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MULTI-AGENT MODELLING IN COMPARISON TO STANDARD MODELLING

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ABSTRACT

Modeling and simulating complex natural systems is a demanding task. With multi-agent simulation a rather new modeling and simulation method is available that is based on a set of interacting autonomous agents. However, designing a multi-agent simulation is very effortful due to the increased amount of parameters of the model. Thus a modeler has to be sure about the advantages that he gains from it. This question is addressed based on an example of a bee recruitment model. Different attempts to represent that model as a Petri-net, a Queuing network or a multi-agent model show the different properties of these frameworks. In the conclusion aspects of a system that is best simulated by multi-agent simulation are summed up.

1 MOTIVATION

The best way of analyzing multi-agent systems that exhibit emergent phenomena or generate unforeseen patterns of spatial aggregation or global behavior, consists of modeling and simulating them. This kind of complex adaptive systems are characterized by locally interacting entities that produce a pattern or a behavior observable on a global scale that is not directly deducible from local behavior (Holland, 1998). Examples can be found in an ant colony as an adaptive superorganism, a moving traffic jam or other complex societal models.

Multi-agent simulation seems to promote a natural form of modeling, as active entities in the original are also interpreted as actors in the model (Klügl, 2001). The origins of this way of conceptualizing a model lie in Distributed Artificial Intelligence that deals with the theory, construction and application of multi-agent systems, i.e. systems that consist of several interacting intelligent entities (Ferber, 1999). Main characteristics of "agents" are their autonomy, their ability for flexible action in reaction to their environment and their pro-activeness depending on motivations generated from their internal states.

However, developing, designing and finally implementing a multi-agent simulation is not trivial. The situation is even worse, as there exists neither an unified formal framework for multi-agent models nor a widely accepted methodology for developing multi-agent simulations. A few formal frameworks for agent-based simulation were suggested, e.g. AgedDEVS (Uhrmacher, 1996) that focuses on the internal model of agents and their representations of social relationships for facilitating the formulation of variable structure models. Another example is PECS (Urban 2000) that seem to be more like an agent architecture, as it is focusing on the different components an agent should be contain.

This mirrors the current situation in Distributed Artificial Intelligence with a variety of mainly logical frameworks for specifying multi-agent systems – e.g. ConcurrentMetatem, that is based on temporal logic (Fisher, 1995) or AgentSpeak(L) (Rao, 1996) as an operational BDI (Belief Desire Intention) Logic. DESIRE (Gavrila and Treur, 1994) as a framework for describing knowledge-based systems based on components, is also used for specifying agent-based systems. Another approach is the application of predefined Z-Schemes suggested by (Luck et al. 1995).

Thus, in this situation – without any help from an accepted, generally applicable formalism – a modeler has to deal with complexity of multi-agent simulations rather on his own. Thus he must carefully think about whether the instrument of multi-agent simulation is necessary and explain why there is no "simpler" method for modeling and simulating the system. This even leads to the basic question, what the advantages of multi-agent simulation are?

In the following we want to tackle the question of suitable formalisms based on comparing different standard methods for concurrent processes applied to an interesting model. After introducing our test scenario, different modeling attempts as a Petri-net or a queuing network model are given. Some thoughts about a potential representation as a cellular automata are followed by a version as multi-agent model. The contribution concludes with a summary of characteristics of systems where multi-agent simulation may be well suited.

2 TEST SCENARIO

The basic question that ought to be answered by the example model is the following: how the nectar input of a bee hive is influenced by a recruitment strategy. The environmental context, determined by the distribution and variability of resources, forms the main input variables to the model. We used two different scenarios – with and without recruitment combined with the communication of the position of the newly discovered resource. The output of the model is measured by the nectar input of the different colonies.

The original multi-agent model was designed, calibrated and validated against experimental and literature data. The model that we used for this study, is a preliminary version of it. However, it is sufficient as it exhibits all interesting features. The detailed concepts of the model are given in figure 1.

