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Modeling Artificial Life Through Multi-Agent Based Simulation

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1. Introduction

The Multi-Agent Based Simulation (MABS) area is placed at the intersection of two distinct areas: Distributed Artificial Intelligence (DAI) and Computational Simulation. This field of research provides a proper infrastructure for modeling and understanding the processes related to social interactions such as coordination, cooperation, training and coalition of groups and resolutions of conflicts, among others. Such understanding is made possible because of the relationship established between local and global behavior, which leads to leading to explicit chains of cause and effect of how internal agent components affect the agents behavior, how this behavior affects the agency and, dialectically, how the agency affect its agents components. Multi-agent simulation models are based on the concept of the individual-program relationship, which allows the simulation of artificial worlds where each entity (interactive computing entity) is represented as an agent that maps a single entity (or a group of them) in the target system. Since the infrastructure of technical and theoretical areas of simulation allows researchers to mimic the essential elements of a target system without having to work directly with the target system itself, it becomes handful when dealing with phenomena such as the spread of fire without hazarding the integrity of the environment and its living beings.

Artificial Life in Computers yields the creation of a laboratory capable of providing the necessary means to study, research, reproduce and maximize the simulations on a specific subject. As stated previously, a simulation model is a particular type of model that aims to represent a given system. However, it differs from classical models in the sense that it facilitates a) the study of how the modeled systems behave under certain conditions, and b) the examination, in varying degrees of detail, the consequences of changing internal behaviors of the system, and vice versa.

The results obtained in a simulation might be of great help in the decision-making process, in the evaluation of systems and in reducing implementation time and costs.

In (Ferber, 1996; Gilbert & Troitzsch, 1999) some simulation goals are presented, namely:

- Discover and formalize new theories and models;
- Develop a better understanding of some features of the real system;
- Test hypotheses of the modeled system;

- Predict future actions and behaviors.

More specifically, (Ferber, 1996) defines that an agent-based simulation model relates to the idea that a system is comprised of all relationships of its inner parts, and in that sense, it is possible to simulate an artificial world based on the relationships of its entities.
The simulation occurs when there is a transposition of the population of a target system [1] to a *conceptual model* equivalent, followed by the encoding of this model to a *computational model*. In this case, an agent (or actor) equates to a real world entity or a group of them. Such actors can be of different natures and with various granularities, such as humans, robots, computer programs, inanimate objects and organizations.
After the establishment of the multi-agent paradigm in the computer science, the role of multi-agent based simulation has been acquiring relevance in a variety of scientific disciplines. In particular, the sources of analogy between agent-based technologies and models of actual social systems, and the efforts towards dealing with such complex systems through simulation models have created this intense interdisciplinary effort that provided ground for the advent of a new scientific field, named Multi-Agent Based Simulation (MABS). As a result, research interfaces were created across various disciplines under the umbrella of a multidisciplinary area that involves researchers from as diverse fields of study as Psychology, Sociology, Economy and Computer Science.
Considering the relatively recent advent of MABS, its multidisciplinary aspect might also pose as one of the biggest challenges to be overcome by researchers, since it requires cutting across traditional boundaries of school of thoughts, mixing different theories, methodologies, techniques and point of views. In this chapter, the principles of multi-agent based simulation are presented, as well as some simulations that exemplify the integration of MABS and artificial life. To accomplish that, the chapter is divided in three main parts: the first part focus on the presentation of MABS concepts and techniques. The second part presents some of the main simulation platforms and frameworks available today and also analyses and compares two of them. The third and final part displays a set of models that aim to simulate artificial life though the use of MABS techniques.

2. Principles of Multi-Agent Based Simulation

The main goal of the Multi-Agent Based Simulation (MABS) researchers is to develop and study simulation models taking into consideration a theoretical-technical framework based on the Distributed Artificial Intelligence field. The general relevance of simulation, and more specifically agent-based simulation becomes so clear that some authors have gone far enough to consider it as a third way of doing science, along with traditional deduction and induction reasoning (Axelrod, 1998). It could be stated that simulation distinguishes from standard deduction and induction in its implementation and also in its goals. A simulation starts with a set of explicit assumptions (as in deduction) but not generally providing any theorems, producing data which are suitable for analysis by induction that come from a strictly set of assumptions.
Following that perspective, a simulation model is a kind of model that represents a specific target system. What makes this model distinct from the others is (i) the chance of studying the global behavior of the modeled system in certain conditions and (ii) the possibility to inspect the consequences of changes in the internal components of the system. An important aspect to be considered in simulation systems is the assurance that both conceptual and

