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Introduction to the Agent Approach

1.1. Introduction

When we need to study a real system made up of interconnected elements, where each of these systems has its own dynamics, it is often impossible to foresee the emergence of a global dynamics for the system. In this case, what is in question is a complex system, because any one modification, even if it is marginal in terms of its one or several constituent elements, may lead to a dramatic change in overall operation of the system. It becomes clear that these phenomena may well be understood and observed only through the construction of a model. Even if in certain particular cases the model may be resolved analytically, as is the case for the Lotka–Voltera prey-predator models [VIA 11], computer simulation is indispensable in all other cases, i.e. in most thematically interesting cases. As such, agent modeling is one possible response for studying complex spatial systems.

Multi-agent systems (MAS) originally came into existence in the 1980s, at the crossroads of *Distributed Artificial Intelligence*[1] (DAI)

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1 DAI is concerned with the design of distributed IT systems which can solve problems using reasoning algorithms.

and *Artificial Life*[2] (A-Life) [FER 95], and are currently extremely popular. What is unique about them is their capacity to make apparent collective behaviors resulting from individual actions and interactions [JEA 97].

Within the domain, MAS are viewed as an entirely simulatory approach, which complements traditional techniques based on analytical, stochastic or other types of models [VAR 13]. As with the object concept [BOO 91], MAS engage a process of structuring thought which helps researchers or those involved in industry to solve the various problems they face. MAS are considered as the logical continuation of the object concept [FER 95, WOO 97] which brings increased modularity due to its ability to adapt, to learn and to be autonomous.

The fundamental principle upon which the multi-agent paradigm is based is that of breaking down complex objects into new, smaller problems, which are easier to model [BER 05]. Thus, the agent paradigm is “more a way of thinking than an implementation technique” [FOU 05]. It simply organizes our thought by analogy with the world around us. It is an elegant and intuitive way of envisaging and representing a complex phenomenon. In fact, this is one of the reasons why this approach has been adopted in a wide range of disciplines such as social sciences, ecology and finance, among others.

In this chapter, we will introduce the concept of the multi-agent system, beginning with a presentation of two examples of the use of such systems, in social sciences and soil sciences. We will then discuss the major trends in modeling and situate agents within the context of this work. Following this, we will formally define MAS before finally applying them to two concrete examples.

2 According to Christopher Langton in [LAN 89], “artificial life is the study of systems constructed by humans that exhibit behaviors typical to natural living systems” (definition taken from [REN 02]).

1.2. Two different MAS shown through examples

In order to illustrate the extraordinary expressive capacity of MAS, we have selected two concrete case studies which lead to two diametrically opposed models. The first case study, from social sciences, is concerned with the mobility between towns of town-dwellers, and the second case study, from ecology, studies soil sustainability.

1.2.1. *MAS in social sciences*

The agent paradigm is a modeling approach which is very well suited to the representation of the human being as an autonomous, intelligent individual, who is capable of learning and communicating with others. The agent approach also offers the advantage of providing a natural representation of the individual [SAN 05]. As a result, the model can be used to address a research question which may apply to a range of disciplines, such as the sustainability of a town, through one of its core components, daily mobility. If we consider a town to be a form of spatial organization, it is one that provides conditions which favor social interaction. As such, it follows that an ever-increasing number of daily transport journeys are required in order to achieve the objective of linking places. Urban spread, the functional specialization of urban areas and the low social value placed on mobility are factors that contribute to this trend and intensify its effects.

The right to a given level of mobility, linked to the desire for increasingly individualized and autonomous lifestyles, may result in significantly reduced accessibility of the town and its services. Given that “too much mobility kills a town”, if a town’s development has to be harmonious and sustainable, then researchers need to identify the conditions according to which daily and individual mobility do not prevent the town from fulfilling its role. This study must also take into account the management of urban growth, which nowadays causes many problems such as urban spread, congestion, energy consumption and production, and risks and dangers to the population.

Under these conditions, it is natural and logical to use the agent approach to model individuals who move around the urban zone according to timetables and certain socioeconomic characteristics: the city-dweller is an intelligent agent attempting to carry out a series of activities; the town is an environment regulated by transport and traffic rules. This approach is quite similar to a city-dweller/agent bijection.

1.2.2. *MAS in soil sciences*

The versatility of the MAS means that the approach is totally malleable, and its use may be adapted at will for the case study or research question to which it is applied: this approach may even be implemented for the study of soils.

Soil is a key component of ecosystems, which is the support for one of the main ecosystem services: the production of biomass (food, fodder, energy, wood and fibers). It is a critical resource, and one that is under threat. It is also non-renewable. As a result, it is essential to promote sustainable management practices both to halt its degradation and to foster its rehabilitation. New techniques for the rehabilitation of soil, such as soil building, are currently being developed. In order to evaluate the level of ecosystem service that a rehabilitated soil can provide, and in order to predict its development and sustainability, computer modeling and simulation tools are required. However, the multi-level character of soils and the overlapping of ecosystem processes involved within them mean that it is often difficult to model their complex systems using a classical macroscopic approach. In fact, soil is characterized by both biotic processes (linked to living organisms such as earthworms) and abiotic processes (linked to non-living elements such as the physics of the materials and the flow of liquids), which interact at various levels, from macro-fauna (such as termites and earthworms) or macro-aggregate (such as silt or clays) to microbes and the micro-structure (clay) of soil. Therefore, it is necessary to use modeling approaches which can handle this overlapping of various levels.

