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University of Le Havre

LITIS

PhD thesis

in Computer Science

by

Rawan M.O. GHNEMAT

Adaptive Modeling for Spatial Emergence within Complex Systems

Defended on June 22th, 2009, with the jury:

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Chapter 1

Introduction

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1.1 Problem Setting

The impressive increase of economical, technological, social, and environmental changes in our world makes their management become a great challenge. Implementing wrong policies to solve such problems can make the problem become worse or can generate new ones. Many of the problems we have to face nowadays arise as non predictable side effects of our own past actions. Most of these wrong policies are not flexible or adaptive, and we cannot change them in order to achieve our goals within a dynamic solution environment. In other words, solving such problems by studying a part of them without modeling the complexity of the different parts can provide an efficient solution for short term but a negative one for long term, leading to non reversible system evolution.

Effective decision making and learning in a world of growing dynamic complexity requires us to search a new way of system modeling and to expand the boundaries of our mental models. We have to develop tools in order to understand how the structure of complex systems creates their own behavior.

Our purpose is to analyze organizations or societies within their spatial complexity. Solving this problem in sustainable way, should start by understanding how the individual behavior in the organization affects the whole system behavior. Observing complex self-organized systems in the nature (like social insects) and understanding them leads to discover concepts of emergence. The power of these systems does not come from any central control but from their flexible interactions with themselves and with their environment in an adaptive way. This problem involves complex networks of location interactions, complex networks of individual characteristics' interaction and even complex networks of multi-scale decision making, that are: the decision of individuals, the decision of services managers and the decision of society development planners.

The global objective of this work is to contribute to better understanding and exploring such complex systems using modelling, simulations and analysis. We develop in the following the objectives and the contributions of this work.

1.2 Objectives

The aim of this study is to model and analyze social organizations from services-users interactions, respecting their complexity. Our objective is to highlight the emergent complexity based on the three main factors: (i) the spatial dimension as a major input for the component interaction, (ii) the self-organization as a major process for the system dynamics and adaptation, (iii) the multi-scale decision making as a major factor for emergence and adaption of the system.

In order to model the dynamics of complex interaction between users and services with various characteristics, we introduce two levels of description: the entities (users) level and the level of organizations (services), as described in figure 1.1. The objective is to

implement an adaptive mechanism for our model structured threefold:

- *The emergent process.* The inputs are (i) the system of spatial users with various characteristics and preferences, (ii) the system of spatial services with various characteristics. The output is the spatial distribution of users over the services system. The process is based on an attraction mechanism involving complex interaction between users and services.

- *The adaptive process.* The input is the spatial distribution of users over the services system which is produced by the emergent process. The output is the response of the services according to their dynamic usage. This response leads to modify the characteristics of the services.

- *The feed-back process.* The input is the new characteristics of the services which are produced by the adaptive process. The output is the new spatial distribution of users according to the services evolution.

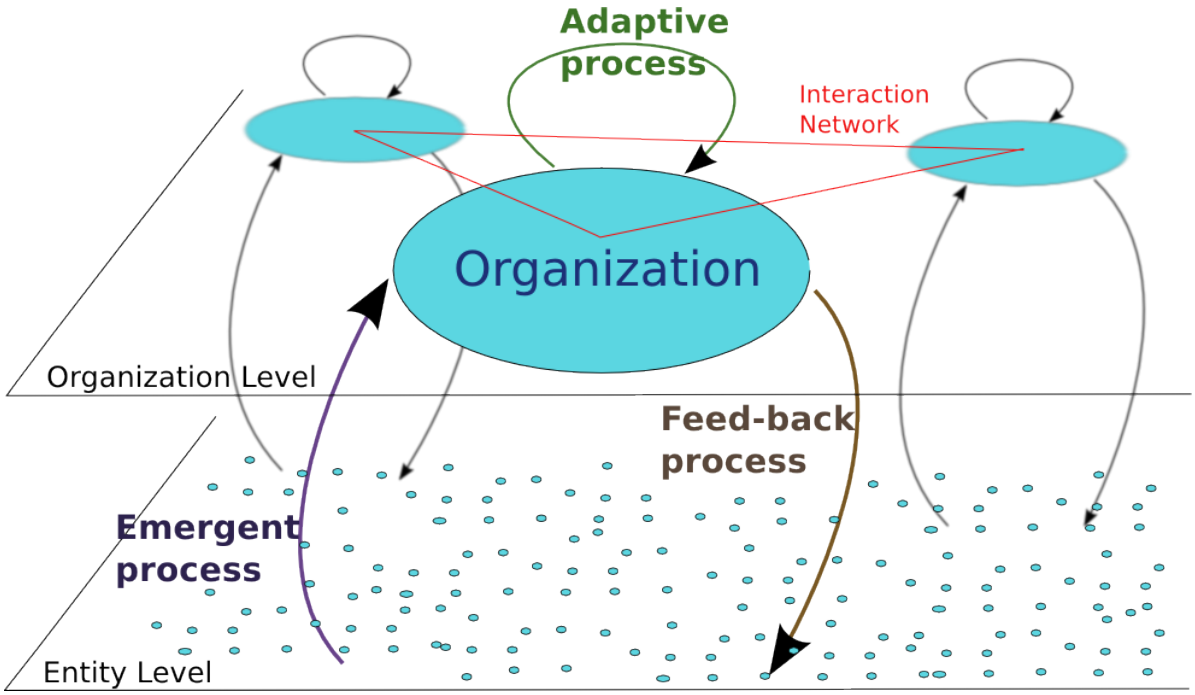

Figure 1.1: Users and Services spatial organizational model

This three faces model produces an efficient tool to study the complexity of the adaptation and evolution of the services-users systems. In urban dynamics, our goals is to understand, simulate and analyze phenomena like gentrification phenomena or cultural services evolution. The final objective is to produce relevant decision making tools based on such simulations and analysis.

1.3 Contributions

The methods developed for this model use

- *Multi-agent systems* in order to respect the distributed nature of the complex systems involved in the model;
- *Swarm intelligence algorithms* in order to implement self-organization processes;
- *Geographical Information Systems* in order to manage the spatial complexity of the model.

A first contribution of this work is to propose a *swarm intelligence engineering system* based on the complex interactions between (i) extended swarm models, (ii) multi-criteria characteristics (users preferences and services offers) and (iii) multi-center systems (the spatial interaction of services). The simulations produced by this model lead to complex outputs which need to be analyzed with respect to their complexity. We propose an analysis methodology for this purpose.

A second contribution is to manage the spatial complexity of the model through the mixing of spatial data integrated in GIS and the swarm intelligence engineering system described previously. Many applications can be simulated using this general model, concerning spatial emergent organization within multi-criteria process, like various urban services-users planning and management. A case-study for modelling urban cultural dynamics is developed and specific adaptive processes are implemented through the swarm intelligence engineering system. Some simulations results are provided using Repast Platform over OpenMap GIS.

These two contributions are facing with the two aspects of our work: (i) developing a conceptual methodology based on an innovative general swarm intelligence model; (ii) developing an engineering methodology based on the capability of our general model to be applied for concrete applications and phenomena.

1.4 Organization of the Document

Part one develops the scientific context. Chapter 2 starts in describing how the concept of complexity emerges in many scientific disciplinary. From the understanding of this transversal emergence, we give then, the concepts of complex systems and self-organization process. The chapter ends with computational aspects which detail how complex systems can be practically computed. Chapter 3 develops the basics of multi-agent systems and more particularly in spatial modelling environment. Geographical information Systems which are the ones of such environments, are presented, including their mixing with multi-agent platform. A contribution of such mixing is given, describing Schelling's segregation model. Chapter 4 describes swarm intelligence algorithms as computable methods for self-organization processes. Social insects algorithms are presented and a contribution describing implementation of nest building is provided using

Repast mixing with OpenMap GIS.

The second part develops the original model proposed in this work. Chapter 5 describes the extension of the nest building model to adaptive multi-criteria, multi-center systems dynamics. Formalism of this extension is described. The different aspects of attraction phenomena processes are defined, using *dominant component mechanism* or *ranking computation mechanism*. Experiments are shown and an analysis methodology of the results in respect to their complexity is studied. Chapter 6 describes an original contribution in swarm optimization, called Community Swarm Optimization in order to compute emergent spatial organizations from genetic automata systems.

The third part develops the case study which concerns urban services and infrastructures dynamics. Chapter 7 describes the context of urban dynamics modeling, in terms of organizations, services and global planning. A review of methods and models are studied then our methodology is provided. The place of new evolution of *location based services* is presented as a technological solution for individual decision making, based on the spatial complexity and using GIS and GPS. This leads to conclude on the multi-scale aspects of the decision making (for users, for services and for planning) involved in our problem. Chapter 8 presents a project funded by "Région Haute-Normandie" concerning urban cultural center dynamics with application to Rouen agglomeration. The complexity of the problem is presented in a practical way and we explain how our work provides the core of the intelligent process leading to simulate this complexity. Analysis of results is given using our swarm intelligence engineering system and its mixing with OpenMap GIS to achieve the concrete implementation expected for the final study concerning Rouen agglomeration.

Fourth part concludes, gives references used in our work and provides the publications in books, journals and international conferences generated by this PhD study.

Part I

Scientific Context

Chapter 2

Complex Systems and Self-Organization

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2.1 Emergence of Complexity in Sciences

Complexity is a relatively new discipline with an immense power to change our way of thinking and seeing the world. This, in turn, can change the way of world understanding and so, the way we "manage", design and structure systems. This allows to create new ways of working.

Nowadays, our world is usually described by huge complexus of interactions: world-wide economy connects firm branches in many countries; politic organizations interact all over the world; high speed communication systems develop interactions between people, their knowledge and culture; global climate exhibits major changes under the interactions of local phenomena.

Our world is a large integrated system of a great number of hierarchical sub-systems. These systems, whatever they are - ecological, social or economical - are complex systems. Some of them, like ecosystems, are essential for our existence and are in the core of global Earth equilibrium. Accurate understanding of complex systems is not possible by isolating their components because of the intensive interactions among these sub-systems.

In the following, the emergence of complexity is described through a framework of interdisciplinary fields (biology, physics, economy, social science, computer science and engineering, ...). To illustrate this emergence, examples of specific aspects of complexity properties are expressed in these sciences. After this review which allows to feel the complexity in these different sciences, we will propose in the next section, a more conceptual and synthetic description of complex systems.

2.1.1 Complexity in Biology and Chemistry

Biology has a special place in Science. Living systems are the basis of our existence. Even if humanity studies them since centuries, the core of the living process is still under research. Major improvements, like human genom decryption, finally has made the understanding of the life roots more complex.

In this section, different examples of complexity in living systems, environmental systems and collective behavior in animal societies are described.

Living Systems

In the middle of the 20th century, after a long period of formalization in many sciences, scientific community was still interrogated about the root of Life (Erwin Schrödinger wrote "What is life?" [108, 28]). At this period, Chemistry and Physics made impressive developments leading to a coherent understanding of a great number of phenomena in Physics. Molecular biology followed these formalisms and allowed to obtain spectacular advances in order to understand many mechanisms in biology. But the life root itself,

corresponding to the basic questions: " Why and how life systems evolve differently from classical systems characterized by their endless increase of entropy ?" was a fundamental question that the main streams of scientific theories were unable to solve because of the lack of a relevent formalism.
Living systems are typically based on dissipative structures in the sense of the "new" laws of thermodynamics proposed by Ilya Prigogyne [97]. These dissipative structures are able to self-organize themselves under permanent continuous energetic fluxes (light for plants, oxygen for breathing human, information fluxes for thinking human, emotional fluxes for consciousness human, ...).

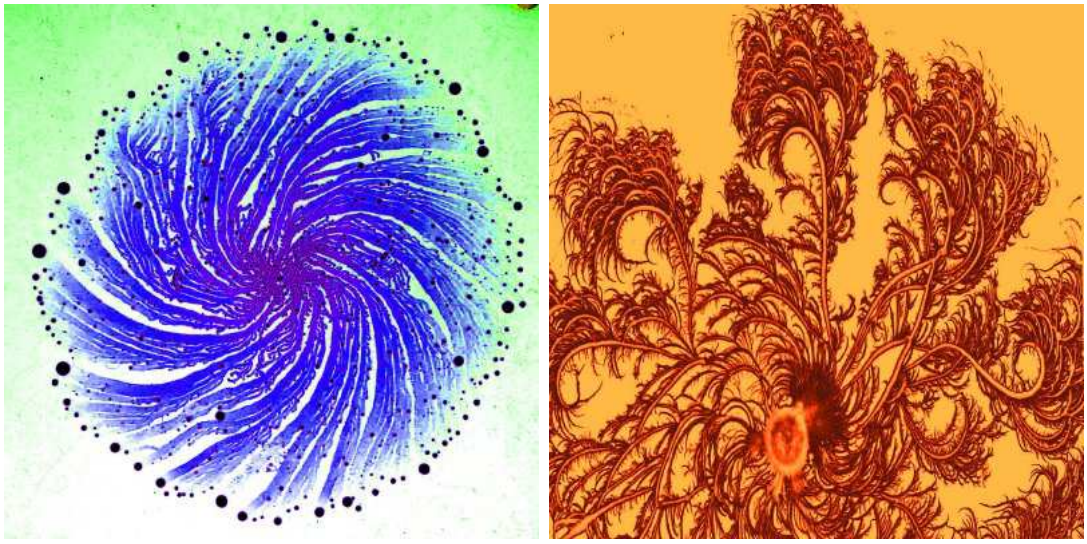

Figure 2.1: Self-organization produced by extern stimulation on Bacteri systems (from Tel-Aviv University - Prof. Eshel Ben-Jacob laboratory [12])

Environmental Systems

Environmental systems are the core of a completely new way of understanding during the last centuries. In the past many biologists studied separately each animal in a very accurate but closed and isolated way. The word "Ecology" was introduced by E. Haeckel in 1866 to highlight the need of linking the individual with its environment. The complex interactions between them has to be considered to understand the individual itself.

In the root of Biology, population dynamics play a major role, allowing to describe how individual systems - the populations - can evolve under many constraints and interactions. Dynamical systems are able to describe global evolutions by the way of synthetic parameters. Such mathematical models are based on differential or integral equations leading to non linear equations which are characteristic of their complexity. One of the challenges of the last decades is to understand the role of individual behaviors inside these global evolutions, how these individual behaviors interact and are able to modify

or influence the whole system by feedback processes.

Natural populations are generally decomposed in hierarchical structures leading to metapopulations [48]. How these hierarchies emerge and how individual links and networks lead to spatial organizations or self-organization is a great challenge whom conceptual roots belong to complexity science. Ecosystem concept defined by Tansley [122] is typically based on systemic approach and focus on the systems formation and evolution within their complexity of the ecological systems.

In such ecological systems, based on individual interactions, spatial interactions within population dynamics can have major effects over the system behavior and can lead to emergent properties of these systems. The following section describes well-known collective behaviors in animal societies.

Animal Society and Collective Behavior

Figure 2.2: Self-organized animal systems

Many animal societies like ants, fishes, birds, bees or wasps ones exhibit collective spatial interactions (see figure 2.2). The movement of fish banks or ant colonies are typically systems which emerge from individual interactions without any centralized coordination. The individual interactions are based and described by individual behaviors and the whole system, emerging from these behavioral interacting systems, can be seen as one alone structured entity, like the brain or more generally a human can be seen as a unique organism composed of many interacting entities.

2.1.2 Complexity in Physics

Fluid Dynamics Instabilities

Physicists are interested since long time with phenomena where spatial self-organization mechanisms appear. In fluid dynamics, hydrodynamical instabilities phenomena have been studied in accurate way since many years. For example, von Karman streets

are well-known structures which are generated behind obstacles included inside laminar flow. These von Karman streets are the output of instabilities which appear on the obstacle border and aggregate in very regular way in order to create vortex formation. These vortices expand following a very recognizable pattern, by contra-rotatif pairs. It is typically a self-organization phenomenon under weak constraints (obstacle in flow) which control only few degrees of freedom and let the flow self-organized in regular way.

On figure 2.3, we show the formation of these von Karman streets within a laboratory experiment. We can observe similar formations inside oceanic or atmospherical flows, the same phenomena observed in the air as shown in figure 2.4 corresponding to a satellite photo over Baja California, Mexico.

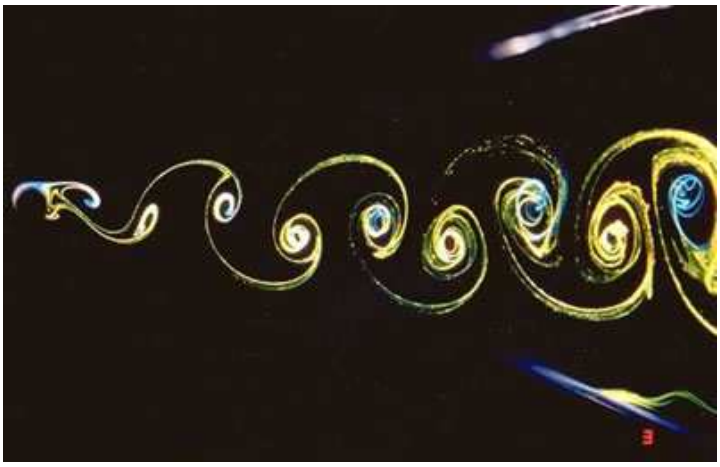

Figure 2.3: Vortex street at the back of a circular cylinder. Copyright ONERA 1996-2006

Taylor-Couette instabilities are other examples of self-organized systems which expand under the influence or the control of few parameters. The classical experiment described in figure 2.5, consists to study the fluid flow between two rotating cylinders, with different rotation speeds. Increasing the rotation speed of the inside cylinder, we can observe various perturbated states described in figure 2.5, until the obtention of vortex formation of regular size. Many scientific works have been made from this experiment which has very surprising and reproducing self-organization's characteristics.

Self-Organized Criticality

The hydrodynamical instability studies described previously have fascinated physicists. They allow to highlight some mechanism based on instabilities, as well as characteristic evolution of dynamically stable states. Following these studies, Per Bak has proposed a general theory for critical self-organized phenomena. This theory allows to describe some systems which are in critical stable state, also called "far from equilibrium". Per Bak claims that the world is constituted of natural and artificial systems in such stability

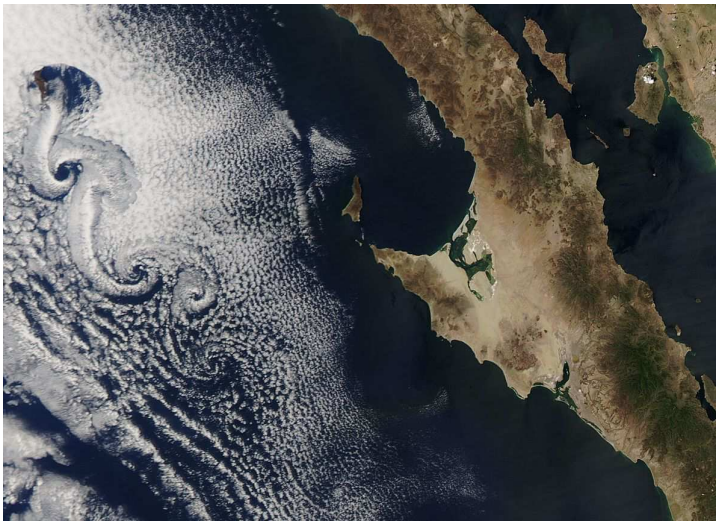

Figure 2.4: Von Karman vortex street over Baja California, Mexico (from U.S. Air Quality - the Smog Blog)

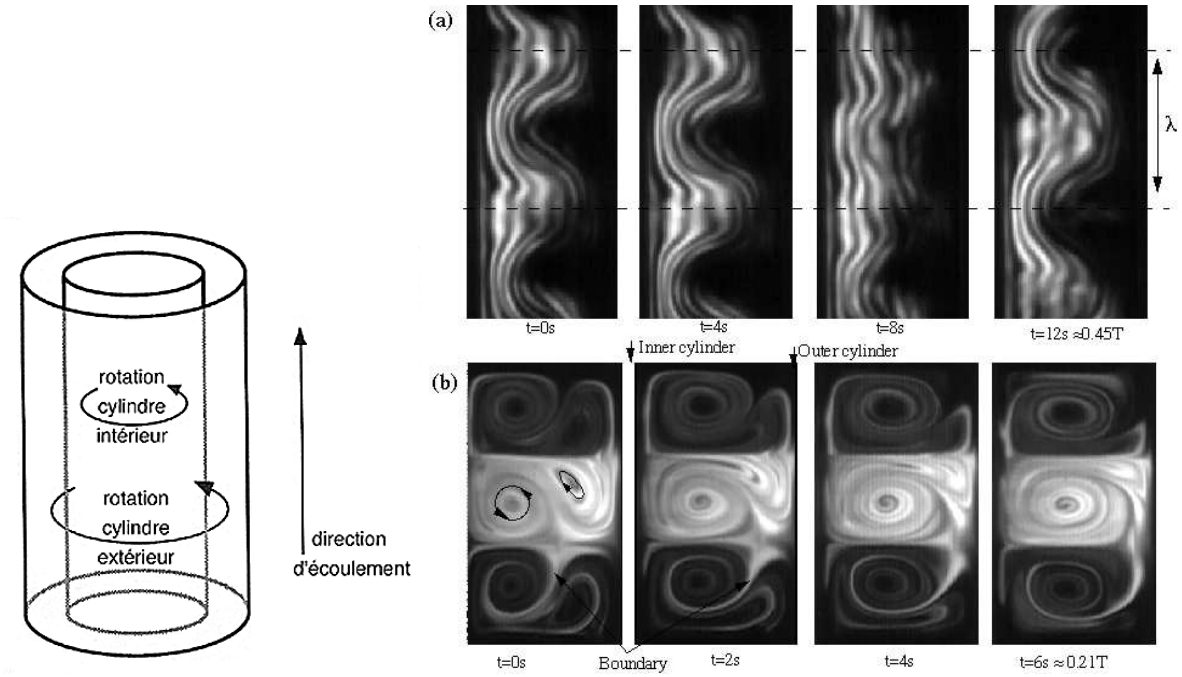

Figure 2.5: Taylor-Couette flow experiment (first figure from the web site of ASBL Nicolas-Claude Fabri de Peiresc, second figure from the web site of Theo Team from LEGI - UMR 5519 - INPG, Grenoble, France)

states which can suddenly evolve and fall (by bifurcation) inside new stable states, sometimes far from their initial stable state. Per Bak illustrates this purpose with avalanche phenomena within sand pile formation. These sand pile formations by grain falling on the pile, are described in figure 2.6.

