefs, intentions, etc., making it easier for non-programmers to understand and even participate in the software development process.

Of course, there are also some disadvantages with MABS compared to DES. For instance, a fully agent-based approach typically uses more resources, both for computation and communication, which may lead to less efficient (slower) simulations. Also, whereas MABS is very appropriate for time driven simulations, it is less appropriate for event driven simulations. In event driven MABS there is a need for either a central coordinator that keeps track of which event to be executed next, or a large amount of synchronization between the agents. Having a central coordinator would be contrary to some of the ideas that motivated a multi agent based approach in the first place, and the synchronization would slow down the simulations considerably.

2.3 MABS vs. Dynamic Micro Simulation

The purpose of Dynamic Micro Simulation (DMS) is to simulate the effect of the passing of time on individuals. Data from a large random sample from some population is used to initially characterize the simulated individuals. Some possible sampled features are, e.g., age, sex, and employment status. A set of *transition probabilities* is used to simulate how these features will change over a time period. The transition probabilities are applied to the population for each individual in turn, and then repeatedly re-applied for a number of simulated time periods.

Compared to MABS, DMS has two main limitations. First, the behavior of each individual is modeled in terms of probabilities and no attempt is made to justify these in terms of individual preferences, decisions, plans, etc. Second, each simulated person is considered individually without regard to its interaction with others. Better results may be gained if also cognitive processes and communication between individuals were simulated and by using agents to simulate the individuals, these aspects are supported in a very natural way.

In the past, both MABS and DMS has been applied mostly in purely social contexts [10], e.g., to validate or illustrate social theories (including biological, economic, and political theories), or predict the behavior of interacting social entities. Examples of such domains are:

- actors in financial markets [1]
- consumer behavior [13]
- people in crowds [21] and animals in flocks [20]
- animals and/or plants in eco-systems [5, 6]
- vehicles (and pedestrians) in traffic situations [22]

In most, if not all, of these simulation scenarios, only social entities are present. The main advantage of MABS explored in these simulations is that it facilitates the simulation of group behavior in highly dynamic situations, thereby allowing the study of "emergent behavior" that is hard to grasp with macro simulation methods. MABS has

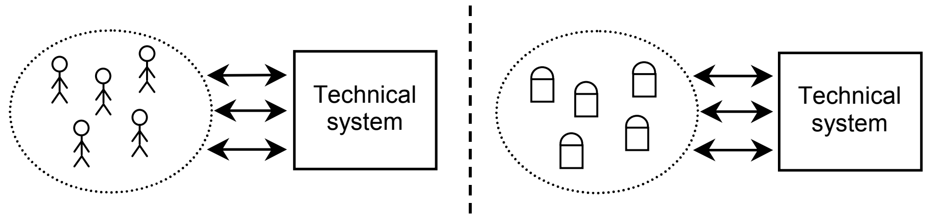

Fig. 1. To the left: the fielded system used by people. To the right: agent-based simulation of people using the system.

proven to be well suited for the simulation of situations where there are a large number of heterogeneous individuals who may behave somewhat differently and is therefore an ideal simulation method for the social sciences.

However, as we have seen there are a number of further advantages of MABS compared to traditional simulation techniques. This suggests that MABS may be a useful technique also for other types of simulation than of purely social systems. We argue that MABS is particularly useful for simulating scenarios in which humans interact with a technical system. (A similar argument has been made by Moss et al. [17] in the context of simulating climate change were humans interact with a physical system.) The purpose of such simulations could then be, e.g., evaluation of the technical system, or for training future users of the system. As a case study, an evaluation of a "socio-technical" system concerning the controlling of intelligent buildings will be described.

Many new technical systems are distributed and involve complex interaction between humans and machines. The properties of MABS discussed above makes this technique especially suitable for simulating this kind of systems. As illustrated in Fig. 1, the idea is to model the behavior of the human users in terms of software agents. In particular, MABS seems very suitable in situations where it is too expensive, difficult, inconvenient, tiresome, or even impossible for real human users to test out a new technical system.

Of course, also the technical system, or parts thereof, may be simulated. For instance, if the technical system includes hardware that is expensive and/or special purpose, it is natural to simulate also this part of the system when testing out the control software. In the next chapter we will see an example of such a case, a simulation of an "intelligent building".