Agent-based modeling is particularly well suited to this context. For example, the Sworm model [MAR 08] describes a dynamic three-dimensional space in the form of a fractal made up of cubic cells. Each cell assumes the role of a soil aggregate with a particular behavior. As such, each cell can be represented by an agent with its own dynamics and its set of interactions, irrespective of its size. Its behavior can be driven by submodels such as the Mior model for the decomposition of organic material [MAS 07] or other models for water retention.

In contrast to the preceding model, the agents no longer represent individuals within a space under study, but rather they represent portions of space animated by biological processes. Due to the sheer number of microbes, it is technically impossible to represent each of them by an agent. Also, the current state of knowledge on microbial individuals means that it is impossible to define behaviors at their level.

1.2.3. *Summary*

It can be seen through these two examples, respectively, from social and soil sciences that MAS are malleable as a function of the context, the state of knowledge of the real system and the underlying research question. The fact that they are different helps our purpose, which consists of demonstrating the versatility of MAS. In this regard, the major challenge to design an agent-based model is not its computer-based implementation, but rather the identification of relevant elements to include in the model, and choosing how to represent them.

Quite apart from the capacity of an MAS to represent a system under study, its proximity to the real system means that it is intuitive and enables interdisciplinary dialogue. For the examples cited above, there is collaboration between mathematicians, geographers, economists and computer scientists, among others. The model becomes an element which brings them together, engenders ideas and favors the emergence of new research questions upon which all parties can agree. This does not at all conflict with the advancement of a particular research project within a particular discipline, which can quite feasibly happen alongside contribution to the common project driven by the model.

1.3. Agents and the major trends within spatial modeling

1.3.1. *Major trends in spatial modeling*

As has been the case in many other disciplines, the systematic and reasoned use of models has been developed over the last few decades with a view to understanding and modeling how spaces operate.

In 1999, the modeling group of GDR Libergéo was formed in order to take stock of all the spatial models developed in various French research centers. This group surveyed 20 or so models and classified them using a model comparison grid, with the aim of describing, classifying and comparing all types of models (e.g. graphic, statistic and simulation).

There are many different definitions of the terms “model”. In 1973, Haggett defined models in the following way [HAG 73]:

> MODEL.– Models are schematic representations of reality, which are created to help us understand and explain reality.

A model may be considered as a formal representation of the theory of a system under study [WIL 74]. More generally, models may be viewed as an abstraction or approximation of reality which is created through a simplified vision of complex real-world relationships in order to make it possible to understand and manipulate them.

Nowadays, it is very difficult to define the position of one model in relation to another, mainly because models have been insufficiently categorized and formalized.

For over 30 years, geographers have been working with models of increasing complexity. From maps to computer models, through choremes and traffic management, forecast or optimization models: differentiating and categorizing models is not always a straightforward business. Whenever we use a map, graph theory or perhaps an optimization model for a town's public transport system, we are working with models and modeling.

In [BRI 00], Briassoulis cites various instantiations of models for the dynamics of territories. These can be classified into four major categories:

1) statistical and econometric models;

2) optimization models;

3) models of spatial interaction;

4) simulation models.

1.3.2. *Properties of modeling approaches*

1.3.2.1. *Statistical and econometric models*

The application of statistical techniques in order to derive the mathematical relationships between dependent variables (factors whose value is influenced by other factors) and independent variables is widespread in the modeling of socioeconomic systems and in other fields [ANS 98].

The most commonly used statistical technique is multiple regression analysis (and its variations such as regression in stages or two-stage least squares regression analysis), although other multivariate techniques are also widely used (such as factorial analysis or canonical analysis) [KLE 07].

Econometric models are applications of multiple regression techniques that are used to analyze economic questions. They are systems of equations which express the relationships between demand and/or supply and their root causes, and the relationship between demand and supply themselves (economic/market equilibrium) [BAT 76, WIL 74]. Generally known as econometric analysis, this set of specialized statistical techniques was developed in order to estimate their coefficients [JUD 88].

The work of Irwin and Bockstael [IRW 02] should be mentioned at this point: they use an economic model to describe to what extent it is worthwhile for the owner of an undeveloped plot of land to transform it into a site for building habitation, depending on the sale value of the land once it has been transformed into a usable site and the cost of achieving this.

1.3.2.2. *Models of spatial interaction*

These models, also known as gravity models, are used to model a variety of types of interactions which result from a multitude of human activities, such as commuting to work, shopping, traveling around town and mobility in general.

Haynes and Fotheringham [HAY 84] define spatial interactions in the following way:

> SPATIAL.– "Spatial interaction" is a general term which is used to cover any movement in space which results from a human process. This includes commuting to work, migration, information, and the flow of goods.