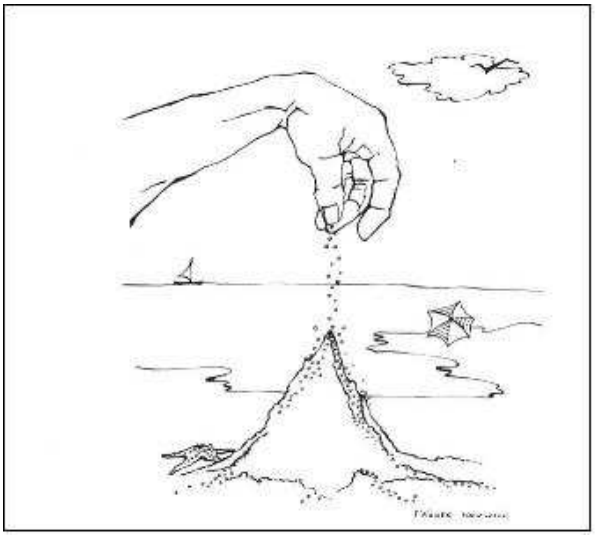

Figure 2.6: Sand Pile avalanche formation after Bak [7]

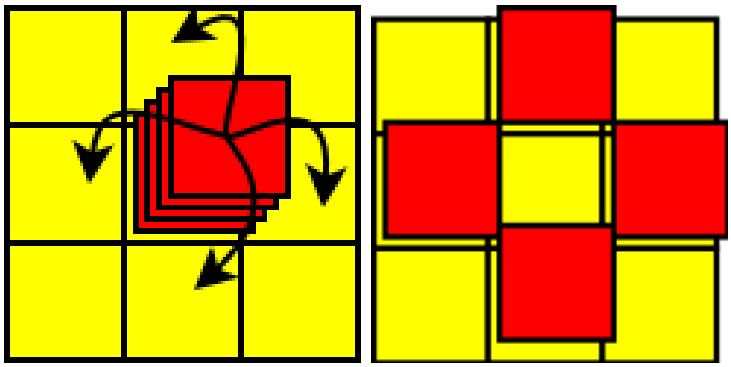

Figure 2.7: Bak's sand pile model rules

From this observation, Per Bak proposes an easy computable process based on a cellular automaton where avalanche phenomena can be implemented. It is a regular grid where sand grains are deposited, allowing to have more than one grain on each grid position. The process is the following: when a grid position has 4 sand grains, these sand grains slip on the neighboring positions as described in figure 2.7.

The application of this simple rule allows to build simulations where avalanche phenomena can appear. On figure 2.8, we represent a simulation based on cellular automata where a number is written on each position, corresponding to the number of sand grains on this position. The first grid (on top left) describes an initial configuration where we add only one sand grain in the middle position, making this position recover 4 sand grains. This position is colored in red and we have to apply the previous rule making the 4 grains slipping on the neighbor position. On the second grid of this figure, we describe the grid after this rule application and we observe that some of the neighbor positions which have received a grain, are now in the critical state and so marked in

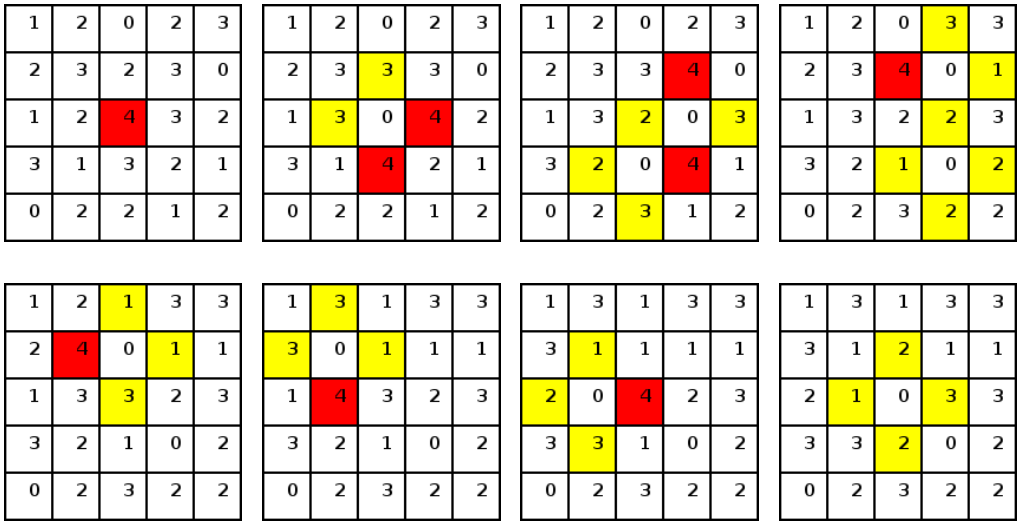

Figure 2.8: Bak's sand pile simulation

red, corresponding to the fact that they contain 4 grains. So, we have to apply again the rule; making slipping the grains on the neighborhood. Finally, the 8 grids of figure 2.8, show all the steps of the avalanche process generated by the only depositing of one grain in the middle grid position, as described in the first grid.

To sum up this avalanche process, we have filled by red color all the positions involved in this process in figure 2.9, with respect to the simulation of figure 2.8. We say that the avalanche amplitude generated by this sand grain falling is 9 (8 red cells are shown but the center cell is involved twice in the avalanche process)

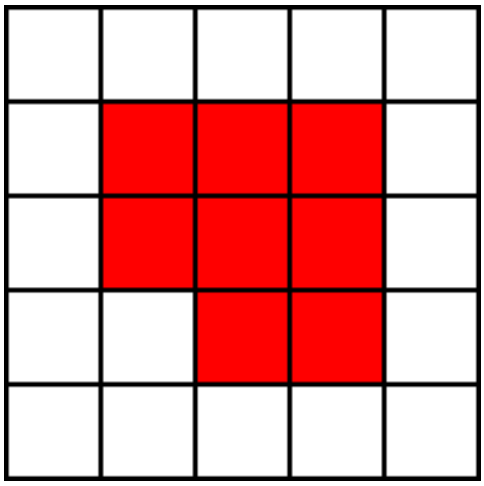

Figure 2.9: Representation of the cells involved in the avalanche process generated by the simulation of figure 2.8

Following the avalanche process presented previously on a very small grid, we can imple-

ment the same rules on a larger grid and iterate the fall of many sand grains in order to record for each one, the avalanche amplitude generated by its falling. We represent then on a log-log scales graphic, the avalanche distribution: their amplitude (in y-axis) in function of the their number during all the simulation (in x-axis). If we run a simulation with thousands of grains falling, we obtain a graphic similar to figure 2.10.

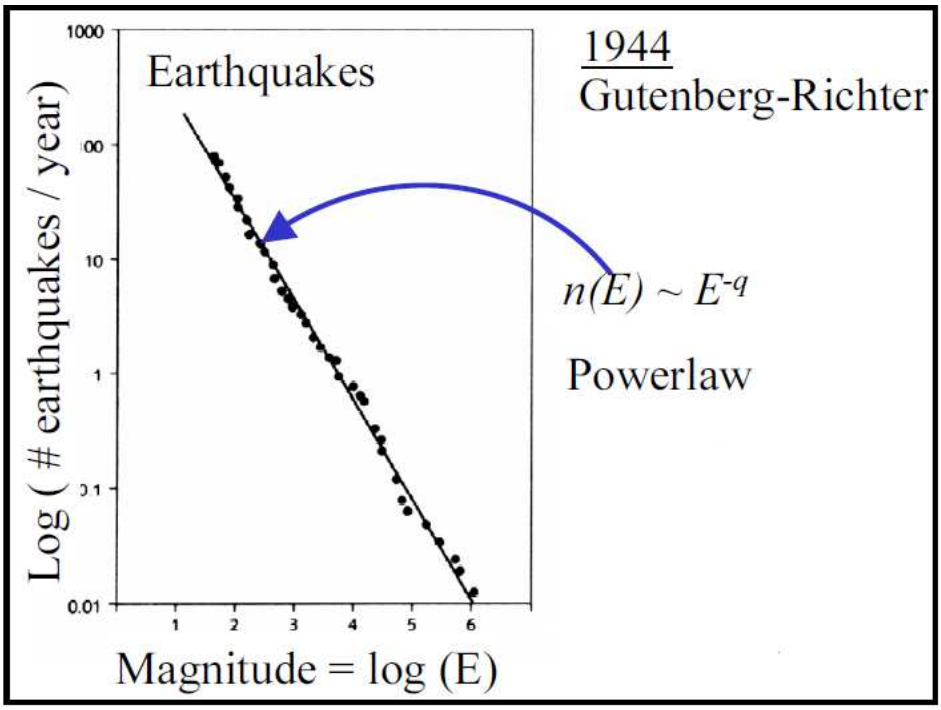

Figure 2.10: Power laws from earthquakes frequencies

This graphic exhibits a law emergence which is characterized by the linear distribution of the points on the log-log scale, meaning that the phenomenon results in a power law:

$$N(a) = a^{-r}$$

where a is the avalanche amplitude, $N(a)$ is the number of avalanches with amplitude a which appear during the simulation and r is a constant number which corresponds to the slope of the line distribution in the log-log representation. There is no known explicit computation (except an approximation after a simulation from the avalanche amplitude distribution) allowing to give *a priori* the factor r.

We have described in this section, an example of emergence property generated by the application of simple rules over a structured spatial environment, called cellular automaton. We will come back, in the following (see section 2.4), to the use of cellular automata as a specific computational tool to simulate complex systems. From now, we want to highlight with the sand pile model, how emergent properties can be developed. The emergent property is here the expression of a general law - the power law - which is

able to describe many natural and artificial systems properties that Per Bak called self-organized criticality. Similar to the laws of avalanche distribution for sand pile model, earthquakes, for example, follow the same distributions: there is a lot of earthquakes of small amplitude but very few of high amplitude. In linguistics, we can observe, for example, the same property: in a huge book, we can find a lot of time some usual words like "the" but with very few frequency, some less usual words. In geographical systems, we can also observe that the town importance follow the same distribution: many small population towns but very few high population ones. All these samples generated an amazing similar property in which their distribution follow a power law, as defined previously.

Emergence in Physical Laws from Robert Laughlin's Theory

Robert B. Laughlin, 1998 Nobel Price in Physics, initiates a scientific debate on the validity of the physical laws [74], facing our world understanding. He claims that the natural laws are emergent. These emergent laws result from a collective behavior and are independent of the individual processes which compose them [19]. This approach about physical laws (which are only models of "natural" laws mentioned previously) escape from the classical reductionist concepts which search from centuries, an elementary decomposition of nature in physical particles from where we can recompose all the world by simple "summation", respecting deterministic processes. Epistemological ruptures which characterize the physics of the 20th century (from Newton laws to relativity or quantum mechanics, for example), generate successive new laws. Each new one consists in going to a kind of more general concept and so is expected to become the universal one. The search of universal laws is non relevant because each of these laws can be finally only the expression of particular emergence on the edge of the natural complexity and lightened by the current knowledge and understanding goals.

Following R. Laughlin, such emergent physical laws are based on the *protection* principle, meaning that the macroscopic description (higher level of description) needs some kind of "protections" from the complexity of their constituents.

One of the most impressive illustration of this protection principle (and the distinction between macroscopic description and microscopic one) is the approach of Stefan Wolfram in [133] who claims to be able to obtain macroscopic fundamentals laws in physics from computer artefact - cellular automaton - which could substitute to the microscopic physical laws.

2.1.3 Complexity in Economy and Social Sciences

As in many disciplinaries, social scientists and economists used differential equations modelling approaches, some decades ago, to formulate some synthetic global descriptions of system evolution. In social sciences, this global description consists in hiding the low level of description of individual behaviors by physical laws for the whole population. Physicists were often the inventors of some fluid and flow models to be adapted

to human society described by homogeneous behavior of their individual. Jay W. Forrester, for example, was the first major reference in urban modelling, using "stocks and flows" descriptions of socio-economic indicators [46]. The urban dynamics and land-use management modelling will be developed in detail in chapter 7.

Economy is generally defined as the study of description and analysis of production and distribution of goods and services. In order to achieve these goals, economy needs to examine the part of individual and social actions which is most closely connected with attainment and material requisite of well being (from Alfred Marshall, see, for example http://en.wikipedia.org/wiki/AlfredMarshall).

From many years, economy uses two scales of descriptions:

- *Microeconomy* where the unit of analysis is the individual *agent* such as a person or a firm.
- *Macroeconomy* where the unit of analysis is the economical system as a whole.

The last scale (Macro-economy) is generally described by global differential systems allowing to represent the global evolution of the system where all *agent* populations are homogeneous and can be represented by a global number evolving during the trajectory of the system evolution.

The lower scale (Micro-economy) represents individual behavior and the development of Individual-Based Modelling (IBM) and Agent-Based Modelling (ABM) gives a very attractive vision for simulating the phenomena at this scale. Moreover, economy studies show how individuals, coalitions and societies seek to satisfy needs and wants. The complexity of such description highlights major nonlinear evolutions in a number of contexts.

Complexity perspective approach and agent-based computational economics approach (ACE) become one of the favorite theories used by scientists in order to consider economy as an evolving system, following John Holland's complex adaptive systems paradigm [62].

W. Brian Arthur, professor at the Santa Fe Institute, and other economists have been interested to view in economical systems evolution, the major influence of *feedbacks* [5]. He gives an interpretation of adaptive complex systems by feedbacks for economy. *Diminishing returns and negative feedbacks* refers to the notion that the return that a company receives for additional effort decreases as the number of units increases. These negative feedbacks explain why industrial companies become less efficient once they grow over a certain size. *Increasing returns and positive feedbacks* refer to the notion that the greater the size of the network, the greater the advantage of each participant of the network. The positive feedback mechanism generates a resulting action which goes in the same direction as the condition that triggers it. W. Brian Arthur observes that the part of economy that are resource-based is still subject to diminishing returns and the part of economy that are knowledge-based is still subject to increasing returns.

Beside system global evolution, individual behavior have been widely used in the new economy, mainly based on microeconomy. Game theory [50] is very often used to illustrate the economical interactions between people. Such theory tries to analyse the possible strategies and implement them inside a regular process which can be represented by some mathematical sequences. Convergence properties leads to explain the benefit or the failure of specific application. Dynamic equilibria, like Nash equilibrium, can be a relevant tools for such studies.

For many complex systems, the dynamics are essential and if some equilibrium can appears, it is generally only a temporary state. In such context, dynamical cooperation and competition processes can be involved in order to model adaptive strategies for dynamical behaviors. Prisonner dilemma is a well-known problem involving such features [6]. Previous works have been made to model adaptive behaviors for prisonner dilemma with automata with multiplicities [140].

Based on such complex systems developments, Geopolitics finds a very relevant context. Agent concept and programming become an attractive way of studying such systems. Interacting networks widely developed nowadays increase the geopolitics complexity. Both game theory and agent-based simulations allow to explain in detail some hypotheses and find root in complexity concepts [29].

Another major contribution of complex systems in economy concerns the market system which presents sometimes inherent nonlinear and unstable behavior leading to chaotic evolution. Recent events show how the complexity of market system is able to highlight its criticality properties, far from equilibrium and far from any kind of external controls. Didier Sornette [114], professor in Geophysics, investigates the complexity concepts to analyze financial crises as critical events, highlighting feedbacks and self-organizations inside economics.

Even if we can feel what is the complexity of such artificial or natural systems, social or economical systems, as we describe then in this section and the previous ones, we need now to progress on general concepts that are able to draw some transverse characteristics or properties of all these systems. We need these general concepts to extract the complexity itself, out of the disciplinary context but crossing all these disciplines. That is what we propose to do in the two following sections concerning complex systems concepts and self-organization processes.

2.2 Complex Systems Concepts

2.2.1 Complex Systems Definition

General system theory has been developed by L. von Bertalanffy in 30's [7 in master thesis]. The goal is to study the general properties of natural and artificial systems whatever their physical nature.

Because of the generic approach proposed by L. von Bertalanffy, this theory is well suited for various applications and allows a large-scale formalism. Systemic and complex system modelling find their roots in this ambitious framework.

Definition 1 *A* **Complex System** *is a set of interacting entities which have the following specific characteristic properties that confer its structural aspects:*

1. *Emergent properties exist and describe the whole system behavior which are not expressed in the entities behaviors.*

2. *Feedback process exists and concerns the reaction of the system over its own entities. There are two kinds of feebacks:*

   - *Positive feedbacks are catalystic functions which increase some emergent properties. These positive feedbacks can for example, be the generator of the system formation, increasing its own constitution;*
   - *Negative feedbacks are stabilizing functions which decrease emergent properties to regularize the system itself, allowing to identify it.*

3. *Energetical fluxes, crossing the system, exist in order to characterize the system as an* **open** *system. These energetics fluxes lead to make evolve the entities interaction system in a dynamical way.*

In figure 2.11, we illustrate this definition, drawing these different concept item inside abstract representation.

As defined, a complex system is a system composed of interconnected parts that as a whole exhibit one or more properties (behavior among the possible properties not obvious from the properties of the individual parts).

The complexity of a system may be of one of two forms: disorganized complexity and organized complexity [wikipedia]. In essence, disorganized complexity is a matter of a very large number of parts, and organized complexity is a matter of the subject system (quite possibly with only a limited number of parts) exhibiting emergent properties.

2.2.2 Complex Systems Properties

After giving a general definition of complex systems in the previous section, we detail in this section their characteristic properties to better understand its meaning. We associate to the definition items, additional concepts or properties linked to these items.

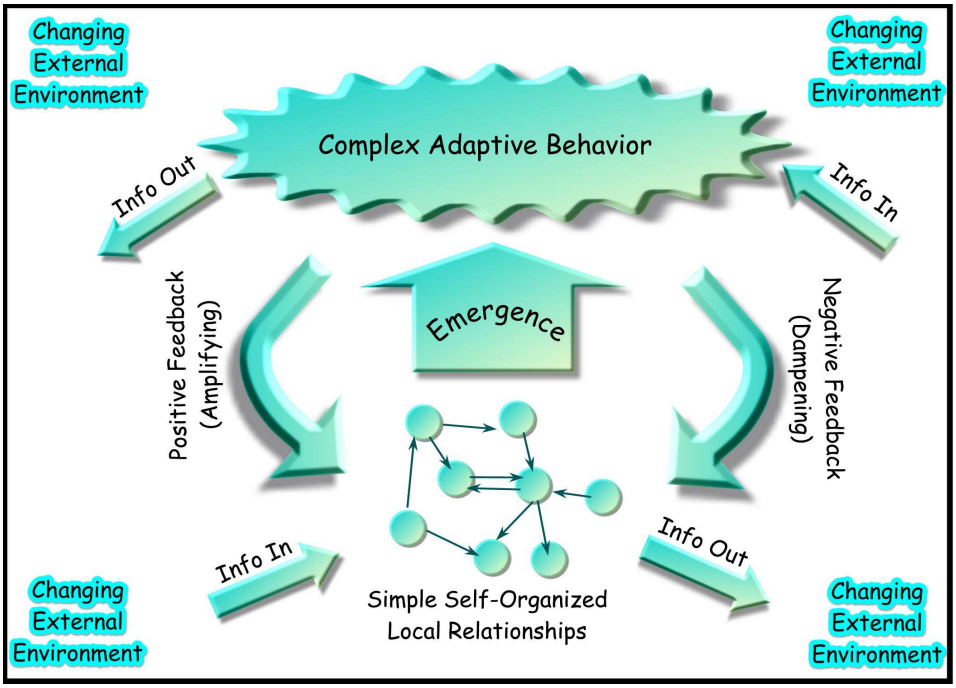

Figure 2.11: Complex adaptive system (from Wikipedia)

Interacting Entities

Complex systems are basically composed of entities which interact within relationships. Typically these relationships are short-range and deal with neighborhood. They are not simple and present nonlinear properties making that small modifications on few entity relationships can produce large effect on the whole system. These properties are known as the "Butterfly effect" which comes from a metaphor used by the scientist Lorentz when he described the sensibility to initial conditions in meteorologic dynamic systems. Because of the high degree of flexibility in complex system, a small perturbation at some place can produce major effects further, by combination of interacting effects.