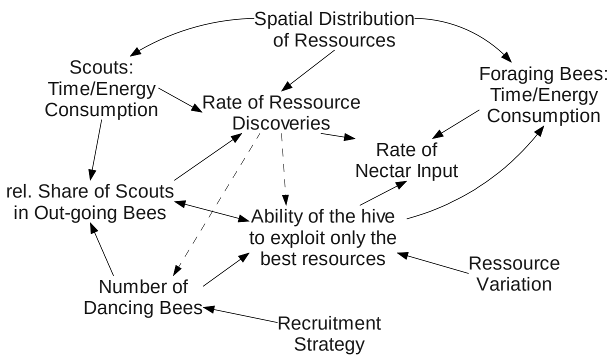

Figure 1. Informal representation of the relations between different (individual and global) variables of the test scenario

The behavior of an individual bee can be described in the following way: A bee normally waits inside of the hive. In some individually perceived situation (lack of energy, etc) it becomes a scout and starts to fly according to some random search until it finds a resource patch. The distribution of resources is one of the input variables of the model. When such a scout successfully returns to the hive, it decide on its further behavior: First whether to recruit other bees for foraging bees at the newly discovered resources by dancing, second if the bee itself returns to the resource as a “normal” forager or alternatively to stay in the hive and wait again. This decision is based on the quality and amount of the nectar in the newly discovered resource in comparison to the quality and level of the nectar storage in the hive. Also the number of potentially recruited bees is depending on the evaluation of the nectar source by the scout who dances more or less intensively. We compared it against a scenario without recruitment. Scouts become forager and might return to their resource without communicating. This part of the model is not as interesting as the part with recruitment for the modeling effort described in this paper, therefore we won’t deal with it further.

Although the recruitment scenario does not require to deal with variable structures in the sense of a variable number of bees, it exhibits some interesting features, that illustrate its complexity:

- Conditional behavior based on internal attributes of an agent and on external perceptions, like the energy level inside of the hive or the position of the memorized resource that the bee returns to.
- Variable interaction partners. Executing the recruitment behavior, it is not predefined, which bees and how many are going to forage at the resource. The interaction between recruiting bee and the waiting bees in the hive cannot be fixed.
- Heterogeneous space as the main input factor.
- Decisions on further behavior based on Evaluations of some non purely local property (energy storage in the hive).

This type of insect behavior is a rather typical application example for multi-agent simulation. There are many other simulations dealing with (pheromone) recruitment of ants. Also task allocations models in combinations with different mechanisms for specialization form good test beds for the method of multi-agent simulation. However, all these models of agents as insects focus just on the behavior of rather simple interacting agents. The situation become much more complex when dealing with social systems consisting of humans. These models cannot concentrate on pure – externally observable – behavior, but also have to incorporate sophisticated internal models of the agents – representing social relationships, individual desires or intelligent generation of behavior, which lead to structural problems in validation. Thus the simpler behavior-oriented multi-agent simulation seems to a justified starting point for a study about alternative modeling efforts.

3 STANDARD METHODS FOR CONCURRENT PROCESSES

3.1 Queuing Networks

Queuing Networks are a standard formalism for performance analysis in production systems. However, (Anderson, 1998) has already successfully applied this framework to the simulation of task portioning and its regulation between foraging and storing bees in a very simple scenario. As the scenario presented here can also be interpreted as performance analysis under different interaction and environmental conditions.

Queuing networks are directed graphs. There are two different types of nodes, servers with or without a queue. Jobs are wandering along the network. The servers represent resources, that the jobs have to be processed by. If the server is busy, the job has to wait in the queue in front of that resource. Every queue may have its special queuing discipline. Connections between the different elements are either deterministic (without branching) or probabilistic (branching or merging).

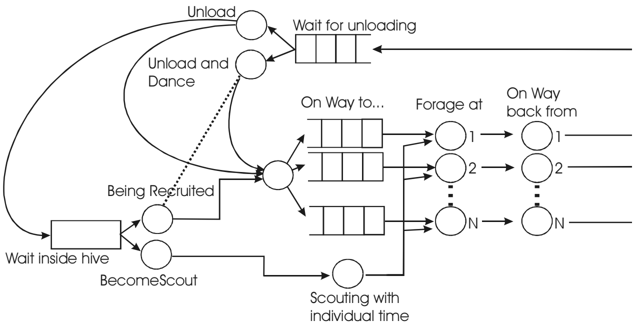

Figure 2. Attempt of formulating the model as a queuing network. The dotted line tries to represent that the servers "dancing" and “being recruited" are depending. The box “wait inside hive” represents a waiting state the end of which end is not determined by a resource.