The study of spatial interactions usually implies the study of two interacting entities and the form of their interaction. In the case of the analysis of the dynamics of territories, the interacting entities are often people living within them or engaging in an activity (most often work or shopping), with origin and destination zones.

These interactions may assume various forms, such as displacements or flows of goods and information.

1.3.2.3. *Optimization models*

Optimization involves using operation research algorithms to minimize or maximize a given objective function. Constraints imposed within the system (such as availability of technologies and capacity levels) and hypotheses formulated concerning the exogenous variables are considered while this optimization is being achieved. Thus, it can be said that optimization models seek the solution to a limited number of problems under certain constraints.

The use of optimization models is generally focused on the improved use of resources available within the system. They are also used to facilitate the achievement of objectives by the entities within the system.

A well-known example of an optimization model is Schlager's *Southern Wisconsin Regional Plan Model* [SCH 65], which offers an objective function in order to minimize the cost of urban development within a given zone of the territory under study, provided that land is available.

1.3.2.4. *Simulation models*

Batty [BAT 76] states that "all mathematical models which include the large scale use of computer systems are considered to be simulation models". However, even though we consider "simulation" to be a modeling technique, it also has a more precise meaning. Wilson [WIL 74] suggests a more comprehensive definition and a precise usage framework for simulation models: simulation techniques involve "a set of rules which make it possible for a set of numbers to be actioned simultaneously, generally through the use of computer systems, though the rules for and the consequences of their application cannot be transcribed in the form of algebraic equations. Sometimes the simulation technique naturally lends itself to solving a particular problem. This happens, for example, when the basic theory is comprised of a set of relationships which imply certain probabilities. Thus, it is necessary to use simulation techniques for situations that are too complicated to be manipulated with direct algebraic techniques".

In this chapter, we take a simulation model to be the animation of a model with a view to gain understanding, insights and even a forecast of future events.

Simulation models are generally categorized according to the level of spatial analysis (level of spatial detail) they refer to, because there is a close link between the spatial level of the analysis and the theoretical level of the aggregation used (or that is possible). A distinction should be made between three scales of models, depending on the reference system under study. For example, if we consider the study of a country:

– local level simulation models (for example, a town or municipality);

– regional level simulation models (a state, county or region);

– global level simulation models (the country as a whole).

A distinction should also be made regarding the level of analysis of the individuals: there are different aggregation levels for models (e.g. individuals, households and social groups).

1.3.3. *How to model a system*

Obviously, in order to model a system, the distance between the model and the system being modeled needs to be made as small as possible. This is a challenging exercise for several reasons. In fact, a very good knowledge of the system being modeled is required, suitable modeling tools need to be found, and the model needs to be created with these tools, while the constraints inherent in the system that is being modeled also need to be observed.

A model always seeks to address a research question. This is a precondition required for the identification of the constituent elements of the target system. To achieve this, it is necessary to reveal the active elements, the interactions between them and the surrounding elements, and to characterize the autonomous entities and their behaviors. The place is also of prime importance, and its topology and properties must be considered. Relationships have a great significance in the process. They are often the key to the complexity of systems. Thus, the model does not need to aim to cover all of the aspects of the modeled system. Rather, it can concentrate on its particularities.

Model validation is a complex stage in this process. How can we ensure that the model is representative of the simulated system? Indicators built into the model may be used as a basis for this investigation; they may be compared to the real-world experimental values. Researcher expertise is also invaluable in supporting this stage: simulation experiment results can be compared with knowledge gained on the ground.

The step-by-step method that we suggest is presented here:

1) definition of the scientific questions that the model aims to address;

2) identification of the target system's constituents;

3) collection of data required to construct the model;

4) definition of the agents and the environment. Definition of the interactions between all the model's elements;

5) implementation of the model;

6) calibration of the model through successive simulations;

7) exploration of the model which answers the scientific questions, or redefinition of these questions.

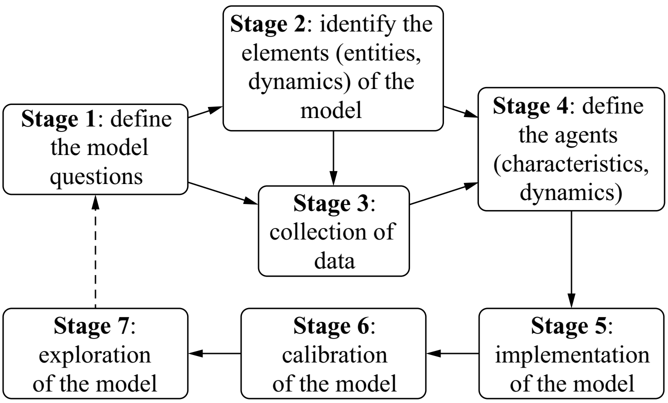

Figure 1.1. *Stages of modeling*

1.4. The agent paradigm

Let us now provide a more formal introduction of the concepts from the world of agents.