This sensibility to modification generates also sensibility to the entity belonging to the system on its boundaries. Moreover, the boundaries of the system can be virtual in the meaning that the system exists but the entities which compose it can change. A water vortex is an example of such stable structure which are crossed by the entities which compose it.

People sometime talk about "strong" or "weak" boundaries without an accurate definition of this terminology. We can consider that a boundary is strong if it involves a great quantity of interaction between itself and entities within the system. A strong connection can lead to close the system and avoid its opening.

Emergence, Hierarchies and Multi-Scale Description

One of the major properties of a complex system is that it is not only the simple sum of its entities. Its entities interact in collective behavior making the system itself emerging from this collective behavior. The whole system behavior (or behaviors) cannot be described inside the entities set because these entities cannot know what is happening in the system as a whole. We face to multi-level or multi-scale description.

A first consequence of this aspect is that the control of the whole system must be obtained from the description level of the system itself, if possible, and it cannot be managed from the entities themselves.

A second consequence of the multi-scale description is that the description level is not only on one level and usually complex systems are themselves composed of entities which are themselves complex systems of lower level. Typically ecosystems are well-known to be hierarchical systems of systems and its stability is larger with the depth of this hierarchy. In the same way, a social system is composed of countries composed of a region set, themselves composed of cities sets, themselves composed of a center set which contains multi-organizations set and groups of people.

Feed-Back and Adaptation

We can understand the feedback process as the tendency of the system to use its own output to make adjustments in its inputs, most systems include some form of feedback. Feedback which is an action on the whole system is a primary means of control to guide the system behavior and adapt it to some evolution. It can take the form of information or energy that enables the system to get back into balance. Even failure in a system is only feedback.

Because complex systems have internal degrees of freedom and because we are only able to act on few of its degrees of freedom, such system cannot be completely controlled and we can only hope to guide it or influence it [31].

In the most general sense, adaptation is a feedback process in which external change in the environment are mirrored by compensatory internal change in an adaptive system. In the simplest case, an adaptive system may act in a regulatory manner, like a thermostat, so as to maintain some property of environment at constant level [45]. An interesting type of adaptation is found in complex systems in which the interaction among the subunits are allowed to change. This process is very similar to a self-modifying program, since the action of the adaptive unit can effect the environment, which, in turn, feeds information back to the adaptive system. Thus, adaptation can be seen as a computation of the most complex form that emerges through the multiplicity and recursion of simple subunits.

Open Systems and Dynamics

The richness of the connections between entities means that communications will pass across the system, but will probably be modified on the way. Dynamics are generally major aspects of complex systems. Because they are open systems, energy and information are continuously being imported and exported across systems boundaries. Because of this, complex systems are usually far from equilibrium: even though there is constant change, there is also the appearance of stability.

Finally, a complex system has a history. Small change can make it evolve in an irreversible way. Usually a young system has no deep hierarchy and this hierarchy depth increases with the development of the system respecting its complexity.

2.2.3 Simplicity, Complication and Complexity

To better understand what are complex systems, we can propose the following classification, from Jean-Louis Le Moigne [85] and Michel Cotsaftis [32]:

- **Complicated systems**
  A complicated system can be decomposed in smaller parts and each part can be analyzed separately to understand component by component, the whole system behavior. We face the reductionism approach, issued from Decartes's method. An example of such complicated system could be a description of car engine that we can analyze piece by piece. The whole car engine is the simple assembly of its components. The whole car engine is doing not more than the sum of its component's contribution, taken in an isolated way.

- **Complex systems**
  A complex system is not reducible to simple systems as complicated systems. If you try to analyze it by parts, you lose the understanding of the whole system itself. Isolating a sub-system consists to break some connections inside the whole system and, as we already explained, breaking connections leads to modify the system behavior. An example of such phenomena can be found in ecosystems and food chains in some specific environment. If you isolate few animals of some species in a food chain and make them live together, they will organize and evolve in a complete different way than in the whole ecosystem from where they are taken.

Following Edgar Morin [86], complexity helps to evolve in the scientific knowledge by breaking with the simplification approach which consists in dividing and reducing science in a set of dissociated knowledge, hiding the connection between these knowledge. Complexity principles are to connect the knowledge, to have new understanding of transversal concepts, and then be able to have new meaning of these concepts even inside each specialty. Moreover, complexity is not in opposition with simplicity because, as we will illustrate by swarm intelligence methods, complex systems modelling consists sometimes to use simple systems but to be able to connect them and to give meaning to the connection network in order to lead to emergent properties from this network links.

2.3 Self-Organization Process

2.3.1 Self-Organization Definition

Self-organization is a phenomenon in which interactions between elements and other factors, tend to create and improve order inside the whole complex system. Such a phenomenon goes against the increase of entropy and leads to energy dissipation. This dissipation has an effect to maintain the structure generated in this way.

So, this phenomenon is a natural tendency of physical dissipative systems or social systems to generate organization from themselves.

No one knows exactly how self-organization happens - it is a "wonder of nature." Birds naturally flock together. Bees naturally form hives. People naturally recognize their interdependence and work together to accomplish shared goals or tasks. They do not always have to be told what to do.

The study of self-organizing systems was originally developed in physics and chemistry describing the emergence of macroscopic pattern out of interaction process defined at microscopic level [23]. Since 1953, this field has been explored by Grassé [56] who studied the individual behavior of social insects and introduced the concept of Stigmergy. “Self-organization is a process in which pattern at the global level of a system emerges solely from numerous interactions among the lower- level components of the system”. Moreover, the rules specifying interactions among the system’s components are executed using only local information, without reference to the global pattern.

From Camazine et al. [27], in other words, each individual entity is organized without any external or central dedicated control entity but by the local interactions simple rules, emergent behaviors (structure or pattern) appear.

Another definition for self-organization is “a set of dynamical mechanisms whereby structures appear at the global level of a system from interactions among its lower-level components”[23].

The self-organized system has the following properties:

- No central control
  There is no global control system or global information available. Each subsystem must perform completely autonomously, adapting to change conditions.

- Emerging structures
  The global behavior or functioning of the system emerges in form of observable pattern or structures.

- Resulting complexity
  Even if the individual subsystems can be simple as well as their basic rules, the

resulting overall system becomes complex, hierarchical and often unpredictable.

- High scalability
  There is no performance degradation if more subsystems are added to the system. The system should perform as requested regardless of the number of subsystems.

2.3.2 Element of Self-Organization

A self-organized system has four basic elements: positive feedback, negative feedback, amplification of fluctuations, and multiple interactions.

Positive Feedback

Positive feedback promotes changes in a system, usually in the same direction as the system is currently moving. It has been described as "simple behavioral rules of thumb" that promote the creation of structures [22].

An example of this is the aggregation of some birds when building nests. Nesting in groups may provide benefits in terms of protection from predators, or ease in finding food. Because of this, birds may prefer to nest where other birds nest. If some birds for some reason decide to nest at a particular location, other birds will be attracted to nest on the same site, because they want to nest where other birds nest. This constitutes a positive feedback in the form that the more birds that nest at a location, the more birds will be attracted to nest at that location, and as a result the nest site will increase in size.

Positive feedback can have a snowballing effect in that it reinforces an initial change in a system in the same direction as the initial deviation. In fact, explosive chemical and nuclear reactions are classical examples of positive feedback. Positive feedback consequently has a destructive potential in that it can create a cascade of change in one direction.

Negative Feedback

Negative feedback counterbalances positive feedback and helps to stabilize the collective pattern. As mentioned above, positive feedback has a destructive potential in that it can have a snowballing effect. This destructive potential can be counterbalanced by negative feedback.

Negative feedback can work in the opposite direction of a positive feedback mechanism, and thus provides inhibition to offset the amplification provided by the positive feedback. By doing this, negative feedback can help shape the amplification into a specific pattern. Negative feedback can take the form of a saturation, exhaustion or competition. It often arises from purely physical constraints, for example in the form of depletion of a resource. The building of a structure may for example be inhibited by the reduced amount of building material that is available.

Amplification of Fluctuations

Self-organization relies on amplification of fluctuations, which is its third basic element. These fluctuations may take the form of random walks, errors, deposition of objects in random positions, and so on. This randomness is a key part of self- organized systems. The random events that occur in a self-organized system are crucial to the system because they allow the system to discover new solutions. The random fluctuations that occur in the system can be amplified, and through this, new structures or solutions may be found.

For example, in the case of ant foraging, a forager may get temporarily lost from its current trail and discover a new rich food source. This food source can then be exploited by the ant colony. If it were not for the error of the first ant this food source would not be discovered, and the colony would not be able to exploit it.

Multiple Interactions

The last element of self-organization is multiple interactions. These interactions may be either directly exist between the individuals of the system, or indirectly through the elements that are handled by the individuals in the system. In this latter form two individuals may interact when one individual modifies the environment, and the other individual responds to the modified environment at a later time. This modification of the environment may, for example, take the form of deposition and removal of objects.

2.4 Computational Aspects of Complex Systems

In the previous sections, we have presented the concepts of complex systems. It is an essential step to understand and to define these concepts allowing to highlight when and how some phenomenon can be recognized by its complex properties. Applied Mathematics, Physics and Computer Science, as sciences of modelling, have to go further in concepts description and have to give formalisms to express complexity and self-organization. In our own scientific approach, based on computer science and computer engineering, we have to propose computable models toward implementation and simulations. We can see complex systems simulations as a tool to understand and analyze system dynamics, leading to decision making processes.

In the following sub-section, we propose a short review of methods and algorithms allowing complex systems implementation, highlighting some of the essential properties belonging to complexity.

2.4.1 Evolutionary Algorithms and Adaptivity

Evolutionary algorithms are an active research field based on the metaphor of natural evolution. The principles of such methods is to describe a dynamic process with a population of individuals. Each individual is represented by a *chromosom* allowing to encode

the data or properties on which the simulation deals. For example, Genetic algorithms belong to evolutionary algorithms and have been initially introduced by John Holland to focus on adaptation in natural and artificial systems [62].

Genetic algorithms are scheduled in two main steps. The first step consists in applying three genetic operators on the population of chromosomes: duplication, crossing-over and mutation. The second step consists in applying a selection process on the chromosome population, keeping only the individuals performing the best values of a fitness function. This second step shows that the genetic algorithm is well-suited for optimization problems [53]. The advantage of this method is that the genetic operators include different kinds of operators: (i) the crossing-over is a kind of combination which composes a new value from two others. This leads to improve some previous solution seen as a candidate to the problem; (ii) the mutation introduces a random aspect allowing to produce a completely new solution candidate to the problem. This contributes to continue to explore the *solutions space* and not only fall into some local optimum, by only combination of previous solutions.

2.4.2 Neural Network and Self-Organized Map (Kohonen Map)

Neural networks algorithms are based on the use of interaction networks of neurons as elementary computing entities. We use here the metaphor of the human brain with two major steps: (i) learning process consists in building the neuronal network, that is the definition of the best value of weights on each edge connecting two neurons. (ii) once the learning process is achieved, we have a whole neuronal network which can be used like a *black box*. This network receives some input and gives in return some outputs. Typically, neural networks have been used in an efficient ways for pattern recognition. More recently, a new kind of neuronal networks have been proposed by Kohonen who proposed a self organized neural network without the need of learning step. Because of this improvement, these new kinds of networks, called Kohonen maps, have been described as self-organized maps. They are able to configure themselves without learning. They are used for example, in non-supervised classification.

2.4.3 Cellular Automata and Diffusive Rules

Cellular automata are well adapted to simulate spatial phenomena and to reproduce self-organized systems.

Cellular Automata Definitions

Generally, a cellular automaton is defined as a dynamic system, composed of cell network (generally regular grids). These cells are in one state belonging to a finite set. The cell evolution is defined by a local rule, according to the state of its neighboring cells.

In a more formal way, we can give the following definition:

Definition 2 *A cellular automaton A of dimension $d \geq 1$ is defined on Z^d, called network containing cells characterized by*

- *$S(i,t)$ is the state of the cell i, at time t;*
- *$v(i,t)$ is the state of the neighborhood of the cell i, at time t;*
- *a transition rule f which define the state of the cell i, at time $t+1$ by:*

$$S(i,t+1) = f(S(i,t), v(i,t)).$$

In figure 2.12, we show a 2D cellular automata, in which each cell has 2 states: white or black. These two states could modelize a dead or living state like in the well-known Conway's life game [49].

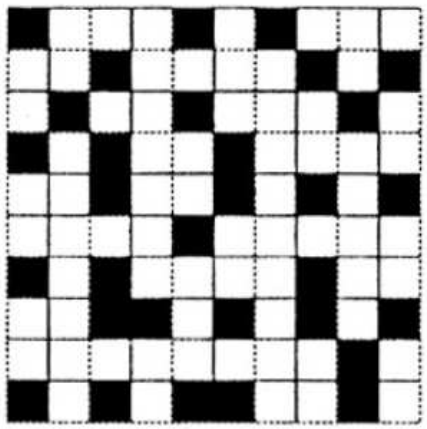

Figure 2.12: Simple 2D cellular automata with 2 states cells

A cellular automaton is characterized by its cells support, called Z^d in the definition. We have to define the domain boundaries which have an important influence on the computation. In figure 2.13, we describe, on the left side, a finite boundary 2D ($d = 2$) regular domain. In the middle of this figure, we introduce a surrounding between the lateral border of the domain which transforms it as a cylinder. In the right side of the figure, we introduce also a surrounding between the top and bottom border of the domain which transforms it as a torus surface.

As an essential part of the previous definition for cellular automata, the cell neighborhood is an essential concept. In a 2D regular grid, the most usual neighborhood definition given are *von Neumann neighborhood* and *Moore neighborhood*. On figure 2.14, we describe these two kinds of neighborhoods and their computation according to

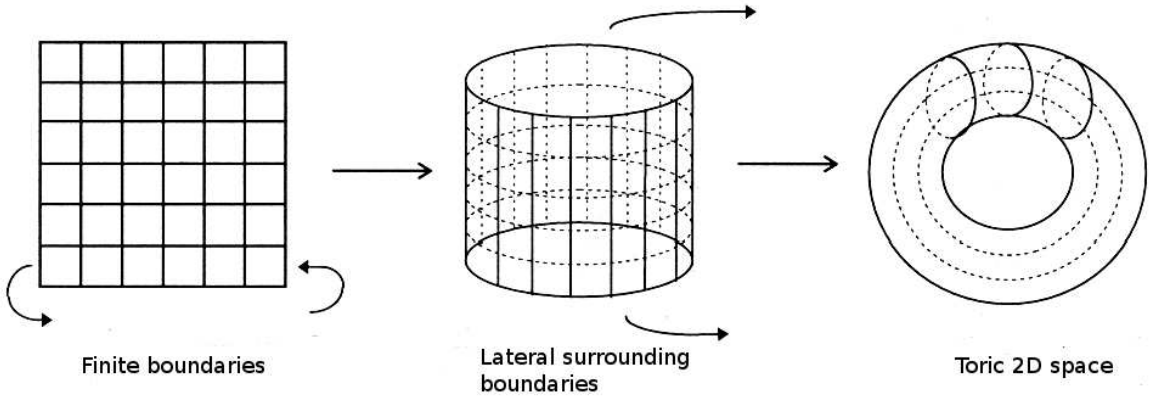

Figure 2.13: Various configurations of 2D space in cellular automata (from Coquillard and Hill [30])

the boundary definitions.

We give now a formal definition of these two kinds of neighborhoods (von Neumann and Moore), generalized to any polygonal cell-based 2D cellular automata.

Definition 3 *In a 2D cellular automaton with support Z^2, the von Neumann neighborhood of a polygonal cell c is the set of cells of Z^2 which share an edge with c.*

Definition 4 *In a 2D cellular automaton with support Z^2, the Moore neighborhood of a polygonal cell c is the union of the von Neuman neighborhood with the set of cells of Z^2 which share a node with c.*

The neighborhood definition has a major effect on cellular automata because we can observe that the transition rules defined previously, are in some way, only diffusive rules. The meaning of this remark is that, any dynamics over cellular automata can only be propagated by neighboring effect. In their paper [72], Langlois and Daudé study the geographical diffusion effect based on cellular automata modeling.

More generally computational grid, as extension of cellular automata on which we can introduce agents, is very efficient and it is the support of many studies presented later in this document.

Cellular Automata Applications

Cellular automata has been developed in an intensive way from the last decades. In the 1960s, the mathematician John Conway proposes his very famous game of life, as an example showing that with a very elementary set of rules, we can obtain very complex unpredictable situations. In the 1980s, the famous physicist Stephen Wolfram who already made major contributions on computer algebra with his system called Mathematica, revived cellular automata research. In his famous book, “a new kind of sciences”,

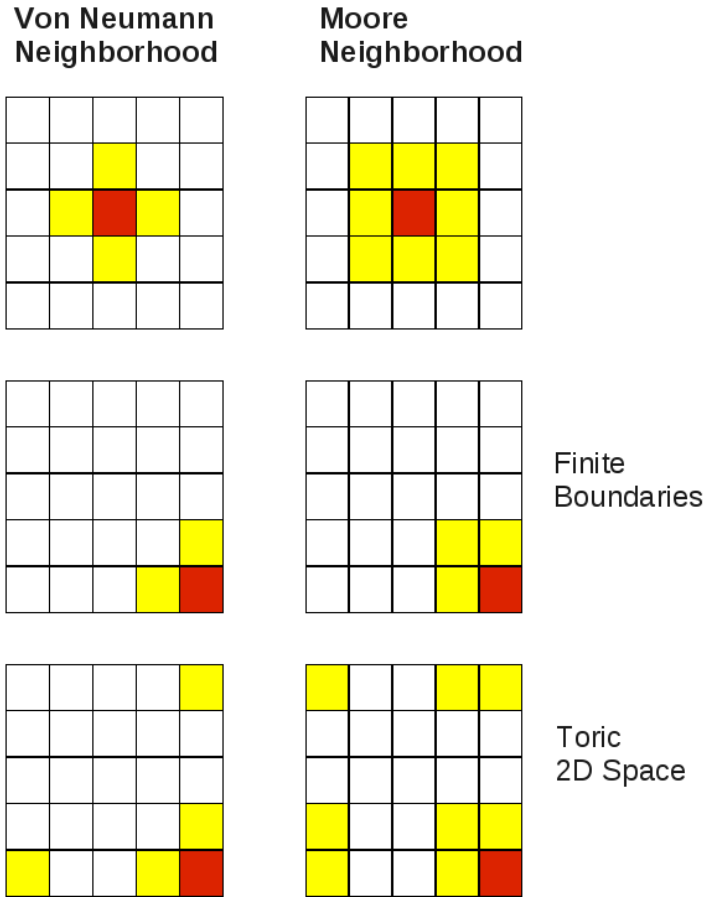

Figure 2.14: Neighborhood definitions in 2D regular cellular automata

Stephen Wolfram [133] presents cellular automata computation. He claims that such computer tools allow him to recover the main laws of physics, as emergent properties of this artificial computing.

S. Wolfram gives more phenomenological and systematic definitions, based on the qualitative result given by the cells interactions toward a complex global behavior. With the consideration that a finite cellular automaton can only produce finite states set (but sometimes of impressive size), he proposes a classification based on 4 classes according to the phenomenology of the automata dynamics. The first class concerns the cellular automata which always evolve to a homogeneous arrangement, with stable configuration. The second class concerns the cellular automata which evolve to stable periodic structures in endless loop. The third class concerns the similar to "aperiodic" and random-like configuration evolution (finite state means that all automata will necessary repeat itself after eventually a very long period but this period has no meaning in the qualitative description here). The fourth class concerns cellular automata where localized structures appear and move in the space with time.

Chris Langton, a famous name for artificial life and the inventor of the swarm simulation

platform [84] in Santa Fe Institute, contributes to define some criteria whom evolution makes the cellular automata go through the different class of Wolfram's classification. He defines a parameter which characterizes the class of the automata and allowing understanding of cellular automata dynamics in term of fixed, periodic, chaotic or complex dynamics.