3 A Case Study (Evaluation)

In a de-regulated market the distribution utilities will compete with added value for the customer in addition to the delivery of energy. We will here describe a system consisting of a Multi-Agent System (MAS) that monitors and controls an office building in order to provide services of this kind. The system uses the existing power lines for communication between the agents and the electrical devices of the building, i.e., sensors and actuators for lights, heating, ventilation, etc. The objectives are both energy saving, and increasing customer satisfaction through value added services. Energy saving is realized, e.g., by lights being automatically switched off, and room temperature being lowered in empty rooms. Increased customer satisfaction is realized, e.g., by adapting temperature and light intensity according to each person's personal preferences. A goal is to make the system transparent to the people in the building in the sense that they do not have to interact with the system in any laborious manner. By using an active badge system [12], the MAS automatically detects in which room each person is at any moment and adapts the conditions in the room according to that person's preferences. This project is currently in its simulation phase, but some fielded experiments at our test site, the Villa Wega building, in Ronneby Sweden, have been made to assure that the performance of power line communication is sufficient for controlling, e.g., radiators.

3.1 The Multi-Agent System

Each agent corresponds to a particular entity of the building, e.g., office, meeting room, corridor, person, or hardware device. The behavior of each agent is determined by a number of rules that express the desired control policies of the building conditions. The occurrence of certain events inside the building (e.g., a person moving from one room to another) will generate messages to some of the agents that will trigger some appropriate rule(s). The agents execute the rule(s), with the purpose to adjust the environmental conditions to some preferred set of values. The rule will cause a sequence of actions to be executed, which will involve communication between the agents of the system. For the format of the messages a KQML-like [8] approach was adopted. The language used to implement the MAS is April [15]. The agent-based approach provides an open architecture, i.e., agents can be easily configured and even dynamically re-configured. It is possible to add new agents or change their behavior at run-time without the need of interrupting the normal operation of the system.

There are four main categories of agents in the MAS: *Personal comfort agents*, which corresponds to a particular person. It contains personal preferences and acts on that person's behalf in the MAS trying to maximize the comfort of that person. *Room agents*, which corresponds to and controls a particular room with the goal of saving as much energy as possible. *Environmental parameter agents*, which monitors and controls a particular environmental parameter, e.g., temperature or light, in a particular room. They have access to sensor and actuator devices for reading and changing the parameter. Finally, the *badge system agent* keeps track of where in the building each person (i.e., badge) is situated. More details about the MAS can be found in [2].

Typically, the goals of the room agents and the personal comfort agents are conflicting: the room agents maximizing energy saving and the personal comfort agents maximizing customer value. Another type of a conflicting goal situation would be the adjustment of temperature in a meeting room in which people with different preferences regarding temperature will meet. We experimented with different approaches to conflict resolution, the simplest being based on a priori reasoning. For instance, the Room agents determine the desired temperature in a room by just accepting the temperature preferred by the person in the room. If many persons are in the room, it either takes the average of the preferred values, or makes use of priorities, e.g., by taking into account only the preferences of the manager and/or visitors. Of the run time solutions to conflict resolution, "coin flipping" using a random number generator is the simplest. A more sophisticated approach is to make use of a mediator, i.e., a third agent able to make an objective assessment of the situation, to resolve the conflict. We made some initial experiments using *pronouncers* [3] as mediators. Finally, we also regarded the possibility of resolving conflicts using negotiation between the agents. For example, an agent may propose that "if this time my preferences are used, yours will be used next time we are in the same room."

3.2 Evaluation of the MAS

Since it would be quite expensive to equip the Villa Wega building with all the necessary hardware in order to evaluate the approach outlined above, we decided to make a preliminary evaluation of the approach (i.e., the MAS) through simulations. In this case, the technical system can be divided into two parts; the hardware, i.e., the building including sensors and effectors, and the software, i.e., the MAS. Thus, we simulate the hardware and let the actual MAS, which will be used in the fielded application, interact with it instead of the actual hardware. Please note that the MAS does not simulate anything, it "just" monitors and controls the building.

Now, we must also simulate the people working in the building. As indicated earlier, we may do this by MABS where each person corresponds to an agent. This agent simulates the behavior of that person (to be contrasted to the personal comfort agents in the MAS which serves the person, i.e., is an agent in the true sense of the word). Fig. 2 illustrates the different parts of the simulation software.