1.4.1. *Basic concepts*

One of the most influential definitions of the concept of agent, which is used as a reference point by the French research community, was suggested by Jacques Ferber in [FER 95]. According to this definition, the agent is:

> CONCEPT OF AGENT ACCORDING TO J. FERBER.– a physical or virtual entity:
>
> – which is able to act in an environment;
>
> – which can communicate directly with other agents;
>
> – which is driven by a set of tendencies (in the form of individual objectives or a satisfaction, perhaps even survival function, which it aims to optimize);
>
> – which possesses its own resources;
>
> – which is capable of perceiving its environment (in a limited manner);
>
> – which has only a partial representation of this environment available to it (it may even possibly have no representation of it);
>
> – which has skills and offers services;
>
> – which may possibly be able to reproduce;
>
> – whose behavior tends to satisfy objectives, while taking the resources and skills at its disposal into account, and as a function of its perception, representations, and the communications it receives.

This definition states the minimum properties that an entity must have in order to be considered an agent. These characteristics may be summarized in four words [WOO 97]:

– *autonomy*: ability to evolve according to its own behavior without external intervention;

– *reactivity*: ability to react to external events;

– *proactivity*: ability to make decisions in a more or less developed way in order to achieve its objectives;

– *sociability*: ability to interact with other agents.

In the same spirit as the above definition, Jacques Ferber interprets the concept of a multi-agent system as [FER 95]:

CONCEPT OF MULTI-AGENT SYSTEM.– being composed of the following elements:

– an environment E, i.e. a space which has a metric;

– a set of objects O: these objects are situated, i.e. for each object, for a given moment, they can be associated with a position in E. These objects are passive, i.e. they can be perceived, created, destroyed and modified by the agents;

– a set of agents A, which are particular objects ($A \subseteq O$), which represent the system's active entities;

– a set of relationships R which brings the objects (and thus the agents) together with each other;

– a set of operations Op which makes it possible for the agents from A to perceive, produce, consume, transform and manipulate the objects from O;

– operators responsible for representing the application of these operations and the world's reaction to this modification attempt, which we will call the laws of the Universe.

This definition can be summarized using four core concepts [OCC 01]:

– *agents*: set of active entities in the system which have their own behavior;

– *environment*: medium in which the agents evolve. Its structure depends on the domain of application. However, it is often spatialized; in other words, it is accorded a metric;

– *interactions*: set of languages and exchange protocols between the agents. These are sometimes low level, originating from physics models, or high level, like language acts;

– *organization*: set of groupings of agents with federating entities where all the agents have a common goal.

This summary has been the subject of a modeling approach named Vowel after the A,E,I,O [DEM 95, DEM 97, DEM 03]. These four components define the concept of multi-agent system in a general manner. There are currently a very large number of formalisms and run-time environments based on this type of approach. Therefore, we will now address the question of whether a multi-agent system is a process for reflection or an implementation tool.

1.4.2. *Interactions*

The richness of MAS lies, to a large extent, in the interactions that occur between agents. These interactions can be expressed in many ways.

The organization Foundation for Intelligent Physical Agents (FIPA) has published a set of rules and standards regarding these interactions. These rules can be summarized as follows [FAP 00]:

– agents can communicate with each other;

– an agent provides a set of services and makes them available to all other agents in the system;

– each agent is responsible for limiting its accessibility to other agents;

– each agent is responsible for defining its relationships, contracts, etc., with other agents. Thus, an agent directly "knows" (through its set of knowledge) all the agents with which it can interact;

– each agent knows, with its name, the way in which it can be accessed from outside the system. As a result, the agents are supposed to interact autonomously and without constraints.

The medium through which these interactions are conducted is variable. The agents can exchange through sending messages, which generally have standardized contents. A large number of works have examined the creation of oriented languages, commonly known as Agent Communication Language (ACL). Some of the best known languages are FIPA-ACL [FOU 02]. This type of communication means that exchanges can take place from point to point or that an agent can be transmitted toward a community of agents.

Another technique is that of the blackboard, which consists of allowing agents a board where they can read or write in order to communicate with the community of agents. This is a transmission pattern.

Finally, there is the type of communication which we will call diffuse. The agents can, through mechanisms of perception and action respectively, perceive a change in others or in the environment, and can act on others and on the environment. This is also a form of communication.

1.4.3. *Types of agents*

All those with an interest in agents agree on the fact that, for pedagogical purposes, there are two main categories of agents [FER 95]: *reactive* and *cognitiv*e. The first category of agents is based on simple behaviors which correspond to a *stimuli-action* strategy. In contrast, the second category of agents has genuine faculties for reflection and adapting its behavior.

Many agent architectures for representing spatial phenomena have been suggested in the literature. In this context, the belief desire intention (BDI) approach describes a humanized decision-making process for agents [RAO 91]. This architecture is based on a simple idea: the achievement of a *desire* is made through carrying out intermediary *intentions* which are identified through an analysis of the agent's *beliefs* about its world.