Previous studies, as mathematical studies of cellular automata dynamics, deal mainly on simple state cell configuration, mainly the cell is white or black, dead or alive. Since a few years, cellular automata find a huge domain of applications in human sciences and specifically in geography. For these applications, the cell states must be more complicated and can allow to describe the state of land-use parcel, that is: non used, with forest, inside rivers, with industries, in urban area, with shopping, with housing, etc. We will present some of these simulations in chapter 7

2.4.4 Multi-agent Systems, Cooperation, Competition and Coordination

The grid rules of cellular automata is generally not sufficient to model all the complexity of some phenomena and we need to add agents entities. In this section, we just give a short overview of agent-based concepts and programming and we will develop them in the following chapter, because they constitute a major contribution in our work.

Mainly, multi-agent systems allow to implement computer programs composed of autonomous entities, perceiving and acting on their environment. These active entities are able to communicate and so to contribute in a collective way to solve some problems. Social behaviors are proposed between agents to describe communication effects like cooperation, competition or coordination, but the principles of problem solving by collective approach have to be built. What agent concept does not define by itself, is how this communication must be organized to finally produce an efficient distributed algorithm to solve the problem. The collective mechanism algorithms must be defined, as well as the agents behavior allowing this collective behavior.

The goal of swarm intelligence is to propose some efficient way to solve such problems, by the accurate definition of agent behavior, with other agents and the agent environment, that leads to emergent collective behavior. These methods and algorithms will be described in chapter 4.

Chapter 3

Multiagent Systems and Spatial Modelling

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The last section of this chapter has been published in ESM'2008 proceedings [150]

3.1 Distributed Artificial Intelligence

3.1.1 A Brief History of Artificial Intelligence

Since the beginning of recorded history, people has been fascinated by the idea of non human agencies or by intelligent machines, but with the development of the electronic computer in 1941, the technology finally became available to create machine intelligence [106].

In late 1955, Newell and Simon developed *the Logic Theorist*, which is considered by many, to be the first program of Artificial Intelligence (AI). The program, representing each problem as a tree model, would attempt to solve it by selecting the branch that would most likely result in the correct conclusion. The impact that the logic theorist made on both the public and the field of AI has made it a crucial stepping stone in developing the AI field.

In 1956, John McCarthy who is considered as AI father coined the term "artificial intelligence" as the topic of the Dartmouth Conference, the first conference devoted to the subject.

In 1957, the first version of a new program, *the General Problem Solver (GPS)* was tested. The program was developed by Newell and Simon. The GPS was an extension of Wiener's feedback principle, and was capable of solving a greater amount of common sense problems. After many programs were being produced, Arthur Samuel wrote the first game-playing program for checkers to achieve sufficient skill to challenge a world champion. Samuel's machine learning programs were responsible for the high performance of the checkers player.

In 1958, McCarthy announced his new development, *the LISP language*, which is still used today. Oliver Selfridge's paper "Pandemonium: A Paradigm for Learning", which proposed a collection of small components dubbed *"demons"* that together would allow machines to recognize patterns, was a landmark contribution to the emerging science of machine learning. In the same year, Marvin Minsky's wrote the paper "Some methods of heuristic programming and artificial intelligence". Since that time many projects has been done and served to increase the pace of development in AI research, by computer scientists around the world [106].

Another turning point of AI development comes in the 1960's and in the early 1970's by the development of knowledge based systems and the experts systems, trying to have thinking machine. From 1980 until now, AI has been become widely used in industrial domains. In the mid 1980's, Neural Networks have become widely used with the Back Propagation Algorithm (first described by Werbos in 1974). We can say that from 1987 until now, AI becomes a science and many revolutions have been accomplished in domains like: robotics, computer vision, and knowledge representation [106].

3.1.2 From Artificial Intelligence to Distributed Artificial Intelligence

A machine that is capable to think and decide is a great achievement for the human being, which directly connected to expert systems.

> "An expert system is a computer program that is capable of replacing human beings in some tasks that considered as extremely complicated which need knowledge, experience and a certain type of reasoning" [44].

This conception is the root and the result of the development of centralized and sequential systems, including control. The decision will be a function of different activities carried out one after another. However, this concept of sequence and centralization meets several obstacles:

1. At the theoretical level, the human intelligence is like science (Latour 1989, Lestel 1986) you can't separate individual characteristics from the social context and the artificial intelligence methods used are based on reductive and optimistic description.

2. At the practical level, computer systems become more and more complex. For example, in complex industrial expert systems, the expertise (various kinds of "know-how", skills and knowledge) which try to integrate into a knowledge base, is possessed by different individuals who communicate within a group, exchange knowledge and collaborate in carrying out a common task. In this case, the knowledge of the group is not equal to the sum of the knowledge possessed by all the individuals: each kind of know-how is linked to specific points of view and can't be brought together to form a coherent whole. So carrying common tasks require discussion, adjustment, and even negociations to resolve conflicts.

3. Problems can be sometimes naturally expressed in distributed context. For example, air traffic control system cannot be completely centralized and it is the result of the interaction of constraints from many control centers concerned by each airplane trip.

The need for different approaches of classical artificial intelligent leads to radical changes from the sequential computation. The need to take into account complex problem solving leads to the development of Distributed Artificial Intelligence (DAI) which is based on the establishment of subsystems sharing environment and able to communicate and coordinate actions. These sub-systems need to be entities relatively independent and autonomous. These entities called "Agents" have sometimes complex mode of cooperation, conflict and competition in order to survive and perpetuate themselves. Organized structures emerge from these interactions and these emergent structures to restrict and modify the behavior of their own agents [44].

We should mention here that there are three main features that facilitate the DAI developments. First, the development of Complex Systems understanding, as a mean of interaction between agents, gives a new way of modeling. This new way of modelling is based on decentralized representation which is composed of interaction network of entities from where emergent properties appear. Second, Object-Oriented programming has proposed a first step in the decomposition of computing, and so in the following, agent oriented programming adds to objects some autonomous properties. Third, the development of huge computer networks promotes the distributed computing which finally allows implementations of these previous concepts.

3.2 Multi-agent Systems Overview

3.2.1 From Object-Oriented Programming to Agent-Based Programming

Agent-Based programming can be perceived as an extension of Object-Oriented Programming, in terms of conceptual description.

Object-Oriented programming proposes an extension of procedural programming approach by introducing the notion of attributes and methods (private methods and public ones). In general, public methods define the interface of the object, allowing the object to communicate with this outer world (see figure 3.1). Moreover, object programming promotes abstract concepts like inheritance, that provides the support for representation by categorization in computer languages. Categorization is a powerful mechanism used in information processing, crucial to human learning by means of generalization (what is known about specific entities is applied to a wider group given a member relation can be established) and cognitive economy (less information needs to be stored about each specific entity, only its particularities). Finally, an object-based program consists in running the main object which will create all the objects needed for the program and solving in a distributed way the problem by the composition of their actions and by the interaction between them. The program must be scheduled and planned in detail by the programmer.

Agent-Based Programming proposes a more complex conceptual description. An Agent still contains attributes and methods but also more sophisticated notions like life cycle, behavior or knowledge database (see figure 3.2). In addition, the interface is composed of two major methods corresponding to perception mechanisms and to actions mechanisms which are described in the following section. Finally, an agent-based program consists in running a virtual world where many autonomous entities will evolve according to the dynamics of the environment and the whole system of agents, during the simulation. The whole evolution of this virtual world can be perceived as unpredictable, according to the complexity of the entities interaction.

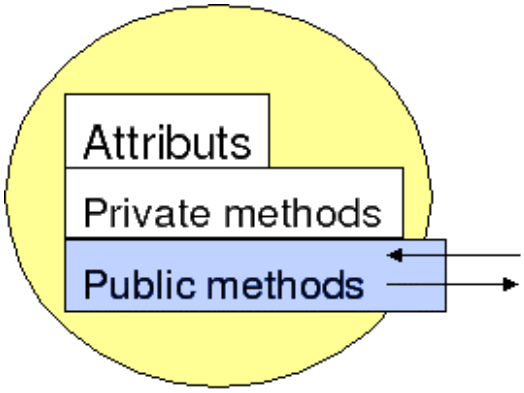

Figure 3.1: Object conceptual representation

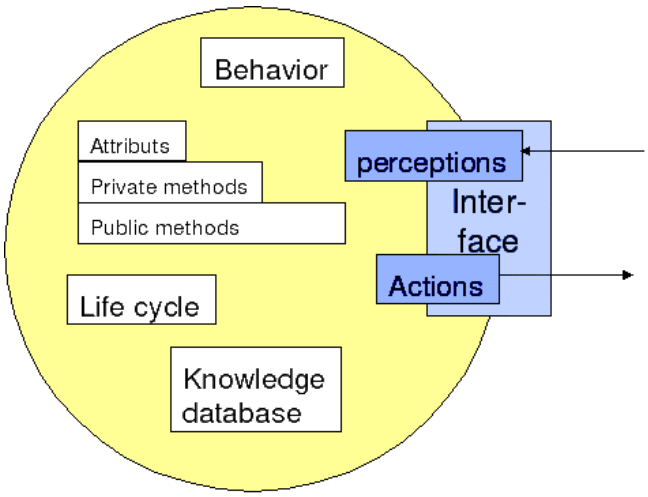

Figure 3.2: Agent conceptual representation

3.2.2 Agent Definition

> "An agent is anything that can be viewed as perceiving its environment through sensors acting upon that environment through actuators " [106].

This simple definition which illustrates in figure 3.3 allows us to illustrate the relation between the agent and its environment in functional aspect.

Following M. Wooldridge [134], we give the following basic definition which is based on behavioral aspect of agent properties:

> "An agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives"

An autonomous action for an agent is its ability of deciding for itself what it needs to do in order to satisfy its design objectives. The environment is an essential notion: it

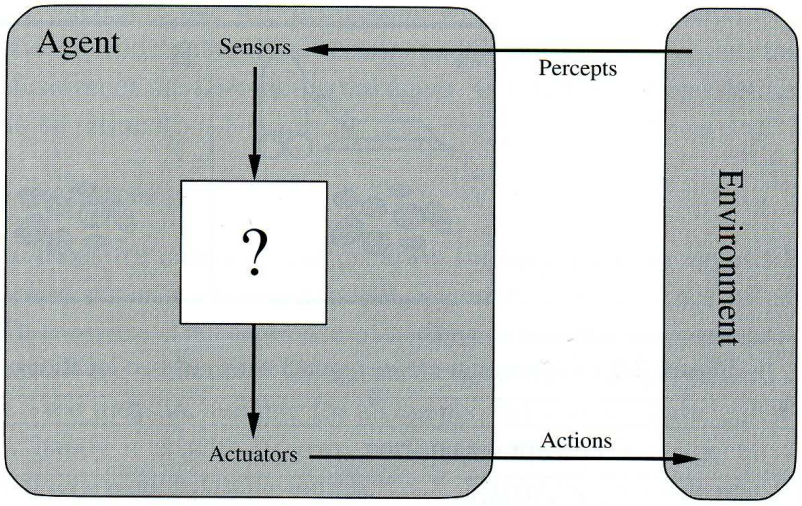

Figure 3.3: Agent basic representation

summarizes everything out from the agent; it is the origin of all external perceptions of the agents. We can then describe the relation between an agent and its environment in the simple following way:

- The agent has some perceptions from its environment
- The agent has the possibility to act on its environment

Between the perception and the action, the agent can develop some less or more sophisticated behavior. According to this behavior we have outlined four basic kinds of agent corresponding to their selecting actions methods [106]:

- *Simple reflex agents*: Simple reflex agents act only on the basis of the current percept. The agent function is based on the condition-action rule: "If condition then action rule". This agent function only succeeds when the environment is fully observable. Some reflex agents can also contain information on their current state which allows them to disregard conditions whose actuators are already triggered (see figure 3.4).
- *Model-based reflex agents*: Model-based agents can handle partially observable environments. Its current state is stored inside the agent maintaining some kind of structure which describes the part of the world that can not be seen. This behavior requires information on how the world behaves and works. This additional information completes the "World View" model. A model-based reflex agent keeps track of the current state of the world using an internal model. It then chooses an action in the same way as the reflex agent (see figure 3.5).
- *Goal-based agents*: Goal-based agents are model-based agents which store information regarding situations that are desirable. This allows the agent a way to choose among multiple possibilities, selecting the one which reaches a goal state (see figure 3.6).

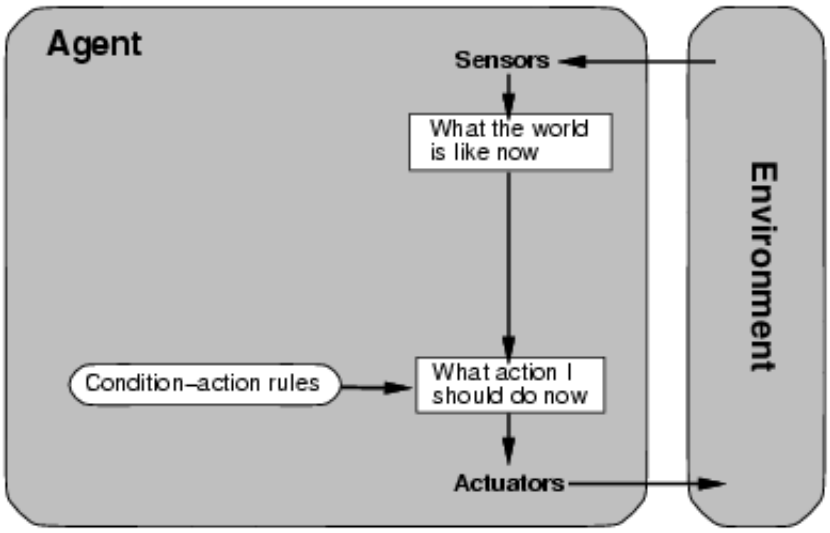

Figure 3.4: Simple reflex agent representation

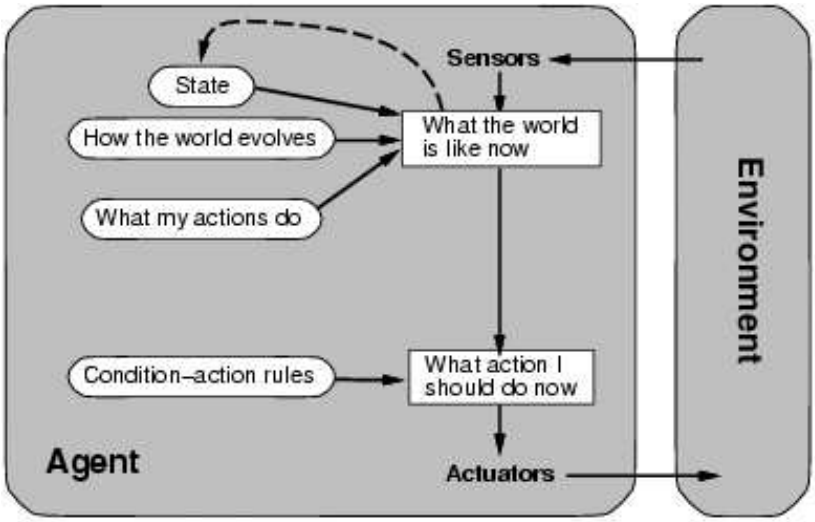

Figure 3.5: Model-based reflex agent representation

- *Utility-based agents*: Goal-based agents only distinguish between goal states and non-goal states. It is possible to define a measure of how desirable a particular state is. This measure can be obtained through the use of a utility function which maps a state to a measure of the utility of the state (see figure 3.7).

In addition, agents can be qualified as learning entities which can be applied to each of the four previous kinds of agents: Learning has an advantage that it allows the agents to initially operate in unknown environments and to become more competent, because its initial knowledge can be improved during the learning process. alone might allow (see figure 3.8).

All the previous kinds of agent representations define a conceptual modelling for mapping

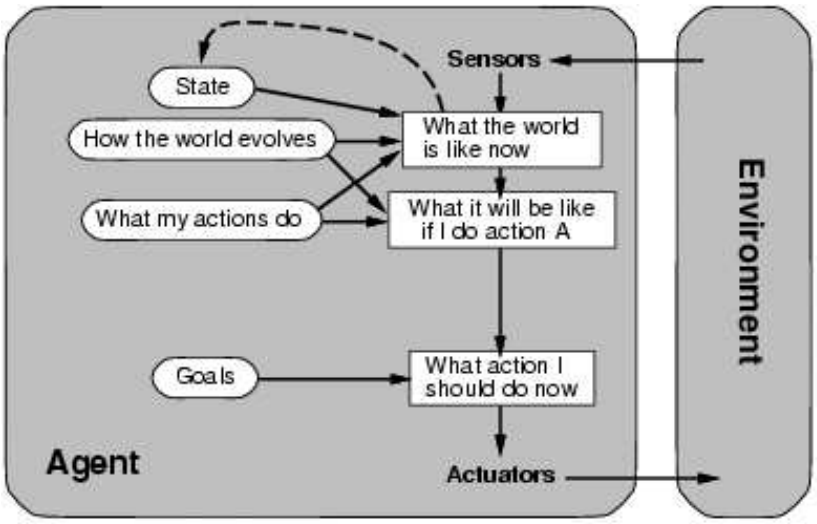

Figure 3.6: Goal-based agent representation

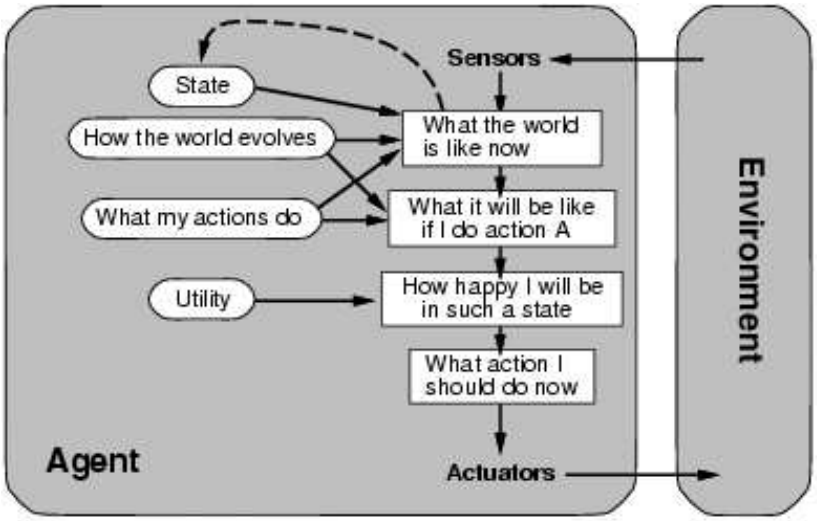

Figure 3.7: Utility-based agent representation

the agent behavior from perceptions to actions. It is important to remark that this mapping classification does not define the agent jobs themselves. These jobs have to be implemented using AI traditional methods (for example: neural network, expert system) or other innovative methods (for example: Boids behavior, ant clustering behavior which are defined in the next chapter).

3.2.3 Multi-agent Systems

Adapting the definition of Ferber [44] the term "multi-agent system" refers to a system consisting of the following parts which characterize the agents interactions between themselves or with their environment:

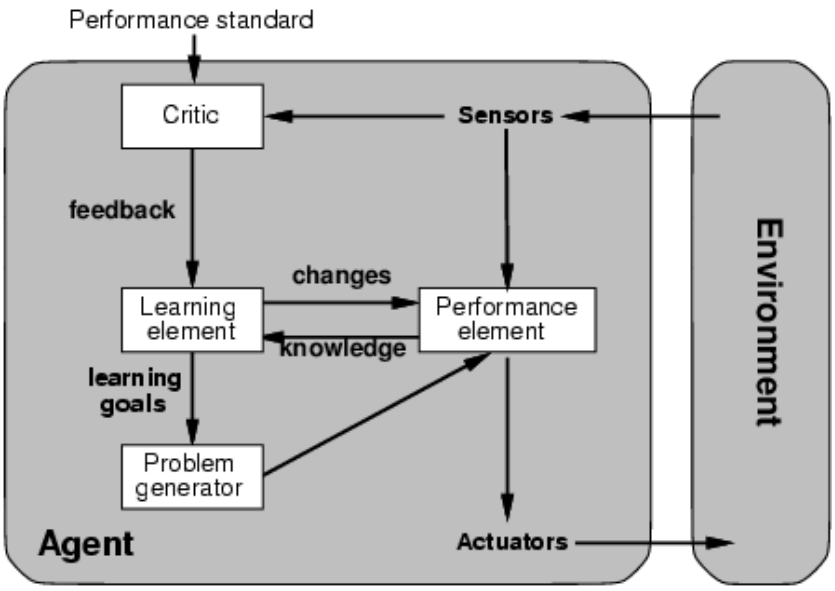

Figure 3.8: Learning agent representation

1. The environment E consisting of the following elements:
   - A set of objects O. Objects can be perceived, created, destroyed and modified by agents.
   - A set of agents A. Agents are a subset of objects ($A \in O$) capable of performing actions - the active entities of the system.
2. An assembly of relations R which link objects and also agents to each other.
3. A set of operations Op enabling the possibility for agents to perceive, manipulate, create, destroy objects of O, in particular representing the agents' actions.
4. A set of operators U with the task of representing the application of the operations from Op and the reactions of the world to this attempt of modification.