[1] The target system is equivalent to the simulation domain and can be real or theoretical.

computational models accurately represent the target system, and that can be achieved by using two processes: validation and verification.
The validation process aims to certify that the conceptual model represents the target system in an acceptable degree of adherence. Thus, the validation processes fundamentally addresses a specific question: Does the simulation outcomes correspond to those from the target system? On the other hand, the verification process' main purpose is to assure that the conceptual model was correctly translated to the computational environment. Specifically, a multi-agent simulation model is based on the concept that it is feasible to simulate an artificial world inhabited by interactive computational entities. Such simulation can be achieved by transposing the population from a target system to its artificial counterpart. In that sense, an agent is similar to an entity or a group of entities of the target system. Moreover, agents can be of distinct natures and granularities, such as human beings, robots, computer algorithms, inanimate objects and organizations.
In a multi-agent based simulation, the relationship between agents can be specified in several ways, ranging from reactive to deliberative attitude approaches. In both cases, agents must be able to decide and perform their actions autonomously. Nevertheless, to ensure a proper execution of the simulation, agents actions must be synchronized through the scheduling of a minimum set of events, and their behavior can be either time-stepped scheduled - performed within each discrete time step - or event-driven scheduled, in which agent actions are scheduled by other agents' actions and/or events.
The MABS area provides a suitable infrastructure to model, study and understand the processes related to complex social interactions such as coordination, collaboration, group formation, evolution dynamics of norms and conventions, free will and conflict resolution, among others. That can be achieved by relating local and global behavior and analyzing how agents can affect the environment and other agents (and vice-versa, leading to explicit chains of cause and effect), how internal agent components affect the agent's behavior, how this behavior affects the agency and, dialectically, how the agency affects its agents components (Gilbert & Troitzsch, 1999).

2.1 Multi-agent modeling

Multi-agent simulations require the development of multi-agent models, which aims to model complex real-world systems as dynamical systems comprised of interacting autonomous decision-making entities called agents. Traditional analytical methods might not be suitable to deal with complex phenomena that are simply too complicated to be analytically tractable, especially when involving non-linear relationships. Multi-agent models have then emerged as an alternative for these types of problems. In recent scientific literature, many denominations for agent-based modeling can be found, such as: Individual-Based Modeling (IBM), Agent-Based Systems (ABS), among others.
An agent-based model is essentially a population of heterogeneous agents, which represents autonomous entities that interacts between themselves and with their environment, allowing the formation of a social system where aggregated structures (patterns) emerge from those interactions. The fundamental principle of an agent-based model is the emergence of social structures and groups of behaviors from the interactions of individual agents. These agents operate in artificial environments and under specific rules that are valid only when taking into account the limitations of each agent regarding their own computational and memory capabilities.

In Table 1 a comparison between a traditional and agent-based modeling is presented (each of the aspects is explored in the subsequent sections of this chapter).

Traditional	**Agent-Based**
Focus on continuous time	Focus on discrete time
Mathematical language (equations)	Descriptive model
Aggregate level granularity	Individual level granularity
Top-down (macro-to-micro) approach	Bottom-up (micro-to-macro) approach
Pre-defined behavior	Emergent behavior
Global control	Local control

Table 1. Comparison Between Traditional and Agent-Based Modeling.

2.2 Main aspects of multi-agent models

Simulation models based on multi-agents are comprised of a number of heterogeneous agents, relationships between these agents and an environment capable of simulating the behavior and interactions of such agents. Also, there is no central authority in charge, as agents are modeled to behave autonomously in a self-organized model based on simple local rules of interactions between agents and the environment. The ultimate goal of such model is to allow the emergence of system-level phenomena resulting from these local interactions between agents themselves and the environment.

A more specific definition of agent would be of a discreet entity with its own objectives and behaviors. Each agent contains internal states and behavior rules, allowing them to interact with other agents and the surrounding environment. Agents are also autonomous and display some degree of initiative, allowing them to behave as object-oriented entities. They are modeled to execute the vast majority of their actions without any direct interference from either humans or other computational agents. Examples of agents include people, groups, organizations, social insects, swarms, robots, and so forth.

2.2.1 Ascending (bottom-up) modeling

Agent-based models are built from agents that have very simple rules defined for their behavior. The interactions between these agents create collective structures in an ascending approach instead of a descending one, where the macro structures and behavior of a system would be modeled and then used to explain micro interactions of its components. Modeling a complex system using a top-down approach would prove much too complex and not appropriate as a complex system behavior is the result of a large number of interactions. An analytical/reductionist approach is also not adequate for modeling complex systems as it assumes that the system behavior can be understood by analyzing its parts separately.