We might be tempted to state that the BDI architecture is ideal. However, the decision-making process for purely cognitive agents (such as BDI agents) demands high use of computer resources (processor calculation time and memory, for example). Their wide-scale use creates performance issues. Brownian agents seem to be a solution, given that they combine the properties of reactive and cognitive agents [SCH 03, SCH 02]. In fact, their behavior derives from the evaluation of a set of variables combined with pure analytical or stochastic laws. In this way, Brownian agents maintain the simplicity of reactive agents, but also have at their disposal behavior imitative of cognition, through the stochastic functions that are a part of them. These kind of agents are suitable for the representation of the movement of a large number of humans, as is proposed in [GLO 04].

In reality, agents and multi-agent systems are designed on a case-by-case basis in order to simulate complex phenomena as much as possible; they are often at the crossroads of reaction and cognition, bringing together internal variables of state and memory, reactiveness and cognition, or determinism and stochasticity of behaviors. As a result, they often present a hybrid architecture which combines:

– *reactive behavior rules* which are based on stimuli received or perceived by the agent (events, messages, observations or stochastic laws); the reactive behavior rules may apply some actions or call some high level cognitive functions;

– *cognitive behavior rules* which use developed algorithms and the agent's knowledge, for example a shortest route algorithm based on a mental map of the space structured in the form of a graph.

This general architecture is developed in more detail as a function of the case study in question, in particular, through the inclusion of an agent architecture (e.g. BDI or adaptive), or even through the definition of an organizational model.

1.4.4. *MAS organization paradigms*

Like all distributed systems, there are two main types of control in MAS: centralized control, in which a master agent manages work, organizes solutions and mediates conflicts, and distributed control where the system is said to be evolutive and where each agent has a total or partial plan of action. In practice, we find totally centralized architectures, totally distributed architectures or architectures that combine both these approaches.

As outlined by J. Ferber [FER 03], during the development of a multi-agent environment, two possibilities are available to us: a development focused on agents or a development focused on the organization. Agent-centered multi-agent systems (ACMAS) are modeled in terms of the mental states of the agent and are very useful in the case of highly cognitive agents. In the case of a complex system, it is impossible to be fully aware of the development and the behavior of the system as a whole solely on the basis of the behavior of the various agents. Their interactions need to be taken into account, and an overall point of view needs to be taken, which is why an ACMAS is not recommended for modeling a complex system.

We will further describe the organization-centered multi-agent systems approach (OCMAS) and the Agent/Group/Role model (also known as an AGR or Aalaadin model [FER 98]).

1.4.4.1. *General principles of OCMAS*

If we consider matters in terms of organization, this provides us with a new approach toward describing the structure and the interactions which appear within an MAS. The organizational level (also called social level in [JEN 00]) is located at a level above that of the agents, which is the only level that is considered in ACMAS.

The organizational level describes the structural and dynamic aspects of the organization. It is based on three principles summarized as follows:

PRINCIPLE 1.1.– the organizational level describes the *what* and not the *how*. It imposes a structure on the actions of the agents, but does not describe the way in which they behave. In other words, the organizational level does not contain a code which can be executed by the agents, but rather it provides specifications regarding the limits and the expectations it is possible to have on agent behavior.

PRINCIPLE 1.2.– no description of an agent and no mental state are present at the organizational level. This level states nothing regarding the manner in which agents will interpret it. A colony of ants is considered an organization in much the same way as the board of a company. The organizational level of mental states such as beliefs, desires, intentions or goals is not discussed.

PRINCIPLE 1.3.– an organization makes it possible to break a system down. Each part (or group) provides a context for interactions between the agents. A group provides the boundaries agents belonging to the same group can interact freely. On the other hand, a group is completely inaccessible for agents that do not belong to it.

These three principles have the following significance:

1) an organization may be viewed as a dynamic structure, whose agents are various components. Joining a group or playing a role may be viewed as integration;

2) modeling a system at the organizational level may leave the implementation choices open, such as the fact that a specific agent plays a specific role;

3) it is possible to create truly "open systems", where the internal architecture of the agents is not specified;

4) it is possible to create secured systems through using groups in a "black box" method, where whatever happens inside cannot be seen from outside. It is also possible to define a security policy in order to exclude "undesirable" agents from joining a group.

1.4.4.2. *The agent group role (AGR) model: an example of OCMAS organization*

The AGR model is based on three primitive concepts: *agents*, *groups* and *roles*, which are structurally connected and cannot be defined by other primitives. These concepts satisfy a set of axioms that unify them.

– *Agent:* an agent is an active communicative entity which can play several roles and can be a member of several groups. An important characteristic of the AGR model, which is in agreement with the second principle described above, is that there is no constraint placed on the architecture of an agent or on its mental capacities. An agent can be as reactive as an ant or as cognitive as a human, without any restriction.

– *Group:* groups are the atomic aggregation sets for agents. A group is formed from a set of agents which share common characteristics, and is used as a context for activities, making it possible to divide organizations into different sections. Following the third principle, two agents can only communicate if they belong to the same group; but an agent may, however, belong to several different groups. This makes it possible to define organizational structures.