3.3 Environments for Agent Simulation

As described previously, environments are important elements for agents which provide percepts and perform actions on them. Multi-agent theory regards the environment as an integral part of the framework. In general, two classes of environments can be distinguished: artificial and real environments.

An agent in the environment is located at some position in space (from the set of locations L). Environment allows agents to have:

- Communications and perceptions.

- Neighborhood, connectivity of the places and among agents.
- Movement possibilities and constraints.

This environment can be *conceptual* or *spatial*. From the conceptual point of view, environments can be classified according to task performing aspects. From the spatial point of view, environments can be classified according to topological aspects.

From [106], the classification on task performing aspects is the following:

- *Observable vs. partially observable*
  In order for an agent to be considered as such, some part of the environment, relevant to the action being considered, must be observable. In some cases (particularly in software) all of the environment will be observable by the agent. This, while useful for the agent, will generally only be true for relatively simple environments.

- *Deterministic vs. stochastic*
  An environment which is fully deterministic is one in which the subsequent state of the environment is wholly dependent on the preceding state and the actions of the agent. If an element of interference or uncertainty occurs then the environment is stochastic. Note that a deterministic yet partially observable environment will appear to be stochastic to the agent. An environment state wholly determined by the preceding state and the actions of multiple agents is called strategic.

- *Episodic vs. sequential*
  This refers to the task environment of the agent. If each task that the agent must perform does not rely upon past performance and will not effect future performance then it is episodic. Otherwise it is sequential.

- *Static vs. dynamic*
  A static environment, as the name suggests, is one that does not change from one state to the next while the agent is considering its course of action. In other words, the only changes to the environment are those caused by the agent itself. A dynamic environment can change, and if an agent does not respond in time, this counts as a choice to do nothing.

- *Discrete vs. continuous*
  This distinction refers to whether or not the environment is composed of a finite or infinite number of possible states. A discrete environment will have a finite number of possible states, however, if this number is extremely high, then it becomes practically continuous from the agents perspective

The classification of environment on topological aspects, as mention by Charles M. Macal and Michael J. North [80], is described in the following, see figure 3.9,

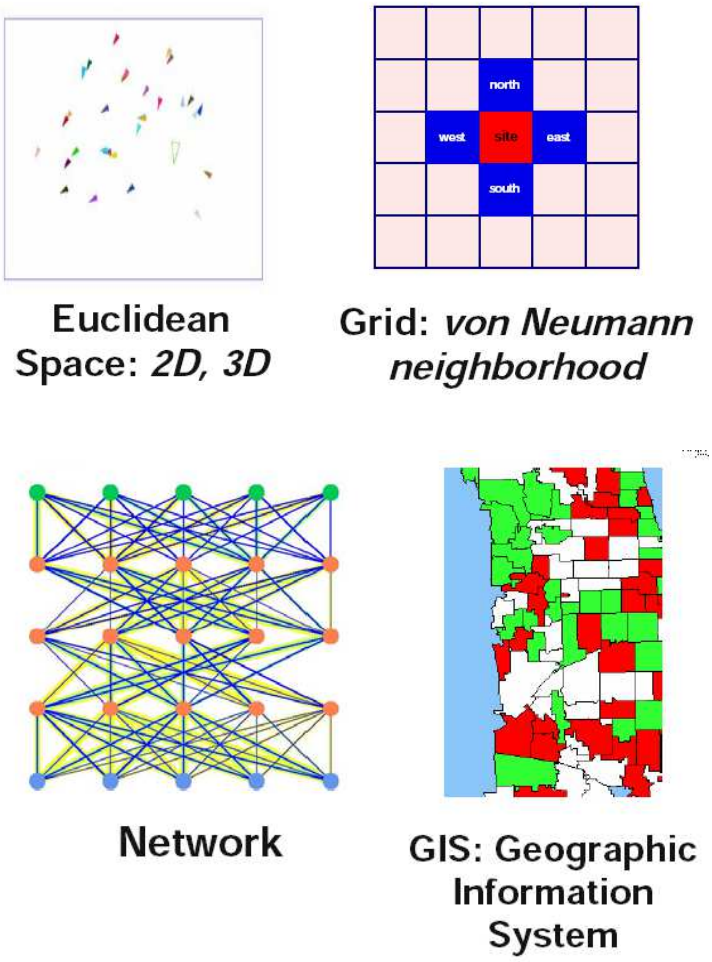

Figure 3.9: Environment classification based on topological aspects (from [80])

- Euclidean space: accurate but non structure. It considers the relationships among distances and angles, so neighborhoods calculation is expensive because each point has a neighborhood that is homeomorphic to an open set in Euclidean space of specific dimension. The cost of the neighborhood computation leads to some limitation in term of terms of entities number.

- Grid and cellular automata: in a grid space, the neighborhood is structured. On 2D-space regular grid, we can define 2 standard neighborhoods: Moore (8 neighbours) and von Neumann (4 neighbours). You can compute in that way the neighborhood easily and efficiently. Cellular automata described in the previous chapter, are examples for grid agent spaces.

- Graphs and Networks: in the previous grid space, the neighbors with which the agents are able to communicate, are in direct contact and the phenomena involved by such process can be considered only as diffusion processes: It is the major limitation of grid or cellular automata. In graphs and networks, we are free to consider all the edges needed between two agents, allowing them to interact, whatever their

position. In fact, graph and network does not represent a real geographical reference and only express abstract relationship network.

- Geographic Information Systems (GIS): these systems are based on spatial data associated to attributed databases. The goal of data representation in GIS is to provide spatial characterization of thematic 'layers' at desired scales and level of detail. Geographic features (like city represented by point or street represented by line) are usually represented in a GIS as spatial features with x, y, and sometimes, z and t (time) coordinates. The next section explains this kind of space.

A new concept called *spatial network* has been proposed recently and has the objective to link the two previous classes [20]. They are defined as networks of spatial elements and are able to deal with two objectives. The first objective is to add georeferencing to the nodes of the graph and to add distance meaning to edges. The second objective is to describe with edge connections, some graph topologies (small-words graphs, random graphs, etc) over spatial geographical sites. Current works on urban morphologies have to deal with such concepts.

3.4 GIS Environment

3.4.1 What is a GIS?

Maps have been used since thousands of years, but it is only within the last few decades that the technology has existed to combine maps with computer graphics and databases to create Geographic Information Systems or GIS. Essentially GIS is an automated information based map. This information which can be stored in different ways, is usually displayed as a computer-produced map. GIS have a great capability to integrate different kinds of huge amount of data. One of the unique feature of GIS is the ability to relate spatial data to relevant non spatial data. From a point in a digital map inside GIS, which may represent the location of a school, the user can point and click on it and so retrieve information regarding this school such as name, level, student population. In typical relational database, the name of the school can be used to retrieve more information about the school. In GIS, we use digital map location to retrieve these information from the database (see figure 3.10).

GIS does not allow only the retrieval of information through the use of geography, it also provides new techniques of displaying this information. GIS software provides cartographic tools to render data inside the visual form of map. We can visualize the points which represent the school by charts which describe the student population. The speed in which such maps can be produced, and the flexibility of the tools provided to create charts and reports are the reason why GIS are highly used in different domains.

One of the most important feature of GIS is its ability to perform sophisticated analysis using geography (spatial analysis) that has traditionally been extremely slow to perform or impossible. For example, a planer might use GIS to quickly determine which parcel

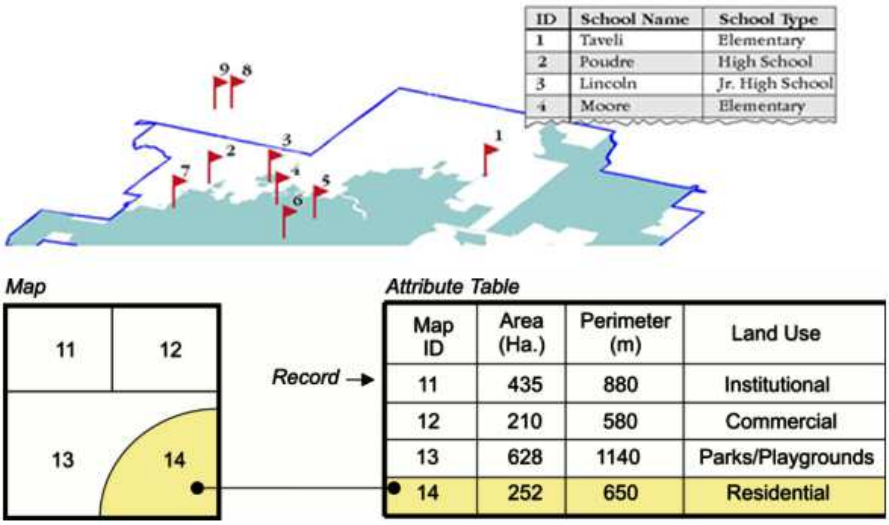

Figure 3.10: GIS links geographic location with information about those locations. The upper part shows a schools features the lower part shows a parcels features.

of land fall within several environmentally sensitive areas. Without GIS, this would normally be performed by overlaying several maps on a light table and visually identifying and recording the parcels that meet the criteria.

With GIS the digital maps are overlaid in the computer by the GIS software, and the results are displaying either as a new map or in typical report form, or both in much less time than required by manual light table process.

This capability of spatial analysis allows a wide variety of professional users: City planner are using GIS to develop and monitor urban plans. Market analysts are using GIS to predict and plan business growth. Environmentalists are using GIS to perform environmental impact studies. Law enforcement officials are using GIS to perform crime analysis and plan the effective deployment of peace officers.

GIS Data Models

Representing the "real world" in a data model has been a challenge for GIS since their inception in the 1960's. A GIS data model enables a computer to represent real geographical elements as graphical elements. Two representational models are possible: raster (grid-based) and vector (line-based).

- **Raster**
  Raster representation is based on a cellular organization that divides space into a series of units. Each unit is generally similar in size to another. Grid cells are the most common raster representation. Features are divided into cellular arrays and a coordinate (X,Y) is assigned to each cell, as well as a value. This allows for registration with a geographic reference system. A raster representation also relies on

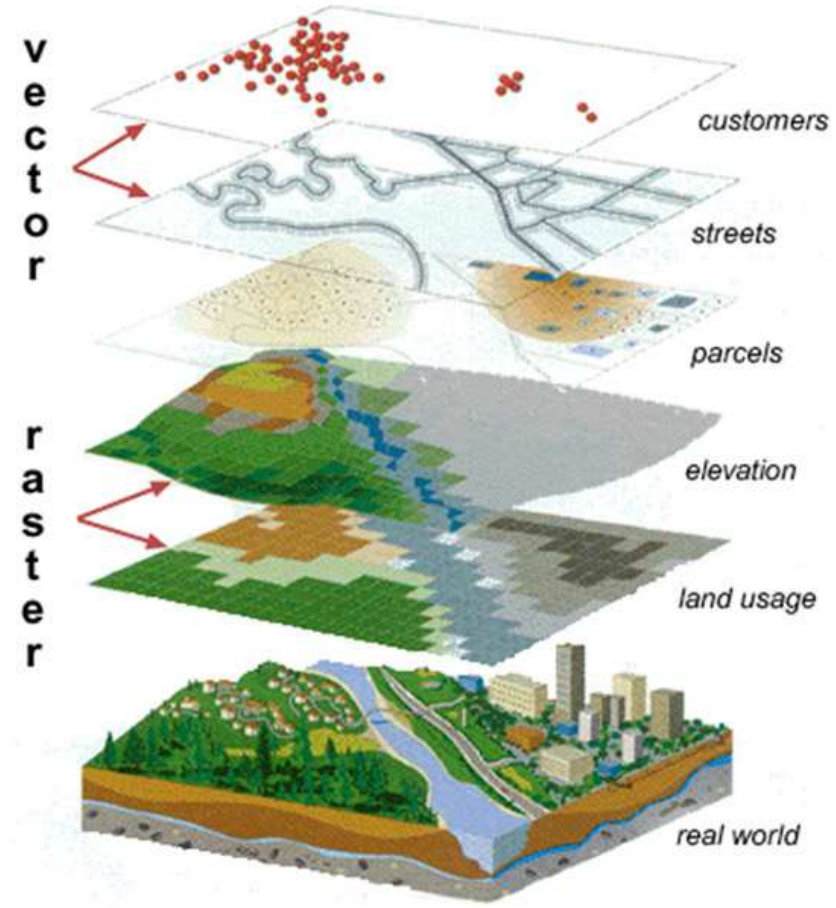

Figure 3.11: GIS data models

tessellation: geometric shapes that can completely cover an area. Although many shapes are possible (triangles and hexagons), the square is the most commonly used. The problem of resolution is common to raster representations. For a small grid, the resolution is coarse but the required storage space is limited. For a large grid the resolution is fine, but at the expense of a much larger storage space. On figure 3.11, the real world representation is simplified in the lower stages, as a grid where each cell color relates to an entity such as road, highway and river.

- **Vector**
  The concept of vector assumes that space is continuous, rather than discrete which gives an infinite (in theory) set of coordinates. A vector representation is composed of three main elements: points, lines and polygons. Points are spatial objects with no area but can have attached attributes since they are a single set of coordinates (X and Y in 2D space) in a coordinate space. Lines are spatial objects made up of connected points (nodes) that have no width. Polygons are closed areas that can be made up of a circuit of line segments. On figure 3.11, the real world is represented in the upper stages, by a series of lines (roads and highway) and one polygon (the river). A real-world entity could be represented by different types of

vector features, depending on the map scale used in an application (e.g. a road can be represented as a line at a smaller scale or as a polygon at a larger scale.)

GIS Data Representation

The existent GIS, almost all of them, adopt the layer-based approach to represent geographic information in map. In the layer-based approach, the spatial data are represented in a set of thematic maps, named layers, which denote some given themes such as road, building, subway, contour, border, and so on. Layer can be vector data or raster data.

Figure 3.12, based on the same data information than the figure 3.11, shows how these data are structured in layers.

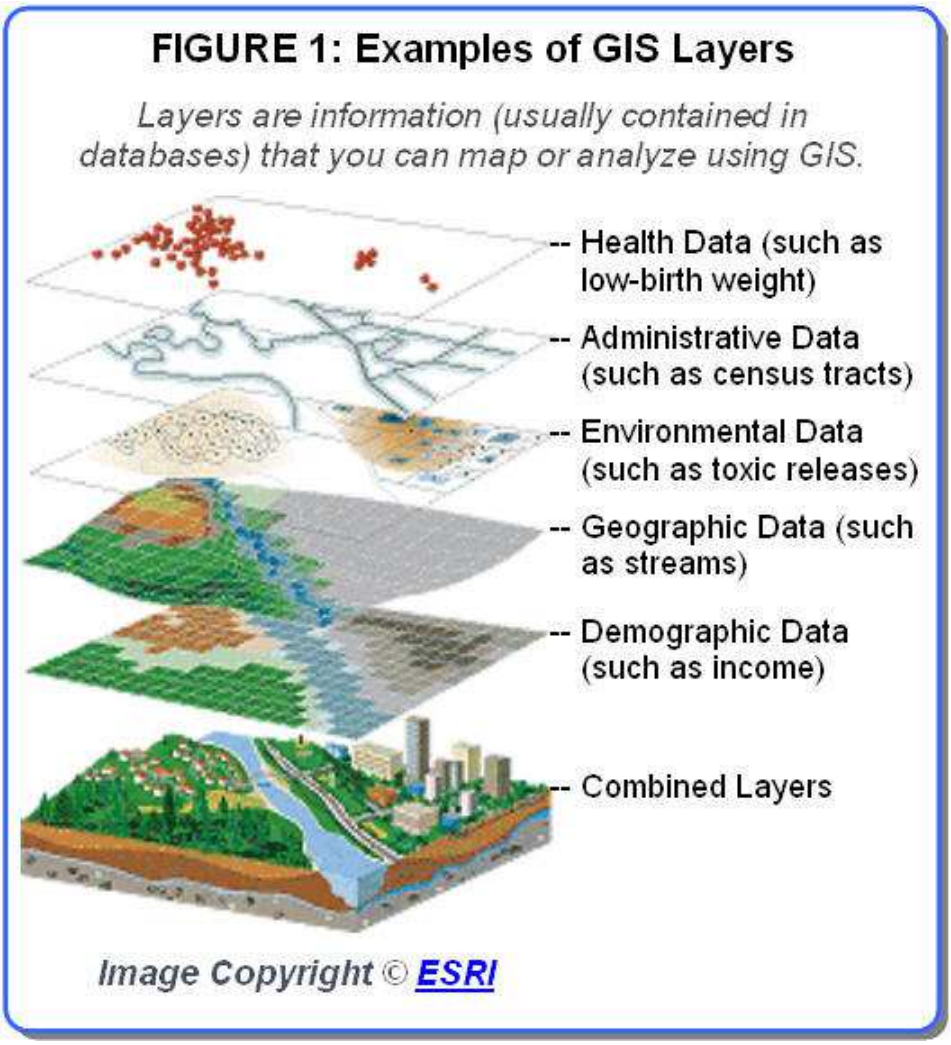

Figure 3.12: GIS data layers

Vector layer made up of number of elements called features: for example, layer of houses

containing points or polygons, represents houses each one of them is one feature of this layer. Each feature has two main properties:

1. Georeferencement with spatial coordinates.
2. Connection with attribute data.

Figure 3.13 illustrates this relation.

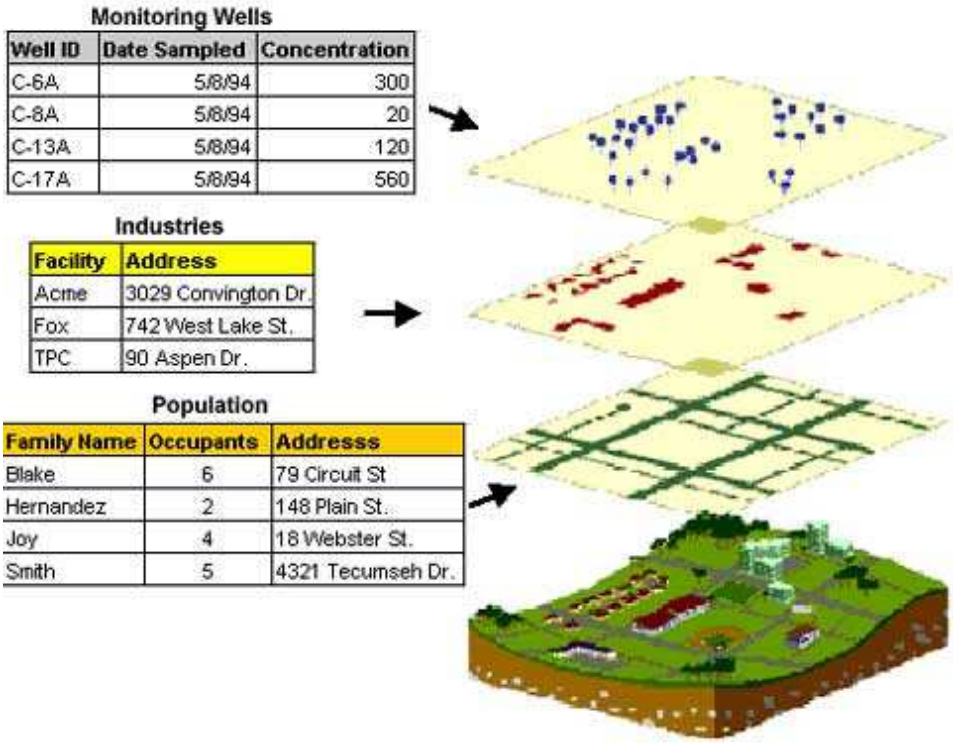

Figure 3.13: GIS data linked to attributes

GIS Data Format

The common format used to save GIS data is *shape* file. A number of files are associated with the shape file format:

1. The shape file itself (.shp) which stores the geographical information and the coordinates of the features.
2. The data base file (.dbf) which records the attribute data for the features.
3. The index file (.shx) which links the data base file to the shape file by the feature identifier (ID).

3.4.2 GIS Evolution: Towards Dynamics, Adaptivity and Intelligent Computation

GIS proposes an accurate information system dedicated to geospatial data. They perform a powerful treatment concerning information requests, information visualization and more generally information returns to users. More than these simple information requests and returns, GIS users expect to have some analysis tools allowing them to give help and assistance. For example, users can have to reach a decision about the location of new housing development that has minimal environmental impact, located in low risk area, and close to a population center. Because of the integration of statistical computations and advanced query processes, GIS can now be useful and produces quickly new thematic map. For example, a thematic map, to represent the population density, can be produced very quickly with different calculation variables (the percentage of men, women, etc.).