Figure 2 shows a possible representation of the test scenario as a Queuing Net with the following properties:

- Waiting inside of the hive seems to be a problematic state, as the termination of this waiting state cannot be associated with a resource, but the internal state of a job. However jobs usually possess no internal structure.
- Returning to the same resource can be modeled with N different loops that deterministically lead one bee-job back to one particular resource. This makes the network rather complex, but allows to represent spatial differences, like the travel time between hive and resource.
- The decision whether to recruit or not is depending on non-local information, but on some quasi-global value of energy state of the hive.
- Recruitment requires to simulate at least two bee-jobs in particular activities, i.e. being processed by two servers in a synchronized way.

3.2 Petri-Net

Petri nets have been accepted as a powerful formal specification tool for a variety of systems including concurrent, distributed, asynchronous, parallel, deterministic and non-deterministic ones (Baumgarten, 1990). It is mainly used for dealing with performability issues in systems with concurrent processes with local behavior. Thus it seems to be provide an ideal framework for modeling a multi-agent system (see also Holvoet, 1995). According its basic definition, the core of a Petri net structure consists of a finite set of places and a finite set of transitions. Places can hold tokens (one or more tokens with or without colors). The colors of the token represent its internal state and allow to formulate behavior in reaction to this internal state. Between a place element and a transition element there are arcs, characterizing the flow of tokens. Transitions may take time or may describe deterministic or stochastic events. In a colored Petri-net a transition or event may change the color, that means it may change the internal state of the token. In figure 3 an attempt for formulating the model using a Petri-net is depicted.

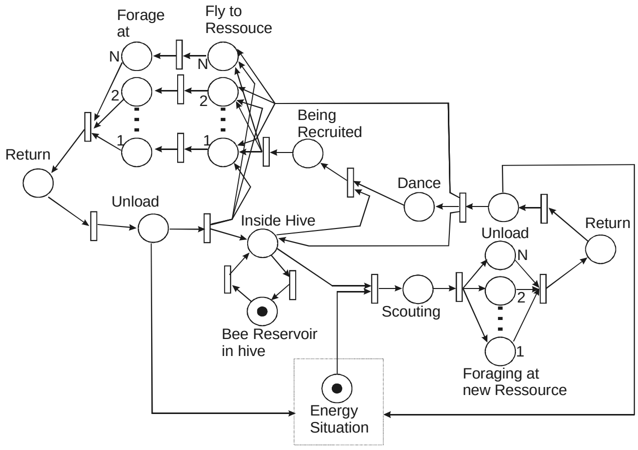

Figure 3. Attempt of formulating the model as a Petri-Net

The process of bee behavior taking bees as tokens could be modeled rather elegantly. The comparison to the quasi global value of energy level inside of the nest could not be represented in a satisfying way: the dotted box and lines just indicate this feature. As the colored tokens may store the information about which resource was visited separated loops for the different resources are not necessary, but if the number of resources is changed, a different net has to be tested. Time delays – according to the duration of the flight to a resource – can be expressed in a timed Petri-net, when the transitions can only fire after the token has resided in the preceding places.

However, there are a few problems. In some situations it is necessary, that a transition fires when just one preceding place carries a token, resulting in just on succeeding place with a token (e.g. scouting → Foraging at a new resource). Additionally it is not clear, how to integrate multiple recruitments, that characterizes the situation when excited by a excellent new resource more than one bee is caused to fly to this resource. The modeled feedback loop - more bees are flying to a good resource than to a worse one – is therefore restricted to the effects of abandoning worse food sources.

3.3 Cellular Automata

A main problem of Petri-nets and Queuing networks is the total lack of mechanisms for representing inhomogeneous space. Flying times and the rate of discovering new resources based on more or less random movement can only be expressed by stochastic terms in a very abstract way. The consequence is that either at every decision point involving abstracted space a probabilistic factor is used, or a fix amount of resources are distributed with predefined flying times, etc. A variable environment that is a central part of the original research effort could not be expressed except by changing the structure of the networks.

Cellular Automata, on the other side, can be seen as purely space based representations. They were successfully applied to bee simulation for several times (for example Camazine, 1991). However, one of the main properties of a Cellular Automaton is that rules are uniformly associated with every cell. That means the rules for every cell are the same (Toffoli and Margolos 1987) and just govern the behavior of this cell in relation to its neighborhood. An agent that is located on a cell can be represented by a certain state of this cell.