– *Role:* the role is an abstract representation of the function, service or identification of an agent within a group. An agent must play at least one role within a group. Roles are local to groups and must be solicited by an agent. Several different agents may play the same role.

The groups may overlap because an agent may be a member of several groups at the same time. This overlap property for groups makes it possible to conceptualize a world where all the agents are at the same level and are not organized in a fixed manner into a rigid structure. Organization and hierarchy occur at the group level and can thus change over time.

The three above-defined concepts of agent, group and role are linked by a set of five axioms:

1) each agent is a member of (at least) one group;

2) two agents can only communicate if they are members of the same group;

3) each agent plays (at least) one role in a group;

4) an agent is a member of the group within which it plays a role;

5) a role is defined with a group structure.

The AGR model makes it possible for us to define a dynamic organization of the agents. The organization of agents within an MAS is an element which structures the process. When the system being studied is considered at different scales, it needs to be possible to see or represent the fact that a group of interacting agents can behave in a specific way and, at another level of abstraction, can act as if they were a single entity.

1.4.5. *Agent platforms*

The current strong position of agent-based modeling has in part been made possible by the development of new platforms which allow modelers, including those who have no information technology (IT) background, to define this type of models with ease. There are nowadays many platforms available for the definition and simulation of agent-based models, some of which are open source. These platforms may be divided into two non-exclusive categories on the basis of the type of languages used to define the models.

The first category of platforms defines models using a generic programming language, such as Java, C++ or Python. These platforms are generally intended for IT engineers and are often more suitable for the development of large models. The best-known open-source platforms for this category are Swarm [MIN 96], Cormas [BOU 98], Mason [LUK 04] and Repast [NOR 13].

The second category of platforms uses a dedicated modeling language to define models. These models are generally easier to use than those in the first category and are therefore intended for a wider range of users. However, the user is required to have algorithmic skills. The best-known open-source platforms in this category are NetLogo [TIS 04] and GAMA [GRI 13].

Platforms in the final category define models using a graphic modeling language. In general, users of these platforms need only have very little knowledge of algorithms, or sometimes even nothing at all. An additional advantage of these models is that they facilitate dialogue between modelers and thematic modeling technicians. However, they are limited to the definition of simple models and do not provide the same rich resources as the other categories of platforms. The platforms in this category include StarLogo TNG [RES 96] and MAGeo [LAN 13].

It should also be noted that there is a current trend to integrate several ways for defining models within a platform. For example, in the latest version of the Repast platform, there are three possible methods for defining models: in Java, in Relogo (where the language from the NetLogo platform is used in a Repast model) and by graphic modeling. Cormas and GAMA also offer graphic modeling tools in their latest versions.

Among all the platforms, NetLogo ranks first because of the simplicity of its use. Even if this platform does not offer the possibility of defining models as complex as those that can be defined with GAMA or Repast, it has the advantage of being very easy to use, even for those who are modeling for the first time, or who have a low level of algorithmic knowledge. Another advantage of this is that many of the other platforms currently available have adopted some of its concepts. This means that it can be a good way to start working with these concepts before moving on to more complex platforms such as GAMA or Repast.

1.5. Observing a phenomenon through agents

Before simulation occurs, MAS are also involved in explicating knowledge linked with the initial research question. There are various possible approaches for structuring the modeler's thought and the formalization of the problem. First, we might mention mathematical approaches such as ordinary differential equations (ODE) and partial differential equations (PDE), stochastic methods (such as Bayesian networks and Markov chains). After this come IT approaches (through simulations), such as cellular robots, individual-based approaches and MAS. In this context, MAS play a very particular role due to their proximity to reality and their adaptability to all contexts.

We will first present a method for modeling a real phenomenon using agents. We will illustrate our explanation with an example from social sciences concerning inter-urban dynamics.

1.5.1. *Two agent approaches to a real phenomenon*

With regard to MAS as modeling tools, there are two major trends [EDM 04]. The first trend is parsimonious modeling, known as keep it simple stupid (KISS), where the observed system is reduced to its simplest representation in order to highlight its dynamics. Thus, we speak of a comprehension model for KISS. The second modeling trend is keep it descriptive stupid (KIDS), in which the observed system is described in all its complexity on the basis of field data, particularly using geographic information systems (GIS), in order to describe the real system as accurately as possible. In this case, we speak of a descriptive model. Typically, in order to understand the difference between the above-cited approaches, we add the following details.

The KISS approach aims to simplify the model as much as possible in order to construct an intelligible controlled environment focused on the system's dynamics which is under study. This can be seen through microscopic or macroscopic observation of the system by simulation. If an example from epidemiology is simplified, the acquired immune deficiency syndrome (AIDS) model from the NetLogo library is obtained. This model describes a homogenous space with infected or healthy individuals, with random circulation patterns, where there is an infection at each meeting. KISS modeling makes it possible to understand the dynamics observed by simulation, taking a certain number of parameters into account. Due to the short timeframe of these experiments, the modeling may be interactive. It is thus possible to define serious or multi-actor games for an almost exhaustive exploration of the value of the parameters, or potentially for the identification of scenarios which might be simulated as a next step, using a KIDS model. The aim of the KIDS approach is to describe the system in the finest possible detail. For example, the individuals in the AIDS model mentioned above would, through this approach, have a realistic circulation behavior (such as pendulum movement, or movement linked to place of residence) which is linked to field studies conducted. Therefore, KIDS modeling comes into its own when what is required is an appreciation of a system's future or a method for evaluating and decision-making policy on the ground. However, the number of parameters involved is often very high, and the calculation time may be as long as several hours, or even several days. This means that KIDS models cannot be used interactively. Before any simulation, the scenario needs to be thought of carefully because it is impossible to completely explore this type of model.