Computer aided systems has been developed on many aspects since a few decades and they provide more and more sophisticated tools to users. GIS is now considered like such systems and one of the major improvement expected by users concerns decision making. How urban planner can choose the good location for housing or equipment taking into account very huge database information managed by GIS, combining many interacting aspects of this information? Another major objective for urban planner is to develop cities with respect to sustainable development. This objective needs to analyse the data dynamically and to understand how a specific urban planning can evolve during time, years and decades. The understanding of the complex adaptive evolution of cities is a major progress for urban dynamics modelling and simulation in order to guide relevant decisions.

We develop in the following some of the advances expected today for GIS development and some of the concepts proposed to answer to these expectations.

Dynamics in Urban Planning

Urban planning has to manage dynamical aspects at different spatial and temporal scales. *Urban sprawl* consists in studying in final output the global spatial development of cities. This study requires to understand the impact of the complex interaction of the phenomena involved in the sprawling: economical aspects, social aspects and environmental aspects. The impact of local influence has to be analyzed also, like the housing mechanism: why people stay or leave their house? Do some segregation aspects will result of their behaviors? To go from these local phenomena until the global behavior evolution of the city development, we need to model this processes by complex systems appoaches and we need to deal with self-organization processes.

On another scale, urban planning needs also to understand the dynamics of the city at the scale of one day or one week in order to analyze the individual mobility of citizen and how they use urban services for their everyday activities. Decision making for

transportation systems needs such understanding and needs to model in their complexity all the citizen actions and behaviors. In a big urban area, the interaction between these behaviors have a major role on these behaviors themselves which have to adapt to other. Use of services and feedbacks of the services on the users, while they are used are major aspects of the understanding of the city dynamics at this scale of description.

Intelligent GIS

Artificial intelligence and multi-agent systems have evolved in recent years within distributed approaches allowing to propose relevent models for social simulations. When linked to GIS, such models can be useful for evaluating, monitoring and decision making. Neural networks, fuzzy logic, evolutionary computation are promising tools toward decision-making functionalities [18, 79, 26]. Our work, based on swarm intelligence for spatial self-organization, use in an intensive way, the concept of adding intelligent processes to GIS.

SDSS

The previous paragraphs on urban planning and intelligent GIS face with decision making involving spatial dimension and the mixing of decision making with GIS are the origin of the term *Spatial Decision Support Systems (SDSS)* which has been developed by Paul J. Densham [39, 40]. This concept speculates on future developments in decentralized decision-making which will dominate the field in the next decades. As an example of such problems, *location-allocation* consist in linking heuristic optimization techniques for matching the supply of various facilities such as schools, shopping centers, hospitals to the demands by the population.

To conclude, we see in this section that GIS will have benefit to integrate advances of complex modelling. These advances are the only ones able to manage the complex objectives like sustainable development (which is a compromise between environmental, economical and social goals) and the complexity of the data to manage.

3.5 Repast: MAS Platform and Spatial Environment

We can implement complex dynamical system using MAS technique. But to implement a complex spatial system, we need to integrate geospatial data with the agent based model. Repast is one of the few agent-based simulation software that support the integration of geospatial data.

Since the 1990s, many multi-agent platforms have been developed on the concept of simulation tools for distributed interacting entity systems, like for example Madkit, Jade, Zeus, etc. Most of them can be used to model complex systems. Some of the most popular to simulate swarm intelligence systems are Swarm, Netlogo, Mason or Repast. Each of them has some specificities. Netlogo proposes, for example, an easy programming language which makes this platform popular to scientists who are not

specialized in computing. We do not make here, a review of multi-agent platforms which can be found, for example in [105] or [99].

3.5.1 Repast Overview

Repast (REcursive Porous Agent Simulation Toolkit) is a freely available agent-based simulation toolkit specifically designed for applications to social science. Repast permits the systematic study of complex systems behavior through controlled and replicable computational experiments. Originally developed by David Sallach and other researchers at the University of Chicago and the Argonne National Laboratory, Repast is now managed by the non-profit volunteer organization ROAD (Repast Organization for Architecture and Development).

Repast provides a core collection of classes for the building and running agent-based simulations, and for the collection and displaying of data through tables, charts, and graphs. A particularly attractive feature of Repast is its ability to integrate GIS (geographical information science) data directly into simulations.

Repast provides functionalities to create, run, display and collect data from agent based models. With Repast, the modelers have to work more in defining agent interactions and behaviors and then to set up the simulation, visualizations, and analysis. For this purposes, Repast provides events scheduling, different types of agent displaying, some basics and template models, Graphics Users Interfaces (GUI) for model manipulation and control, displays snapshots, data collection, data recording, batch simulation, charting.

To summarize, making an agent simulation using repast needs:

1. Specifying the model itself (the agents, their attributes, their interactions with each other and with the environment and their behavior (written by the modeler).
2. Displaying agents, scheduling the events, running the model, controlling and manipulating the simulation itself (written by Repast functions).

Figure 3.14 represents a simulation running in Repast with various tools for visualization and analysis.

Repast implementation languages

To define the agents behaviors and interactions, Repast has different implementation languages. Repast has been developed as a derivative of the Swarm simulation toolkit [84]. Currently Repast can be implemented in three different programming languages: Java (RepastJ and RepastS), Microsoft.Net (Repast.Net), and Python (RepastPy):

- **Java - RepastJ**
  RepastJ is the original java package containing the core of Repast and all its

Figure 3.14: Repast tools

functionalities. The other Repast languages are extension of the java package for script writing (RepastPy) or for advanced interface (Repast Simphony) or simply translation (Repast.NET)

- **Python - RepastPy**
  RepastPy have the benefit of the scripting aspect of the langage Phyton. It propose a first version of easier way to develop in Repast by point-and-click. Advanced GUI for model development is proposed. We have to mention that an integration of Repast as a ArcGIS extension is based on RepastPy and proposed with the name Repast Analyst.

- **Microsoft.Net - Repast.NET**
  Repast.NET is a translation of RepastJ for the Microsoft.NET framework.

- **Repast Simphony - RepastS** The main work in Repast development was made in the last years by the creation of a friendly user interface for modelling. A great part of the models can be automatically generated through visual interface but with some limitations for developers used to write themselves their whole package. A stable version of RepastS only appeared in the end of 2006 and the integration with GIS was available later with few documentation.

Choosing the appropriate language implementation for Repast depends of the working context. A sophisticated library needs more than simple interface and RepastJ is often needed for such purpose. The most complete GIS interface is provided with ReapstJ which is integrating the original Java Package of the open-source GIS OpenMap. The work developped here is based on RepastJ.

3.5.2 Spaces in Repast

An important point of coupling GIS with MAS is the representation of the space or the spatial data in GIS. The spatial data in GIS can be represented in two forms (raster, vector), as explained in the sub-section 3.4.1. In Repast we have three kinds of spaces which are used by agents and define spatial relationships between them: network space, cellular space and Euclidean space.

We can represent digital raster image in GIS by cellular space in Repast. Agent can be either the cells themselves or can sit on these cells and interact with the surface generated by this digital image. So, each agent has an (x, y) coordinate in 2D-space and the space contains the agents which allow to define the agent movement and also neighborhoods calculation easily.

Figure 3.15 shows how we can link a raster data from a GIS shapefile to a Repast grid space.

For vector GIS data 3.4.1 representation in Repast, GIS vector data can translate to agent based model in Repast using vector space type by considering each feature with its attributes in GIS layer as an agent with its attributes in agent based model.
GIS data support in Repast can be done by providing a set of Repast classes in the model which allows to work directly with these data.

Finally, we have to mention that Repast has the capability to integrate libraries to manage GIS softwares: ESRI's ArcGIS and OpenMap. With ESRI, the shape file integration is not direct and we need to use Java interface package (GeoTools) to access ESRI software functionalities. With OpenMap, the interface is direct because of the native language for OpenMap (and Repast) is Java. As OpenMap is an opensource project, Repast simply includes the Java package corresponding to the OpenMap program.

In the next section, we will describe an original implementation on Repast of a well-known social model proposed by Thomas Schelling. This model leads to spatial self-organization process. We implement it on a 2D-grid space.

3.6 Schelling Model: Spatial Self-organization Using Repast

Thomas Schelling's city segregation model illustrates how spatial organizations can emerge from local rules, concerning the spatial distribution of people which belong to different classes. In this model, people can move, depending on their own satisfaction to have neighbors of their own class. Based on this model, a city can be highly segregated even if people have only a mild preference for living among people similar to them.