However, the consequence is that even agent movement can only be expressed in rather complex way, as a rule can not change the state of more than one cell concurrently. Individual behavior of the agents also has to be integrated into that one uniform rule set. Therefore, Cellular Automata are seldom used for simulating multi-agent systems themselves, but are a popular mean for representing an interesting environment (Cohen et al., 1989, Epstein und Axtrell, 1996)

4 MULTI-AGENT MODEL

In a multi-agent model the model mainly consists of the description of the agents – of their behavior and their initial state. Agents perceive their environment via sensors and exert changes in their environment with their effectors. The behavior of an agent determines how the sensory input is related to the effectory output. This behavior can be described – in a rather simple form of agent, e.g. using rules or an activity automaton. This description is interpreted and produces the dynamics of an agent during simulation. To concentrate on the behavior alone is not sufficient as the interactions of the agents are often the most difficult part due to synchronization problems, etc. Thereby the modeler has to solve the problem to design interacting agent behaviors that lead to the desired over all system behavior. This is by no mean trivial and there exists no methodology or formal framework to support this process. The situations becomes more complex, when the agent behavior has to exhibit properties of pro-activeness or not a priori defined flexibility. Intelligent agent architectures are necessary, incorporating (reactive) planning facilities based not only on a model of the environment, but also on social models of the other agents.

For the bee communication model a behavior-oriented description is sufficient. That means, that the bee agents are not equipped with true reasoning capabilities but their behavior is explicitly described. Figure 4 shows the behavior of a bee agent in an enhanced UML activity diagram. This diagram specifies not only the different activities of one agent, but also the relations to the environment based on explicit interaction description (Oechslein, 2001). The configuration of the complete model contains an additional description of the spatial environment and its dynamics. In the test model these are several maps with distributed resource objects according to parameters that resemble the relevant properties of the different habitats.

This kind of representation is very powerful. However it lacks the formal conciseness like Petri-net, Queuing networks or even cellular automata. Primarily it is just a means of communication and not a precise model. The graph depicted in figure 4 is not directly comparable to the models given in figure 2 or 3, as the information in the formal figures is sufficient to simulate the model without ambiguity. The price for it is the aggregated and abstracted information that it contains. The multi-agent model represented in figure 4 contains much informal information, but based on the additional interaction nodes (in form of comment nodes) the ambiguity is reduced.