In order to provide a clearer idea of the KISS and KIDS approaches, we will provide a concrete example of their use in the section that follows.

1.5.2. *Agent modeling through an example: the MIRO project*

The *Modélisation Intra-urbaine des Rythmes quOtidiens* (MIRO) project (financed by *Programme de Recherche Et D'Innovation dans les Transports terrestres* (PREDIT) 2004-2007, *Agence Nationale pour la Recherche* (ANR) 2009-2013, *Ministère de l'Ecologie, du Développement Durable et de l'Energie* (MEDDE) 2014-2015) aims to explore, through computer simulation, the possible impacts of urban policies on the spatiotemporal accessibility of a town to citizens, and the consequences that these policies have on the daily mobility of the citizens. It also aims to establish territorial diagnostics (local gains and losses in terms of accessibility) and social diagnostics (populations which are favored or disadvantaged by the different tested policies). Finally, it facilitates the exploration of the possible global impacts of the modification of individual behaviors, which focuses more on the bigger picture than on the maximization of one individual useful feature. The agent approach makes it possible to see the town through various points of view through scenarios that modify its structure, its services and its inhabitants with the aim of observing the new dynamics which result from these changes.

From this point of view, a comprehension model (of the KISS type) and a descriptive model (of the KIDS type) which show the same dynamics, but with different modeling goals, would complement each other perfectly.

1.5.2.1. *The SMartAccess model*

SMartAccess is a pedagogical comprehension model which allows the user to construct an imaginary town and to test urban planning hypotheses.

The synthetic character of this model means that it is perfectly suited to testing urban structures (such as compact towns or urban villages); it is also suited to defining, in an iterative and interactive manner and based on a large number of macroscopic and microscopic indicators, urban configurations that meet certain sustainability criteria. One of its aims is to help users become aware of how difficult it is to take charge of the development of a complex urban system; this becomes even more difficult when we want to achieve several goals, some of which are mutually incompatible.

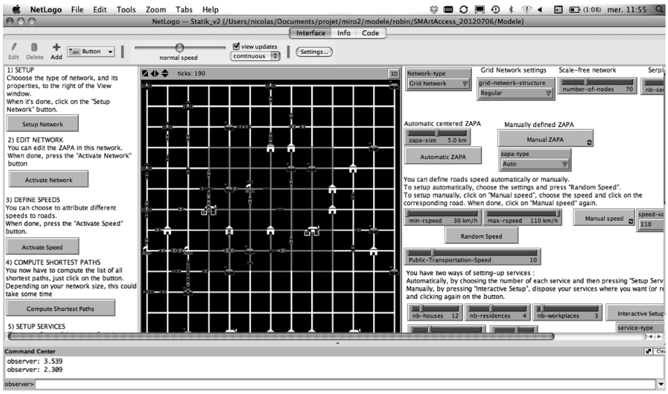

Figure 1.2. *Screenshot from the SMartAccess model. For a color version of the figure, see www.iste.co.uk/banos/netlogo.zip*

1.5.2.2. *The GaMiroD model*

GaMiroD is a descriptive model which has been applied to the towns of Dijon and Grenoble. It was developed using the GAMA platform [DRO 13], which allows the simulation of several hundred thousand inhabitants. In contrast to the SMartAccess model, the GaMiroD model attempts to describe the towns of Dijon and Grenoble, and their dynamics, as accurately as possible.

This model has been developed in line with the available field data, which are:

– *structure*: the road network is built using the geographic information systems of Dijon and Grenoble, which address not only the existing physical network but also the rules for circulation on it (e.g. direction of movement and speed restrictions);

– *description of services*: most of the two towns' services are described following the classification categories of Siren data. As a result, each building in each town is classified according to one or several functions (e.g. residential, school, shop and supermarket) and opening hours are indicated;

– *population*: population of the models mirrors the real population of 120,000 and 400,000 individuals, respectively, for Dijon and Grenoble. This “synthetic” population is built using INSEE data from 1999 and a survey on household mobility from 2009.