A

```
ncols          30
nrows          30
xllcorner      528000.00
yllcorner      500000.00
cellsize       30
NODATA_value   -9999
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1 2 3 4 5 6 7 7 6 5 4 3 2 1 0 0 1 2 3 4 5 6 7 7 6 5 4 3 2 1
1 2 3 4 5 6 7 8 7 6 5 4 3 2 1 1 2 3 4 5 6 7 8 7 6 5 4 3 2 1
1 2 3 4 5 6 7 8 8 7 6 5 4 3 2 2 3 4 5 6 7 8 8 7 6 5 4 3 2 1
1 2 3 4 5 6 7 8 9 8 7 6 5 4 3 3 4 5 6 7 8 9 8 7 6 5 4 3 2 1
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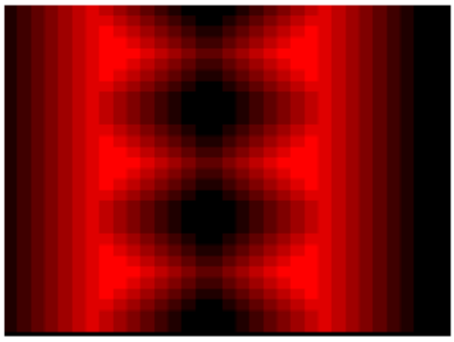
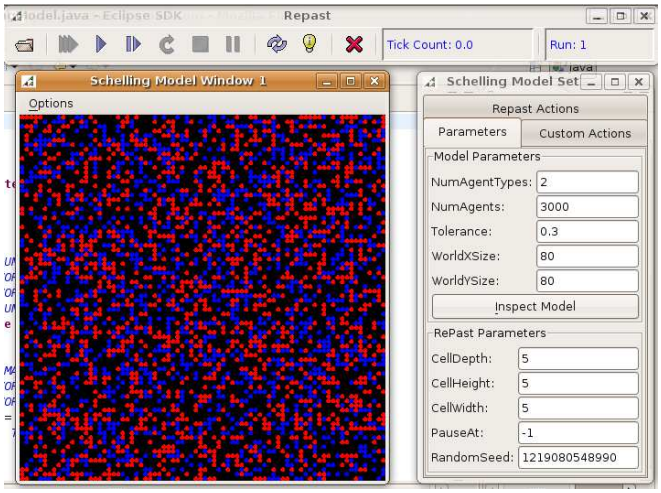


B

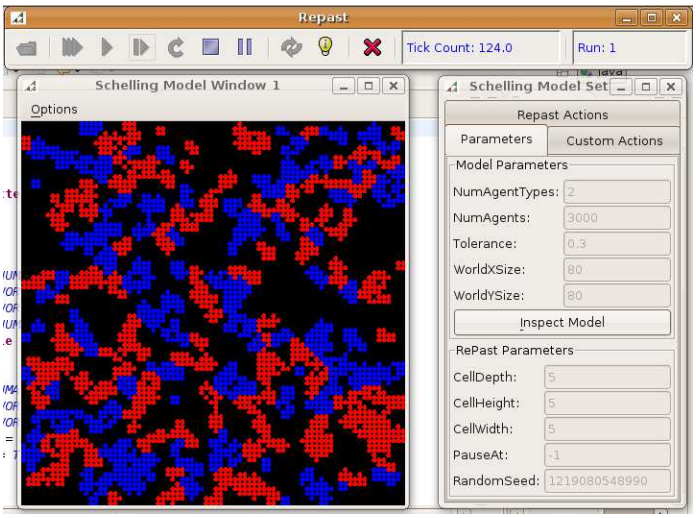
Figure 3.15: Reading in a raster data and creating a landscape (ESRI ASCII file) A: the original file from a GIS. B: the resulting space created in Repast.[34]

In this model, each person is an agent placed on a 2D-grid (in his original presentation, a chessboard was used by Thomas Schelling). Each cell can be considered like a house where the agent lives. Each agent cares about the class of his immediate neighbors who are the occupants of the abutting squares of the chessboard. Each agent has a maximum of eight possible neighbors. It computes the rate of the neighbors of its own class from its eight possible neighbors. Each agent has a tolerance rate determining whether he is happy or not at his current house location. If the rate of the neighbors of its own class is under this tolerance rate, he decides to move to live in another free place in the 2D-grid.

The exact degree of segregation which emerges in the city depends strongly on the specification of the agents tolerance rate. It is noticeable that, under some rule specifications, Schelling's city can transit from a highly integrated state to a highly segregated state

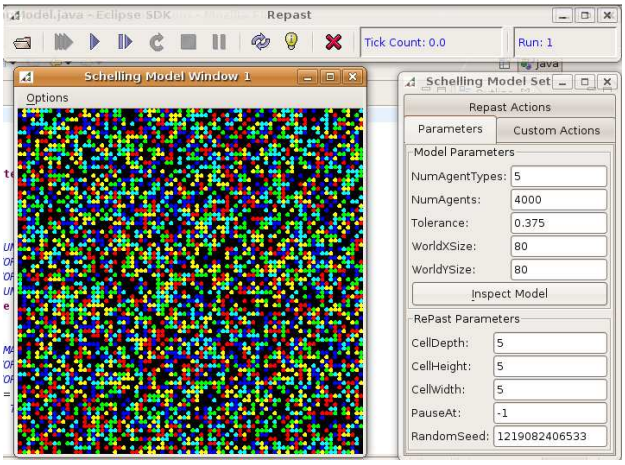


(a) Initial situation

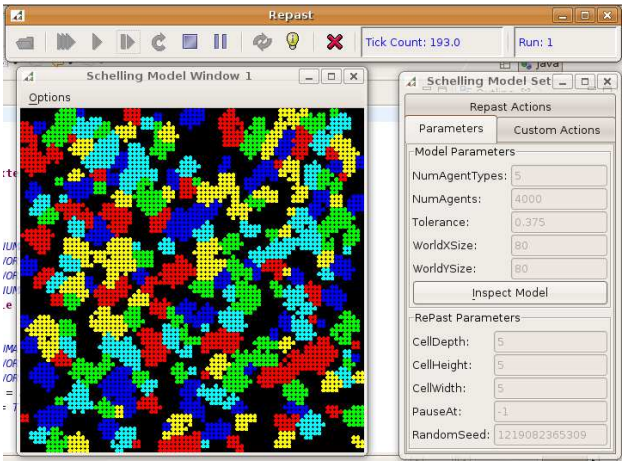


(b) Stable situation after 124 iterations

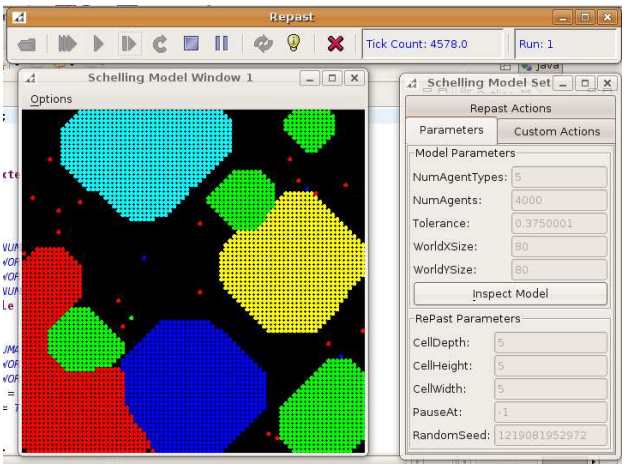
Figure 3.16: Standard 2 populations seggregation Schelling model on Repast



(a) Initial situation



(b) Final Stable situation for a tolerence rate = 0.375 and corresponding to 3 neighbours over 8



(c) Final Stable situation for a tolerence rate greater than 0.375 and corresponding to 4 neighbours.

Figure 3.17: 5 populations seggregation Schelling model on Repast with density = 0.625 and with 2 values of tolerance rate

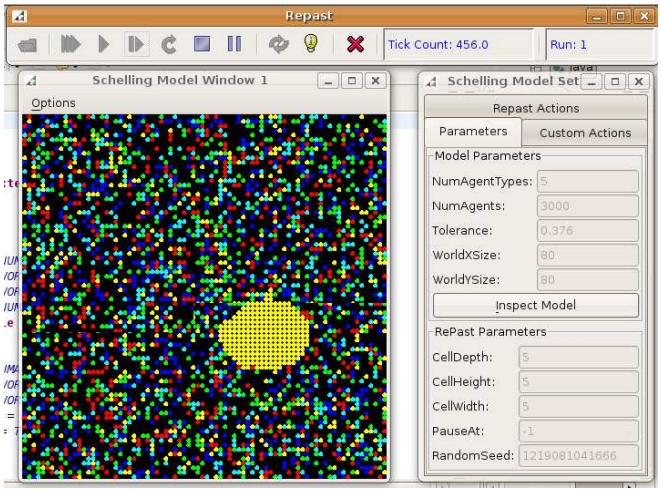


Figure 3.18: Singular situation for 5 populations seggregation Schelling model with density = 0.47 and with tolerance rate = 0.376

in response to a small disturbance of the local rules. We can observe some bifurcation phenomena which leads to chain reaction of displacements.

In figure 3.16, we show an implementation of this algorithm using Repast. Here, we show the "classical" and original problem, modelling the segregation phenomenon with two population classes, described by red and blue squares. Both, the initial population distribution and the final stable distribution are given.

In figure 3.17, we detail the impact of tolerance rate on the segregation result. In this figure, we extend the original problem based on 2 population classes to 5 classes population. Part (a) describes the initial distribution according to a whole population density equal to 0.625. Part (b) describes the stable population distribution for a similar tolerance rate for each agent, equal to 0.375, corresponding to 3 neighbors on 8. This value is a *discrete* bifurcation point from where all small additional value leads to a very different distribution. To illustrate this phenomenon, part (c) describes the population distribution for a tolerance rate greater than 0.375, corresponding to 4 neighbors. The final population distribution is completely different than the one in part (b).

Figure 3.18 describes some singular formation which can appear in very few cases, when we go over the bifurcation point. Generally in this situation, no global clustering formation appears. But in very few cases, some small cluster kernels can appear from random moves and then grow.

Chapter 4

Swarm Intelligence for spatial self-organization

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Some parts of this chapter has been published in AIP journal [142]

4.1 Principles of Swarm Intelligence

The term "Swarm Intelligence" is generally attributed to Geraldo Beni and Jing Wang for their work on cellular robotic systems, which are self-organized, and generate patterns through nearest-neighbor interactions [15]. The concern of swarm intelligence is to design methods and algorithms implementing collective behavior by emergence of population or community interaction.

The major inspiration of swarm intelligence methods comes from biology, social insects, fish school and bird flocks which are amazing natural examples of such emergent collective behavior and movement (figure 4.1 shows examples of such collective displacement).

Figure 4.1: Collective displacement of fishes, ants and birds

In reference to the previous chapter, we can say that swarm intelligence deals with how to manage simplicity for complexity. The goal here is to give some computable algorithms based on a distribution of interacting entities which have simple behaviors. In the one hand, the ability of these methods is to model the emergence of a complex global behavior. In the other hand, because of their distributed structure, it is generally easy to compose these methods with others and to link parts of behavior entities to additional processes. We will use these augmentation capabilities in our work and benefit of the complexity development resulting of such composition.

In the following, according to the problems on which we will develop our work, we will focus on the role of the space inside these methods. Is the space only a parameter or is it an essential part from self-organization process to find a solution? Another important topic, facing the self-organization process generated by these methods, is: Do we let the swarm population evolve freely in self-organized way towards an unknown configuration or do you need an evaluation to control the swarm evolution in order to achieve and find some solution under specific constraints?

4.2 Flocking Methods

In this section, we present in the first sub-section a model based on collective movements inspired by birds flocking. This model typically allows to express emergence of collective systems from individual behaviors. In the second sub-section, we present a new popular optimization algorithm called Particle Swarm Optimization which is mainly based on this bird flocking models. This algorithm typically allows to find emergent solution from distributed collaborative solvers.

4.2.1 Boids

Flocking models concern algorithms describing the movement of birds flocks. The main contribution in this topic, is the "Boids" model invented by Craig Reynolds in 1987 [104]. In this model, we describe the behavior of individuals according to their neighborhood in order to obtain an emergent global movement of the whole system. There is no central control of the bird flock, but each individual bird is moving, with respect to the following three rules (described also in figure 4.2):

- **Separation**. This rule makes the individuals move away from other birds that are too close, to avoid collisions.
- **Alignment**. This rule makes the individuals move in the average direction and velocity of its neighbors.
- **Cohesion**. This rule makes the individuals move toward the average position of the local flock perceived.

In this model, there is undirect communications and interactions between birds which are based for each bird, on the perception of neighbor position and velocity. These indirect communications are the efficient core of the swarm self-organization.

The boids moves are computed as the weighted average of these three rules. According to the weights used, different qualitative swarm formation geometries can be observed: linear or compact. The effect of specific behaviors like leadership (the ones who have greater importance in the cohesion and alignment rules) or renagade (the ones who don't follow the boids rules from time to time) has been also studied in detail. Such particular behaviors are studied in order to reach some way of controlling complex systems

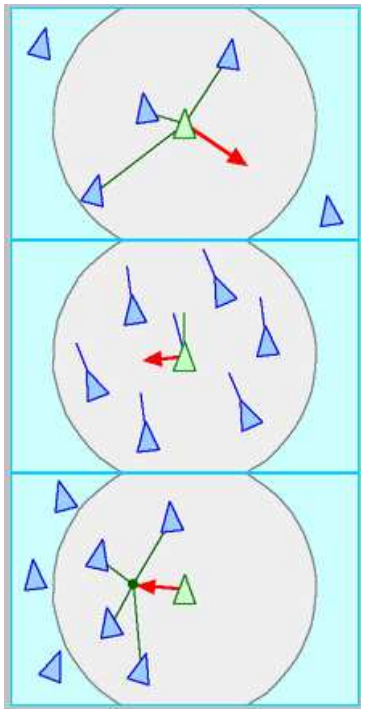


Figure 4.2: The 3 rules of Boids model: separation, alignment and cohesion (from C. Reynolds)

respecting their complexity [33].

Applied engineering applications are developped using the Boids systems. Collective movement of autonomous vehicles have typically benefited of such rules. Nasa has been active to use such algorithms for deep space exploration using multiple, small aircrafts. Collective robotics has also benefited of implementing such processes for collective movement [1, 8].

4.2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an optimization algorithm proposed by J. Kennedy and R. Eberhart [67] and inspired by the collective behavior of bird flocking. In PSO, a group of particles are moving inside a search space, finding some optimum. The particles can communicate between themselves in a local space of perception.

Like in the Reynold's Boids model, the particles in PSO are moving, taking into account the movement of the others, allowing a collective research. Each particle is able to memorize its best position that it discovers (that is the position with optimal value discovered until now). The fly direction of each particle is influenced by its own previous experience and it is a composition of its best previous position and the other best solutions of the particle group that it perceives in its neighborhood.

In some way, we can say that the search space is a catalyst to the collective solution. From the search space, the particles obtain information from their neighborhood and from the space, they can evaluate their own position according to the problem to solve.

PSO is a simple and a distributed solver which constitutes a powerful search technique which has been applied to a wide variety of optimization problems with success.

4.3 Social Insects and Ant Systems

Social insects are one of the most relevant examples of natural swarm intelligence. The mechanisms involved in these collective behaviors are better understood with the notion of Stigmergy which is developed in the first sub-section. In the following three ones, we describe three main classes of collective behavior, existing for example in a natural ant society, and we explain how they lead to algorithms which enable us to solve difficult engineering problems. We conclude this section by one of the most important application of ant systems: swarm robotics which is a major evolution in robotic research in order to produce robust and adaptive systems.

4.3.1 Stigmergy

The concept of *Stigmergy* has been introduced by P.P. Grassé to describe the termite building process when they produce sophisticated piles or arches for their nest building [56].

Grassé describes the nest building activities as successive loops of stimuli and responses:

- The termite is stimulated when it meets some previous elements used for the building.
- Its response is to contribute to the building by adding new elements for it.
- By its contribution, the termite will incite other termites to continue the building.

The major aspect of this concept is that it involves indirect communications, based on the environment itself or on the result expected by the process. It is a kind of positive feedback as we described previously.

We can classify the stigmergy concept in two classes: the quantitative stigmergy and the qualitative stigmergy.

Quantitative stigmergy concerns successive stimuli which are quantitatively different and modify the probability of response of others insects. For example, pillar construction in termites, mass recruitment in ants or corpse aggregation in ants (see figure 4.3).

Qualitative stigmergy concerns different stimulus-responses associations. For example stimulus 1 causes individuals to respond as A; stimulus 2 causes individuals to respond

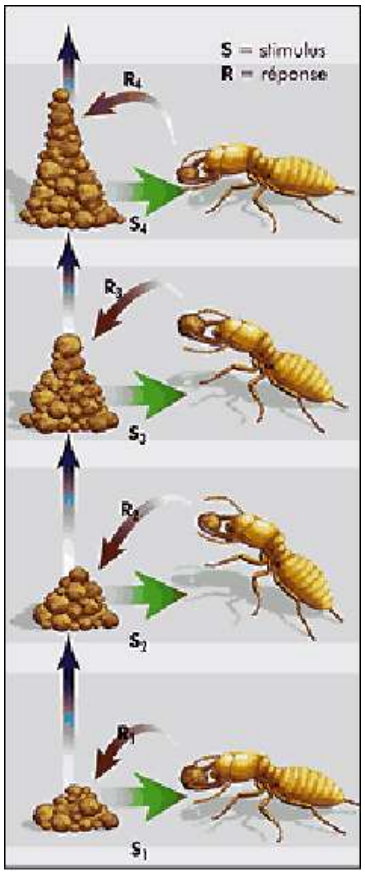


Figure 4.3: Quantitative stigmergy concept.

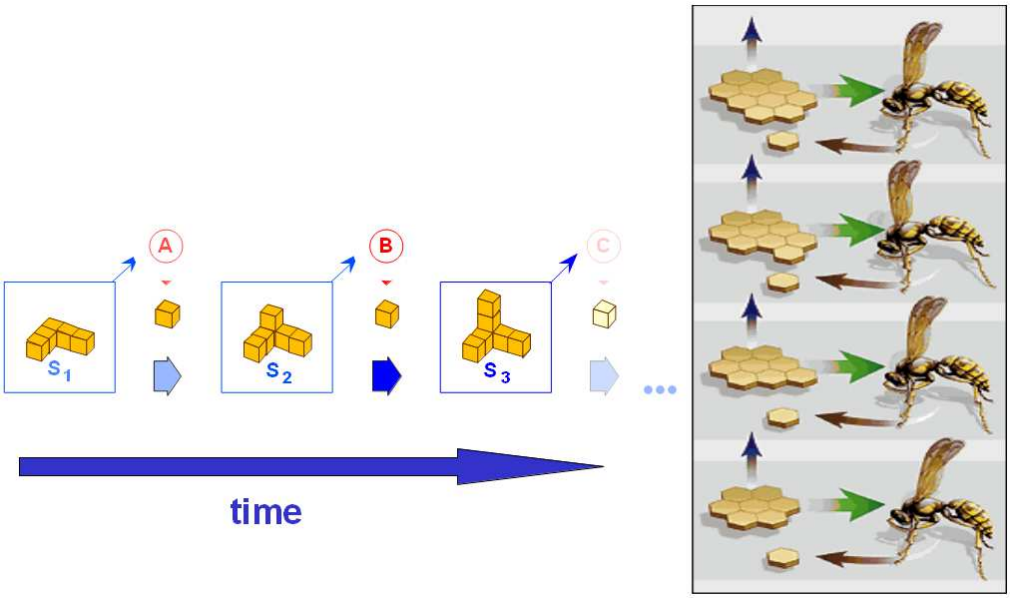


Figure 4.4: Qualitative stigmergy concept in Polistes wasps nest construction.

with B and stimulus 3 causes individuals to respond with C. Nest construction in poliste wasps is an example for qualitative stigmergy. Figure 4.4 shows the successive different stimulus (S1, S2, S3) which lead to different responses (R1, R3, R3) respectively.

Figure 4.5 shows a natural and an artificial simulation for wasp nest construction for two different configurations. Qualitative stigmergy leads to better understand some very sophisticated building that social insects are able to produce for efficient use.

Figure 4.5: Natural wasp nest construction (on the left) and modeled wasp nest construction (on the right).

4.3.2 Ant Colony Optimization

Natural Ant Foraging Mechanism

One of the most impressive collective work involved in natural ants is the foraging mechanism for food research. A famous experiment, made by Jean-Louis Deneubourg, explains the essential aspect of this mechanism [54]. In figure 4.6, we can see a simple device with two different lengths of allowing ants to go from the nest to some food place.

The principle of the mechanism is the production, by the ants of a chemical trail, called pheromon, which it puts on the environment. The other ants are able to smell the pheromon trail deposited on the environment and are attracted by it. It is typically a phenomenon induced by stigmergetical mechanism because ants do not communicate directly but they use the environment to indirectly communicate and to increase the emergence of the collective processes.

The natural processes can be described by the following steps :

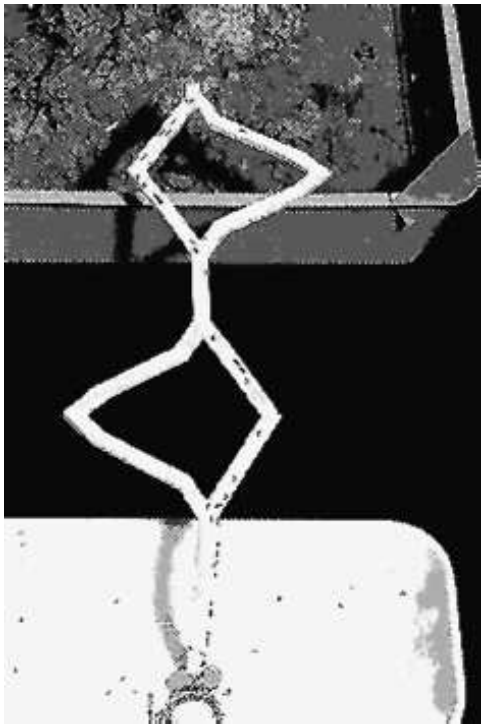


Figure 4.6: Ant foraging Jean-Louis Deneubourg's experiment

- Ants move on the device and initially choose one path randomly.
- Ants put some pheromone during their movement.
- When an ant reaches the food source, it comes back by the same path (using its own pheromone) and puts additional pheromone on its path to indicate an efficient way to find food.
- Ants come back faster when they use the shortest path and the mechanism of pheromone deposit becomes more important on this path.
- Pheromone trail, as chemical product put on the environment, has the property to evaporate with time.
- After the simulation start and some pheromone has already been deposited on the environment, an ant which has to choose a path, preferes to choose the one with higher intensity of pheromone trail. But, an important aspect is that it is only a preference and not a systematic choice (what we can call a probability in mathematical language). In that way, ants continue to explore the environment to detect better solutions. So, if the initial random choices is not the best one, it is possible to finally find it. The pheromone evaporation makes some wrong initial solutions disappear with time.

Ant Colony Optimization for Engineering Problem

We present now an engineering problem which can be modeled and solved by an ant foraging process.

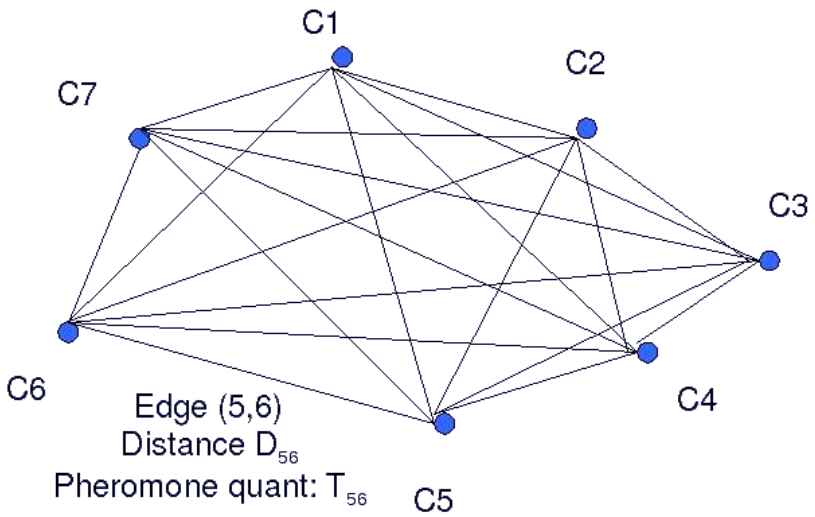


Figure 4.7: Graph for Travelling Salesman Problem (TSP)

The engineering problem is the well-known Traveling Salesman Problem (TSP) which consists in finding the shortest cycle linking n towns completely interconnected, crossing one and only one time each town (formally, the solution is the minimal hamiltonian cycle from a weighted complete graph). Figure 4.7 presents an example of such a graph.

We present now a synthetic algorithm:

- When an ant k is on the town i, it computes the probability to go to the town j by the formula:

$$p_{ij}^k(t) = \begin{cases} \dfrac{(\tau_{ij}(t))^\alpha \left(\frac{1}{D_{ij}}\right)^\beta}{\sum\limits_{l \in J_k(i)} (\tau_{il}(t))^\alpha \left(\dfrac{1}{D_{il}}\right)^\beta} & si \quad j \in J_k \\ 0 & si \quad j \notin J_k \end{cases} \tag{4.1}$$

  In the previous formula

  - J_k is the set of towns not yet visited by the ant k.
  - The numerator means that
    - The more the pheromone trail $(\tau_{ij}(t))$ is, the more the probability $P_{ij}^k(t)$ is
    - The less the distance (D_{ij}) is, the more the probability $P_{ij}^k(t)$ is

  * Some constant parameters (α, β) are used to control the relative importance of these two parts