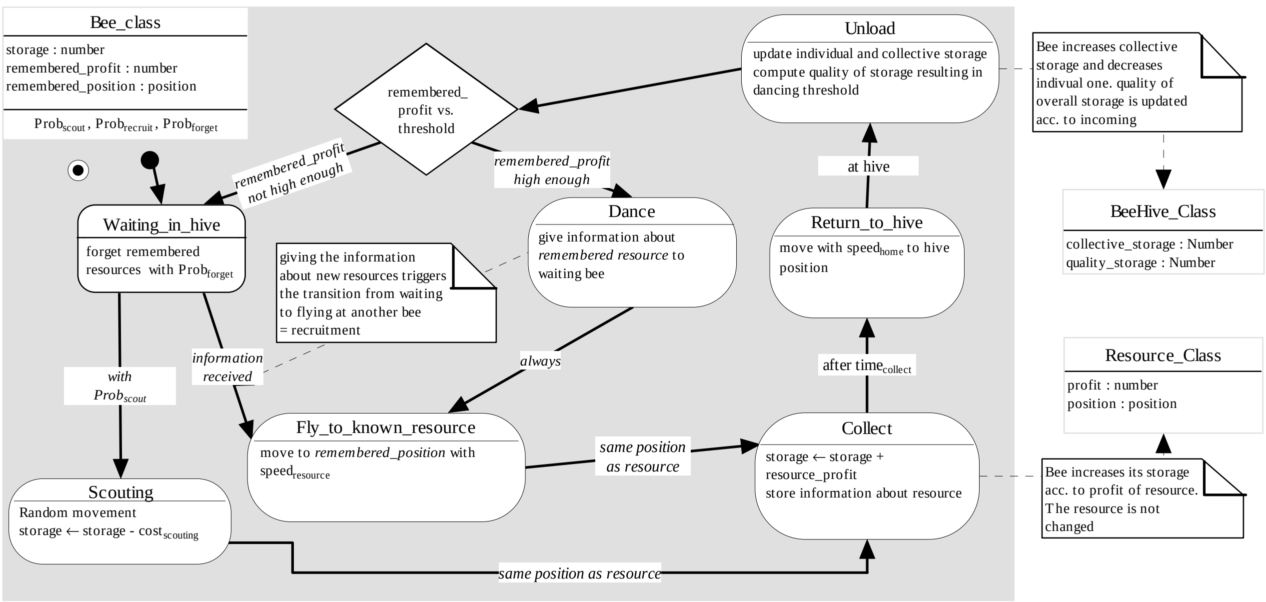

Figure 4. Bee behavior in a multi-agent version of the model (enhanced UML-activity graph)

5 DISCUSSION AND CONCLUSION

Based on the attempts to represent the same model in different frameworks one may propose some properties for a modeled system that advise the use of a multi-agent simulation.

- When feedback loops in the agents behavior are important, but the conditional behavior they are based on is not purely locally determined. When the ability of the entity to decide is not only based on its local surroundings but also must relate to more or less global properties or values, then a multi-agent simulation is well suited.
- When the feedback loops are not fixed in the sense that the number of affected entities is not predefinable or the existence of the feedback loop is depending on additional factors, then the formulation of flexible agent behavior has advantages to network structures with fixed connections.
- When inhomogeneous space is relevant, then abstractions using stochastic terms for flight times, etc. might not always be sufficient to reproduce the effects of space onto different behavioral patterns, or at least make a valid representation of behavior unnecessarily complex compared to an multi-agent model. The problem seems to be still more sophisticated, when the configuration of the relevant spatial patterns has to undergo dynamic changes.
- When flexible conditional or even adaptive individual behavior has to be formulated, then it could be easier to concentrate on the behavior of an agent than to describe a network that is passed through by a token, even if it carries an internal structure. Adaptivity of behavior was not a central point in this study, but is also an important feature that is rather directly represent-able in an agent-based model, whereas it causes problems in other modeling frameworks.
- When interactions with flexible individual participants have to be represented, then it might be hard to formulate it using either uniform entities or predefined sequences of processes. When it is not irrelevant who the interaction partner of a particular agent is, or the agent may flexibly decide not to interact at all, then a focus on the agent, its behavior and reasoning may be advisable. Another advantage of multi-agent simulation consists in its un-fixed interaction participants. That facilitate the modeling of variable agent numbers. When an agent has to be erased or a new agent enters the scenario, it may start interacting with the other agents without complex re-configurations of the system. However, this advantage is relative to the application domain.

As mentioned above multi-agent simulation currently has a lot of drawbacks. The huge parameter space that has to be searched for valid system behavior causes an immense effort on justification, modeling and simulation. The lack of a formal framework makes the un-ambiguous presentation of a model a rather hard task. Thus there a some properties of the original system that on the other hand make the method of multi-agent simulation not advisable, although it seems to become a rather popular method.

- If it is not clear, what parts of the system can be identified as agents, then multi-agent simulation is not apt. Components with simple non-autonomous behavior or systems with fixed direct connections between components with well defined input-output behavior can be tackled with better developed methods.
- If the considered space has a large extension or the agent numbers are huge, then an abstraction of homogeneous space and homogeneous societies may still be satisfying. A macro simulation approaches might to be sufficient. One has to regard that a simulation of millions of agents takes very much time, especially compared to the computations necessary for simulating a set of differential equations.
- If a formal analysis of the model without simulating is necessary, e.g. for detecting deadlocks, etc., then a modeling method resulting in an exact and explicit model is necessary. Such a modeling method does not yet exist for multi-agent models. This restriction might change as there is a lot of ongoing work about formal specification in distributed artificial intelligence aiming at tools for software specification and verification.

As a conclusion one might say that multi-agent simulation is not a new modeling paradigm that solves every problem of the established ones. But it has many advantages, so that its application in particular domain, e.g. biology, sociology is very promising. But the frameworks and methods for actually designing and simulating a multi-agent model are somehow immature, therefore theorists and practitioners in multi-agent simulation can learn a lot from established modeling techniques.

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