So a bottom-up model is therefore more suitable for complex systems such as the ones applied to artificial life simulation, as the bottom-up approach focus instead on simple rules of behavior for small parts of a system - its agents - and how they interact with each other, making use of computational power to simulate a large number of those agents and their interactions, allowing emergent patterns to be observed and studied. The model can then be easily manipulated in terms of addition or removal of its micro-level individual properties and how these changes might affect the macro-level social phenomena. For instance, a bottom-up model for an ant colony would describe ants in a micro-level and in terms of their behavior as individuals in the colony and how they communicate to each other. A simulation tool

would then be used to mimic the colony environment where several individual ants are put to communicate and perform tasks, allowing an observer to study the emergence of colony-level social phenomena.

2.2.2 Complex systems

The word "complexity" has roots in two Latin words: "complexus" which means "totality" and "completere" which means "to embrace". So complex system are formed by two or more interlinked components that creates a network of objects interacting with each other, displaying a dynamic and aggregated behavior. In this context, the complex adjective is not to be confused with complicated. Moreover, in a complex system the action of a single element might affect the actions of other objects in the network, making the famous paradigm 'The whole is more than the sum of its parts' even more true.

In fact, complex systems are made of several simple behavioral units that influence each other mutually in an intricate network of connections that ultimately generates a global complex behavior. As a result of such a systematic behavior, many properties of a complex system can only be observed during its collective behavior and cannot be identified in any of its fundamental units. One example of a complex system is the fire propagation phenomenon. An adequate (non-analytical) approach to treat complex systems, more specifically the fire propagation phenomenon, is to use simulation techniques based on Cellular Automata (CA). Simulating complex systems allows researchers to (a) propose new structures or alternatives to treat social systems, studying and understanding their existence and operation; (b) have a better understanding of the social, anthropological, psychological aspects, etc. used to describe and explain the analyzed phenomena and (c) to use existing theoretical models already proven effective when dealing with institutional and social processes.

2.2.3 Unpredictable systems

Unpredictable systems are complex systems with a high degree of instability and unpredictability in the decision-making process, and such aspects need to be treated in a dynamic manner. According to (Lempert, 2002), agent-based models are often useful under conditions of deep uncertainty where reliable prediction of the future is not possible by either in a best estimate or probabilistic approaches (such as the ones in traditional simulation models).

In his work, (Lempert, 2002) argues that agent based models are useful at describing the behavior of inherently unpredictable systems. According to him, the predictive policy analysis is an example of application of agent-based simulations, as police simulators may be effective in situations where the standard methods of predictive policy analysis are least effective. Also, in dynamic and unpredictable systems, agents must be modeled in a way that their deliberation and responsiveness are balanced so that they act appropriately. This must be done to avoid long deliberations that might impact the performance of the simulation but also to avoid agents to become too reactive to choose the best action to execute.

2.2.4 Emergent behavior

According to (Axelrod, 1998), 'emergent properties' of a system can be described as the large-scale effects of locally interacting agents, noticed as non self-evident, stable macroscopic patters arising from individual agent's local rules of interaction. Below is a non-exhaustive list of situations when agent-based models are useful for capturing emergent behavior:

1. The interactions between agents are discontinued, nonlinear. This can be particularly useful when describing complex individual behavioral. Discontinuity proves much too complex by using traditional analytical methods (for instance, differential equations);
2. There is a significant necessity of designing a heterogeneous population of agents. The heterogeneity allows agents with clearly distinct rationality and behavior to be modeled;
3. The topology of the agent's interactions is complex and heterogeneous. This can be particularly useful when modeling social processes, specially the inherent complexity of physical and social networks.

Emergent phenomena can also be formalized as requiring new categories to describe them, which are not necessary to describe the behavior of the model's underlying components (i.e. agents) (Gilbert & Terna, 2000). In some models, the emergent properties can be formally deduced, but they can also be unpredictable and unexpected, as anticipating the consequences of even simple local interactions sometimes proves to be a hard task. Also, according to (Axelrod, 1998), an example of emergent phenomenon can be seen in a model where agents represent consumers and have local behavior rules that allow them to choose and buy brands of video tapes according to the availability of machines on which to play it. Only by analyzing the agent's local rules, one would not intuitively notice that the simulation model is most likely to lead one format to completely overcome the other.
Moreover, mathematical analysis might be limited in its ability to derive the dynamic consequences in models where, for instance, agents have an adaptive behavior influenced by their past experience. For this type of situation, a simulation model is usually the only feasible method.