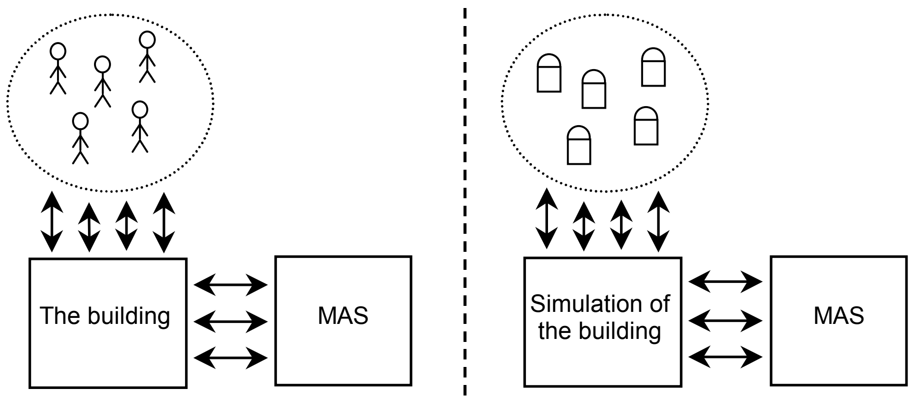

Fig. 2. Fielded (left) and simulated (right) use of the intelligent building control system.

By just specifying a few parameters that characterize the behavior of a person (e.g., which rooms she/he normally visits and how often, and the mean value and standard deviation for the time when certain events takes place, e.g., arrival to the building), we can easily create an arbitrary number widely different simulated persons. As we also want to simulate the building without the MAS in order to estimate the amount of energy saving and increased personal comfort the MAS can achieve, some additional parameters are needed, e.g., the person's tendency to forget to turn off the lights etc. A presentation of the simulation scenarios and the results can be found in [4].

The simulation of the physical properties of the building was based on the thermodynamical models described by Incropera and Witt [14], which were discretized according to standard procedures (cf. Ogata [18]). All the thermodynamical characteristics of a room are described by two constants: the thermal resistance, *R*, which captures the heat losses to the environment, and the thermal capacitance, *C*, which captures the inertia when heating up/cooling down the entities in the room. (In all simulations below we use the sample time 1 minute.). The temperature, T_{xi}, in room *x* at time *i* is described by:

$$T_{xi} = \frac{1}{1 + \frac{1}{R_x C_x}} \left(T_{x(i-1)} + \frac{P_i + \frac{T_{outi}}{R_x}}{C_x} \right) \tag{1}$$

where P_i is the heating power, T_{outi} the outdoor temperature, and $T_{x(i-1)}$ is the temperature one minute ago. Thus, the dynamics of each room is simulated using a traditional equation-based model, indicating the possibility integrating different simulation paradigms in order to explore their respective strengths.

4 Concluding Remarks

In the last chapter we gave a high-level description of a project aimed at investigating the usefulness of multi-agent systems for the design of control systems for intelligent buildings. The purpose of this case study was to argue for the use of MABS when *evaluating* complex technical system that are distributed and involves interaction with humans. A number of advantages of MABS can be identified, e.g.:

- Since each person is simulated by a separate agent, it is easy to simulate persons with very different behavioral characteristics.
- It is not necessary create a long event list prior to the simulation. The pro-active behavior of people moving from one room to another etc. is easily achieved. Only some parameters describing the simulated person's behavioral characteristics is needed.
- Well-structured simulation software.

- It is easy to increase performance since different groups of people may be simulated on different machines (also supports scaling).
- Very flexible simulation scenarios can be constructed since it is easy to add another person to (or remove one from) the scenario during a simulation.

In the case study, the evaluation of customer satisfaction was rather primitive. Although MABS probably is the most suitable simulation technique for making this kind of evaluation, it is difficult to define a truly meaningful metric for customer satisfaction. The best we can do is to continually measure the difference between the desired values of the relevant environmental parameters (according to the preferences specified by the person in question) and the actual values of those parameters during a simulation. However, we believe that there are more subtle aspects that influence the satisfaction a person gets from a system such as this. Unfortunately, these are probably difficult to define explicitly (and therefore hard to measure) but are at least as important. One such aspect regards personal integrity. How comfortable is it to know that your manager may know exactly where you are at any time? Thus, it seems difficult to make such an evaluation based only on computer simulations; it is necessary to let real persons use the system. Note, however, that this is not a limitation only for MABS, but for computer simulations in general.

We have not here demonstrated the usefulness of MABS for the purpose of *training* people. However, it is not difficult to find domains in which MABS seem to have a great potential, e.g., car driving [7], managing troops and other military units, managing companies, etc.

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