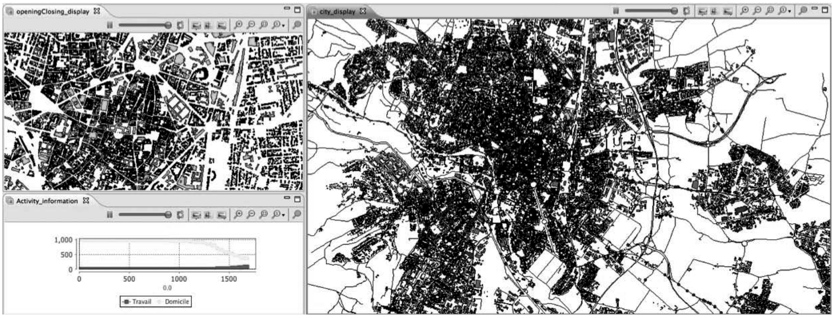

Figure 1.3. *Screenshot from the GaMiroD model. For a color version of the figure, see www.iste.co.uk/banos/netlogo.zip*

The aim of these two case studies was to enable testing of scenarios involving change in the urban environment. The studies were also linked to local public policy actions arising from a desire to achieve sustainable development: (1) the construction of a dedicated infrastructure for public transport and (2) the implementation of an urban regulated traffic zone to reduce pollution. Applying the GaMiroD prototype for both sites facilitated the detailed verification of whether it would be possible to reproduce the protocol, and made it possible to test the model’s calculation abilities for two towns of differing sizes.

1.5.3. *Critical analysis*

Through the SMartAccess and GaMiroD experiments, we can clearly see the approach’s level of expressiveness: one problem can be tackled from several points of view, with an extended scale and detail of description. The closeness of the approach to the real system and available field data enable the exchange of knowledge and skills between modelers and field experts. The agent model can thus become a basis for discussion. It plays the role of an intuitive representation of a complexity being studied, while also playing a role in the integration of all of the contributions of the various actors involved. It links a simple idea on the system with theories and concepts, all the while using field data. This centralizing role of the agent model makes it possible to capitalize on the experience and skill of all the disciplines which are collaborating in the project. Discussions and negotiations lead to the controlled emergence of a model whose simulation provides a virtual reproduction of the modeled realities through a scenario which needs to be observed. The observation of this scenario thus leads to the validation/invalidation of an initial collective understanding of the real system and makes new phenomena, which had not yet become apparent, observable. Bringing all the points of view together and opposing them with each other guarantees the quality of the modeling process and the simulation results, even though there is no formal framework. Experience has shown that the MAS which correspond to the method supported in this book are rarely very far from reality.

In fact, the extreme versatility of MAS makes them an approach which is fit for many purposes, and which can be adapted to any situation. However, the high level of flexibility of MAS may also be a point of weakness: the permissiveness of such systems is a source of modeling errors and of uncertaincy in the models. It may lead to conditions favorable to uncontrolled increase in complexity and combinatorial uncertainties. This, in turn, leads to difficulties in the verification and validation of data.

As a result, one of the primary concerns of a modeler is the production of a model which can be trusted, where the simulations based on the model really do simulate the system which is under study. To achieve this, modelers must pay much attention to the modeling hypotheses, data and inevitable simplifications. For example, for the modeling of road traffic within a town, one of the first simplifications for modeling would be to break down the sections of the road network into cells of the same size. Vehicles then move from cell to cell over time. Another simplification might be to define a temporal budget and to carry out the circulation around the model in line with this budget.

The greater the distance traveled, the larger the expenditure of the vehicle in terms of the budget. If the goal is to study interactions between vehicles, for example to make it possible to observe an "accordion" phenomenon on a portion of the network, the first modeling assumption discussed will be well suited to this purpose, because it shows the space that the vehicles occupy (each cell is occupied by one vehicle at the most). However, the second simplification makes it possible to ensure that a vehicle will reach its destination within a given time, but it does not allow the observance of friction between vehicles. Thus, we have two models of traffic, where one describes the interaction between vehicles and the other is concerned with journey time. The second simplification would be suited to studying the accessibility of a town's services.

The choice of one modeling strategy over another is made through intuition and modeling experience or through a trial and error method based on experiment plans. To return to the above example, if we try to study accessibility using the first simplification, we will notice a significant error in the time of travel in relation to the theoretical journey times; these errors will disappear if we use the second approach. Additionally, tests also facilitate the refinement of the model constants, such as the spatial size of a cell for the first simplification.

Thus, validation and verification of the model are a significant and essential part of the modeling–simulation process. As we have previously stated, validation requires broad experimental experience acquired through a large number of simulations (several thousand, or even several hundred thousand), where results must be compared to field data. Verification is more formal. It cannot be envisaged for the model as a whole, but can only be applied to certain individual aspects of the model such as exchange protocols between the vehicles, or that a vehicle never leaves the road. It should be remembered that any model is a point of view on a reality, but it is never actually real in itself.

Modeling strategy and modeling validation are addressed in sections 2.5 and 4.4, respectively.

1.6. Summary

This chapter has presented the basic concepts of MAS. We have introduced the core definitions and the organizational paradigms. We have also presented the key trends in spatial modeling in order to place agent models into context. The examples that we have provided have also shown the rich expressiveness of these systems when it comes to creating models of complex distributed systems. However, before we can build models and explore them through simulation, we need to address the question of description formalisms in agent models.

The next chapter will aim to demonstrate how to manipulate these various formalisms.