2.2.5 Open systems and self-organization

Self-organization is a process where the organization of a system is not guided or managed by an outside source. Self-organizing systems normally represent open systems and might typically display emergent properties. Open Systems in turn can be described as a system with high environmental adaptability through quick incorporation of new elements, information and ideas. On the other hand, a closed system resists the incorporation of new ideas and risks atrophy, ceasing to properly serve the environment it lives in.
Self-organization is considered an effective approach for modeling the complexity in modern systems, allowing the development of systems with complex dynamics and adaptable to environmental perturbations without complete knowledge of future conditions. According to (Gardelli et al., 2008), "*The self-organization approach promotes the development of simple entities that, by locally interacting with others sharing the same environment, collectively produce the target global patterns and dynamics by emergence. Many biological systems can be modeled using a self-organization approach*".
Some examples of self-organizing environments include food foraging in ant colonies, nest building in termite societies, the comb pattern in honeybees, brood sorting in ants, decentralized coordination for automated guided vehicles, congestion avoidance in circuit-switched telecommunication networks, manufacturing scheduling and control for vehicle painting and self-organizing peer-to-peer infrastructures, among others.

2.2.6 Local and global control

Governing laws of behavior for individual agents in a multi-agent simulation model can be implemented as either local, global or a combination of both. The decision depends on the type of simulation being modeled and the constraints imposed by the problem being solved.

According to (Parker, 1992), emergence might occur solely based on the interaction of the local control laws of the individual agents, which might not be aware of any global goals. However, this approach might not be sufficient to model some simulations where agents are expected to cooperate towards a global goal, and a hybrid model with both local and global control might offer a solution. Still according to (Parker, 1992), the key difficulty when designing control laws governing the behavior of individual agents is to find the proper balance between local and global control and how to design such controls: as global goals designed into the agents, as global or local knowledge or through a behavioral analysis method.

3. Multi-agent based simulation platforms

This section presents two frameworks that aid in the building and execution of SMA's: Swarm (Group, 2009) and Mason (Cioffi-Revilla & Rouleau, 2010). In this context, the main aspects of each platform are covered in order to establish a comparative overview among these platforms. Although the scope of this section is limited to these two platforms, it is worth emphasizing that there are many others multi-agent frameworks being used by scientists, for example Repast, NetLogo, and etc.

3.1 The Swarm Platform

The Swarm Platform was created in 1994 at the *Santa Fe Institute, USA* by Christopher Langton with the help of other researchers. It was written in *Objective C*, but later a *Java* interface was also developed. The Swarm Platform offers multi-agent researchers a good variety of resources such as memory management, action scheduling, graph generation, real-time simulation updating/interference, etc.

A Swarm can be described as a type of animal behavior characterized by the reunion of many similar entities that together seem to behave as a bigger, single organism, such as a school of fishes swimming at the sea or a swarm of bees flying in the sky. This type of behavior displays a noticeable degree of flexibility (a swarm of insects adapting to environmental changes such as the wind, rain, smoke, etc.), robustness (a global objective will still be pursued - and most likely achieved - even if some of the members of the swarm are lost during the execution of the task), decentralization (there is no central control as in a fish shoal) and self-organization (insects in a swarm will organize themselves to achieve a global objective).

Following that philosophy, the Swarm Platform was developed to allow the mimic of such features and concepts, modeling the agents with reactive features and actions. A second feature provided by this platform is the creation of hierarchical models. In other words, it could be possible to design multi-agent simulations which the agents are composed by other agents, forming a multi-agent simulation by itself, or a simulation of nested simulations. This allows the formation of systems with a high level of complexity.

3.1.1 The Swarm Platform architecture

The basic component that organizes agents in the Swarm platform is called SWARM. A SWARM can be described as a collection of agents under a schedule of events and represents the entire model, as it contains all agents within then model as well as the representation of time. The basic architecture of a swarm simulation is comprised of a MODELSWARM, an OBSERVERSWARM and, optionally, simulation PROBES. Figure 1 displays the basic architecture of a simulation in the Swarm Platform.

The MODELSWARM contains the conceptual model implementation, and is comprised by a SWARM and optional sub-swarms. In this architecture, active and passive agents are defined

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