  The denominator is the sum off all non null possible numerators (for all towns still to be visited). It allows to obtain a probability value between 0 and 1 (the sum of all possibilities is 1).

- When an ant finds a solution as a whole cycle between all towns, it deposits some pheromone on all edges of the cycle, in quantity inversely proportional to the length of the cycle (L_k):

$$\Delta\tau_{ij}^k(t) = \begin{cases} \dfrac{Q}{L_k} & si \quad (i,j) \in T_k(t) \\ 0 & si \quad (i,j) \notin T_k(t) \end{cases} \tag{4.2}$$

  where Q is a constant parameter.

- On each edge (i, j), the pheromone quantity is updated from the step t to the step $t + 1$, by adding all the contribution of each ant to previous pheromone quantity:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^k(t) \tag{4.3}$$

  where ρ is an evaporation factor which allows that some first paths/solutions could be replaced by better ones, as explained before.

In figure 4.8 (from Antoine Dutot's PhD [43]), we can see Java applet where this algorithm is implemented in order to reproduce Jean-Louis Deneubourg's experiment. On the left side of this figure, we see in yellow color, the greater intensity pheromone trail which is obtained after several iterations of the processes. On the right side of the figure, we replace the nodes of the graph, replacing the shortest path by the longest one and we let the system running and finding the new best solution as we can observe on the figure. This computation highlights that Ant Colony Optimization is robust and is able to adapt when the environment changes (like natural ants can do also). It is an essential aspect and property for us when we have to deal with dynamical systems and simulation.

4.3.3 Task Allocation

A lot of insect societies are composed of several castes which allow to distribute collective tasks to individuals. The caste constitutions can be made on physiological properties, like age intervals, or they can be made only on behavioral aspects. This natural task allocation has adaptive properties which allow to dynamically modify the class belonging of some individuals to adapt to the collective need.

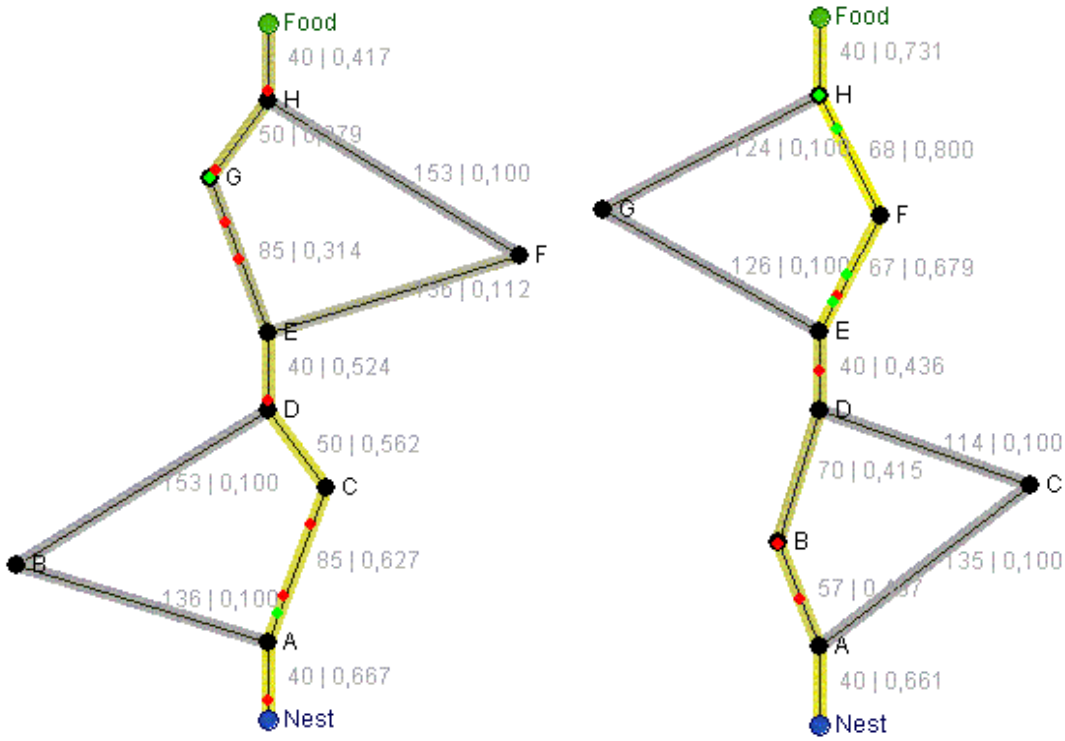


Figure 4.8: Ant foraging (from Antoine Dutot's Java applet [43])

An algorithm has been proposed to model this natural task allocation and it is based on adaptive response thresholds processes. A specific task is associated to a stimuli, similar to a pheromone trail, inciting individuals to achieve it. Each individual has its own response threshold, according to its caste belonging. When individuals from some caste disappear and if the caste does not have enough individuals to achieve the task allocated to it, its task stimuli increase in order to attract more individuals.

Response Threshold Model Formulation

If we consider s, a specific task stimuli quantity and Θ, the response threshold for this task for a specific individual

- if $s << \Theta$, then the response probability is low
- if $s >> \Theta$, then the response probability is high

The probability to achieve the task can be computed with

$$T_\Theta(s) = \frac{s^n}{s^n + \Theta^n}$$

where $n > 1$ is the threshold degree.

Response Threshold Model for One Task

We suppose that we have one task to achieve. A stimulus of intensity s is associated to this task and increases when the task is not achieved. X_i represents the activity state of one individual (its value is equal to one if it realizes the task and 0 elsewhere). Θ_i represents the task response threshold for the individual i. The probability to make the inactive individual change its state to realize the task can be computed with:

$$P(X_i = 0 \rightarrow X_i = 1) = T_{\Theta_i}(s) = \frac{s^2}{s^2 + \Theta_i^2}$$

where the threshold degree is equal to 2.

We suppose that the probability to change the active state to an inactive state $P(X_i = 1 \rightarrow X_i = 0)$ is equal to p, a constant value, similar for each individual. $1/p$ corresponds to the mean time to realize the task.

The stimulus intensity has to change, according to the importance of all the task realization:

$$s(t+1) = s(t) + \delta - \alpha\eta_{act}$$

- δ is a constant quantity corresponding to the intensity increase by time step;
- α is a constant quantity corresponding to the intensity decrease because of an individual activity;
- η_{act} is the number of active individuals achieving the task.

We suppose now that we have two populations, one with a low response threshold and the other with a high response threshold. If the first population disappears then the second population will finish to achieve the task which was not originally affected to its speciality.

We can extend this model to manage concurrent execution of multiple tasks.

Postman Allocation Task Example

To illustrate the task allocation algorithm, we take the classical well-known problem of postman allocation [22]: we have to deal with the mail attribution to a postman company on an urban area splitting in several zones.

The probability for a postman i, which is affected to the zone z_i, to respond to a task of intensity s_j which are emitted from the zone j is

$$p_{ij} = \frac{s_j^2}{s_j^2 + \alpha\Theta_{ij}^2 + \beta d_{jz_i}^2}$$

- Θ_{ij} is the postman i response threshold for a task in the zone j;
- d_{jz_i} is the distance between j and z_i;
- α and β are two parameters of relative influence between the previous quantities.

Each time a postman moves from the zone j to take mail, his response thresholds have to be updated:

- $\Theta_{ij} \leftarrow \Theta_{ij} - \xi_0$,
- $\Theta_{il} \leftarrow \Theta_{il} - \xi_1$, $\forall l \in \eta_j$ (zone j neighborhood),
- $\Theta_{ik} \leftarrow \Theta_{ik} + \phi$, for the other value of k,

where ξ_0, ξ_1 and ϕ are learning coefficients.

In [22], this algorithm is applied to 5 by 5 zones, cyclic grid with 5 postmen. At each time step, 5 zones make their task pheromone intensity increase with the value 50.

We give the following value for the parameters: $\alpha = 0,5$, $\beta = 500$, $\Theta_{ij} \in [0;1]$, $\xi_0 = 150$, $\xi_1 = 70$, $\phi = 10$.

When a postman replies, he cannot respond to any new task during the time corresponding to the distance that he has to do to achieve his task.

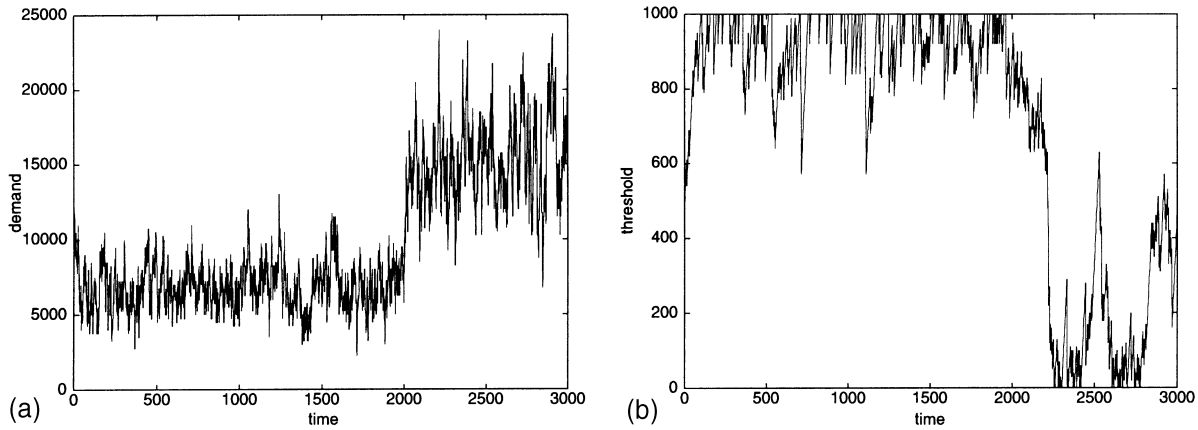


Figure 4.9: Postman task allocation simulation (from [22])

We observe a self-organization process which consists to specialize adaptively postmen to specific zones. In figure 4.9, one postman has been removed. On the left part of the figure, we can see the increasing of the intensity of the request of the zone allocated to the postman, after his removing. The right part of the figure describes for another postman, the threshold evolution corresponding to the first postman's zone. As this second postman was not initially allocated to this zone, the threshold is high in the begining of

the curve. But as new tasks from this area do not find any postman to manage them, they finally attract the second postman. This second postman adapts his own behavior in order to change his threshold to this zone and make it decreases.

4.3.4 Clustering

Ant clustering algorithms are inspired by the corpses or larvae classification and aggregation that the ants colony are able to do in the real life. The ants are moving inside a closed area and are able to move some material which are randomly put on this area. After a while, and without any kind of centralized coordination, the ants success to create some material clusters.

As we explain in the previous sub-section on stigmergy, the collective process is based on some indirect communications. The goal of the processes is to make some aggregation of objects. The ants start building such elementary aggregations and then the small clusters formation acts on the social insects as feed-back and in that way, the clusters progressively increase. In figure 4.10, we can observe this mechanism and the 4 views correspond to 4 time steps. Progressively, we can see that the clusters size are growing as the time increases.

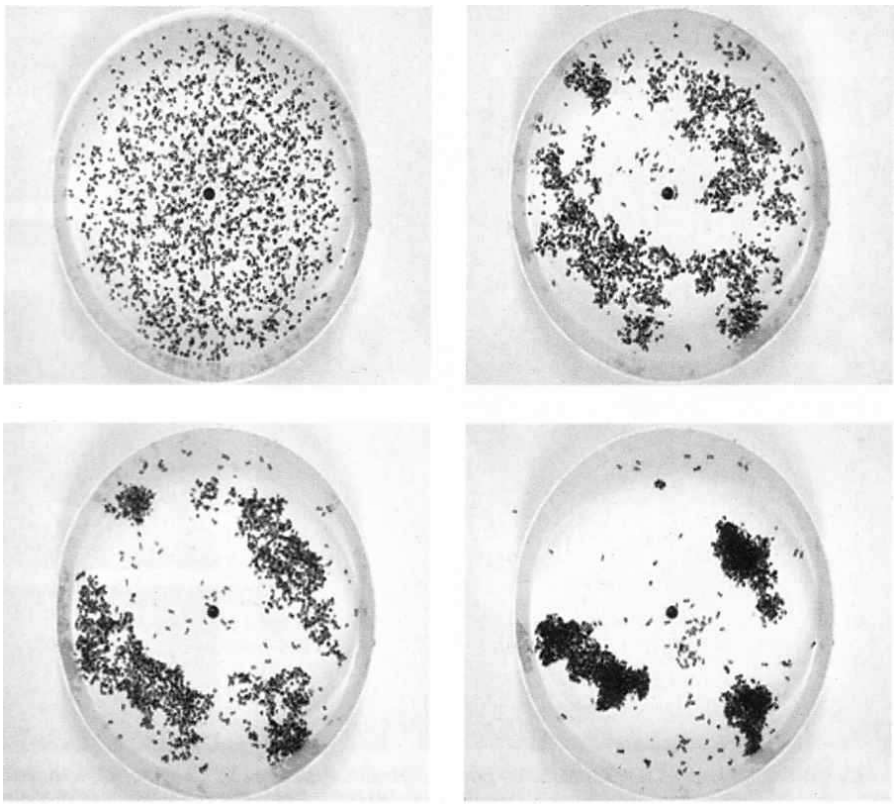


Figure 4.10: Natural ant clustering (from [22])

The algorithm is based on the following rules which are very simple behavioral rules that each ant implements :

- When an ant is moving without carrying yet material and finds some material, the ant will take the material respecting the probability number :

$$P_p = \left(\frac{k_1}{k_1 + f}\right)^2 \tag{4.4}$$

  where f is the material density that the ant perceives locally around itself and k_1 is the threshold. It is easy to check that if $f << k_1$ then P_p is near the value 1 and if $f >> k_1$ then P_p is near the value 0.

- When an ant is moving when carrying some material, the probability to deposit it is computed by :

$$P_d = \left(\frac{f}{k_2 + f}\right)^2 \tag{4.5}$$

  where f is still the material density that the ant perceives locally around itself and k_2 is another threshold. It is easy to check that if $f << k_2$ then P_d is near the value 0 and if $f >> k_2$ then P_d is near the value 1.

In figure 4.11, we develop an implementation of this algorithm using Repast platform [103]. The java version of this platform includes some packages allowing to interface with geographical database and geographical information systems (GIS). In figure 4.11, the graphical output windows are made under OpenMap GIS software which is developed using Java language. On this figure, the materials moved by the ants are the small grey circles, the ant moving without material are the green circles and the ant carrying material are the red circles.

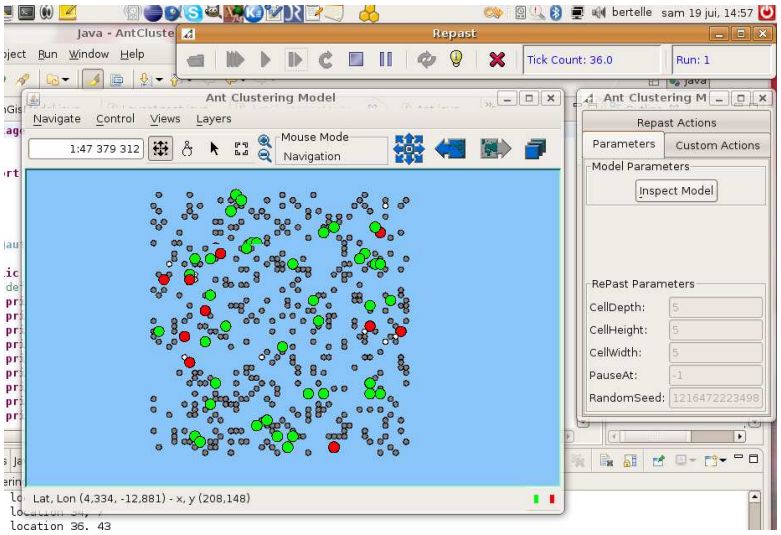
4.3.5 Swarm Robotic Based on Ant Systems

During a long period, humans tried to build artificial entities which could be similar to themselves. Robots are mainly perceived as a tentative in that way, building a robot similar to a human is really a thrilling problem but finally not so useful.

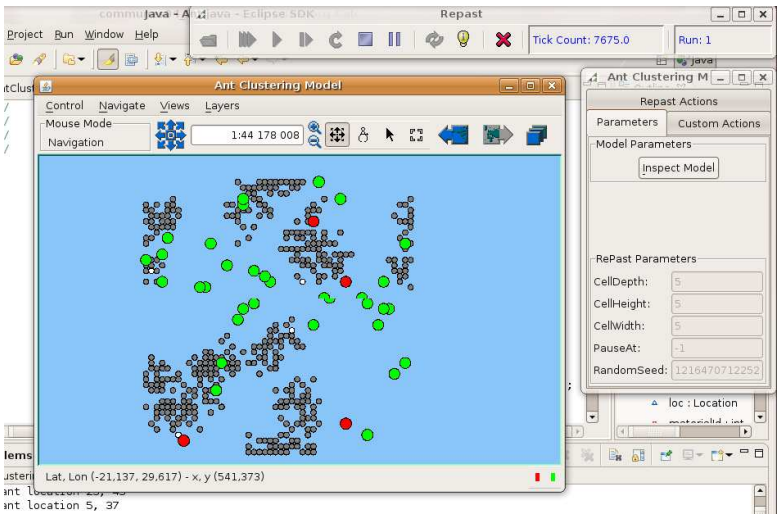
With the distributed way of conception and the development of DAI (Distributed Artificial Intelligence), Robotics has found a new way of development.

The novelty and interesting properties of swarm robotics approach is to reproduce the system-level functioning properties observed in social insect systems, especially robustness and flexibility. These are essential properties for deploying large numbers of robots.

With robustness, we mean that swarm-system robots can continue to operate despite large disturbances. This robustness is based on the use of redundancy, decentralized coordination and simplicity of the individuals.



(a) initial step



(b) intermediate step

Figure 4.11: Ant clustering simulation using Repast on OpenMap

By flexibility, we mean that swarm-system robots can offer modularized solutions to tasks of different nature using different coordination mechanisms. Finally, we expect that a desired collective behavior emerges from the local interactions among elementary robots and between the robots and the environment.

Swarm robotics is now a thrilling topic and some projects are now starting to be managed, using these principles. We just want to focus our attention on the European "swarm-bot" project leaded by Marco Dorigo [20]. The idea of this project is to use a swarm of small and simple autonomous mobile robots called S-Bots.

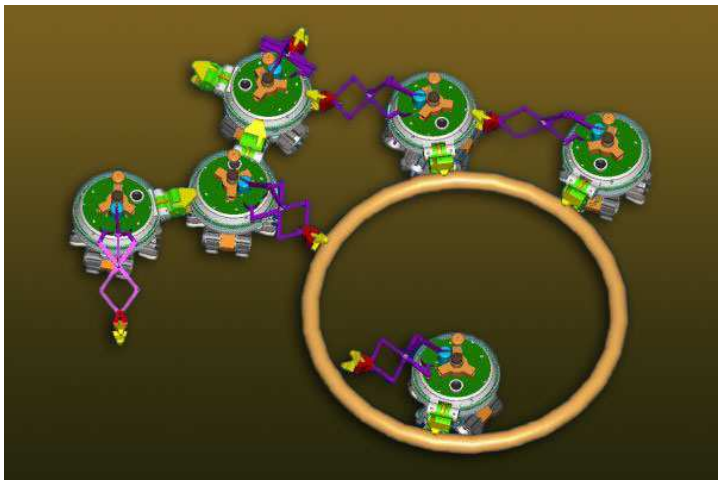


Figure 4.12: Swarm-bot project [120]

S-Bots have a particular assembling capability that allows them to connect physically to other S-Bots and to form a bigger robot entity, the Swarm-Bots (see figure 4.12). A Swarm-Bot is typically composed by 10 to 30 S-Bots physically interconnected. S-Bots can autonomously assemble into a Swarm-Bot but also disassemble again. This feature of the S-Bots provides Swarm-Bot with self-assembling and self-recognizing capabilities. Such a concept, by taking advantage from the collective and distributed approaches, ensures robustness to failures even in hard environment conditions.

4.4 Collective Building Systems

In the previous section, we have presented self-organization methods for ant clustering which can generate unpredictable clusters. For many applications, we can use this model as it is, because we need to express some spatial constraints where the clusters are expected. In this section, we present such problems, starting to describe natural processes which involved spatial constraints for self-organization development.

4.4.1 Natural Template in Collective Building

Termites mounds, ant nest, bees and wasp hives are some examples of a complex structures which emerge from the interactions between the social insects and their spatial environment. One of the mechanisms used in these structures is templates (the others are: self organization mechanism, stigmergy mechanism). The template is a pattern existing in the environment and used to construct another pattern [22]. Temperature, humidity, chemical gradient, physical templates are different kinds of templates that we can find in different natural structures. Now we give in details three natural structures.

Ants Nest Structure: Brood Sorting in Spatially Different Areas

Some ants use humidity and temperature gradients to distribute their brood. On figure 4.13, we see how this distributon is made in soil along depth. As the diurnal rhythm of the temperature gradient in the soil changes the local temperature, the ants collectively shift the brood upwards or downwards in the soil. This way, the brood is always incubated at the adequate temperature, figure 4.13 shows an example of ant nest structure.

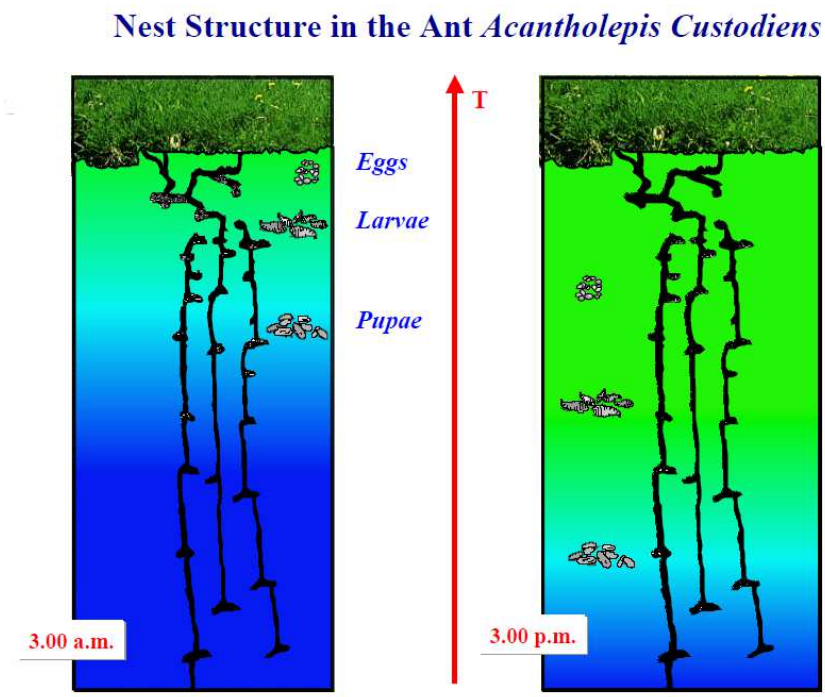


Figure 4.13: Nest structure in the ant Acantholepis Custodiens from [22]

Termites Nest: The Royal Chamber Construction

Physogastric termite queens of macrotermes subhyalinus emits a pheromone that diffuses to create a pheromonal template in the form of decreasing gradient around the queen

body (see figure 4.14). It has been shown experimentally that a concentration window or a threshold exists that controls the workers building activities. A worker deposits a soil pellet if the concentration of pheromone lies within this window [cmin, cmax]. Otherwise, they do not deposit any pellet and destroy existing walls. The workers construct this chamber by erecting walls to a certain distance around the queen. As the queen grows, the queen pheromone emission grows also and the termite workers have to adapt the chamber permanently, so that it always perfectly fits to the queen.

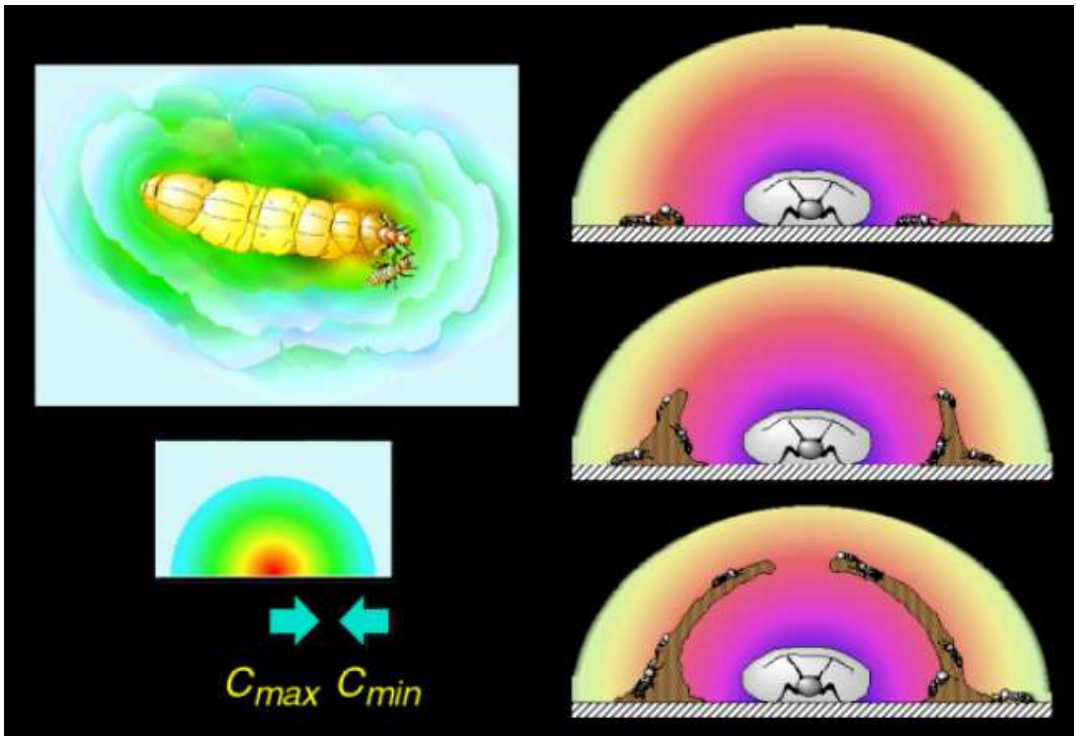


Figure 4.14: Royal Chamber construction from [22]

Ants Nest: Wall Building Around Their Brood/Adult

Another example of template (combined with self organization mechanism) is the one proposed by Leptothomx albipennis ants which construct simple perimeter walls in a two-dimensional nest at a given distance from the tight cluster of ants and brood and which serves as a chemical or physical template. The template mechanism allows the size of the nest to be regulated as a function of colony size (Each worker always has about 5 mm^2 of floor area in the nest) [22]. Deposition behavior is influenced by two factors:

- The local density of grains.
- The distance from the cluster of ants and brood.

The probability of depositing a grain is:

- Higher when both the distance from the cluster is appropriate and the local density of grains is large.
- Lower when the cluster is either too close or too far and when the local density of grains is small.

When the distance from the cluster does not lie within the appropriate range, deposition can nevertheless be observed if grains are present. Conversely, if the distance from the cluster is appropriate, deposition can take place even if the number of grains is small (see figure 4.15).

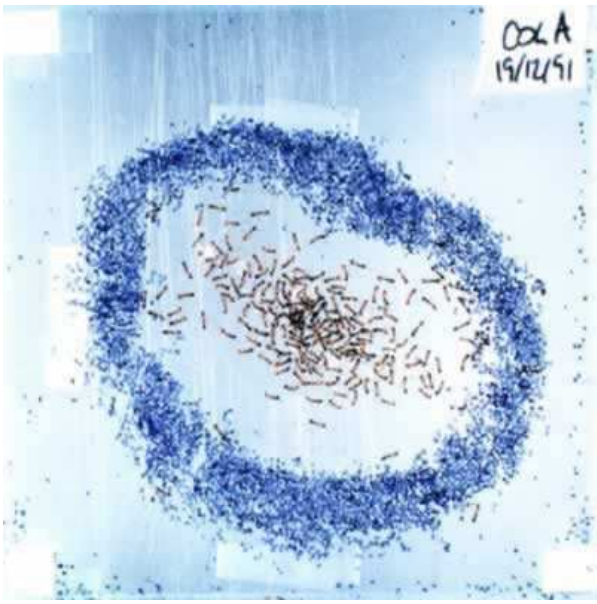


Figure 4.15: Ant wall [27]

4.4.2 From Natural to Artificial Systems

Swarm intelligence research consists in implementing and simulating biological social insects processes in order to propose meta-heuristics. Then these meta-heuristics are used to model complex phenomena involved in some engineering applications (see figure 4.16).

This section presents some of these computational methods used in natural template and collective buildings modeling.

A Reaction-Diffusion Model of the Termites Royal Chamber Construction

Deneubourg [38] proposes an analytical continuous spatio-temporal model describing the evolution of the material deposited on space by termites.

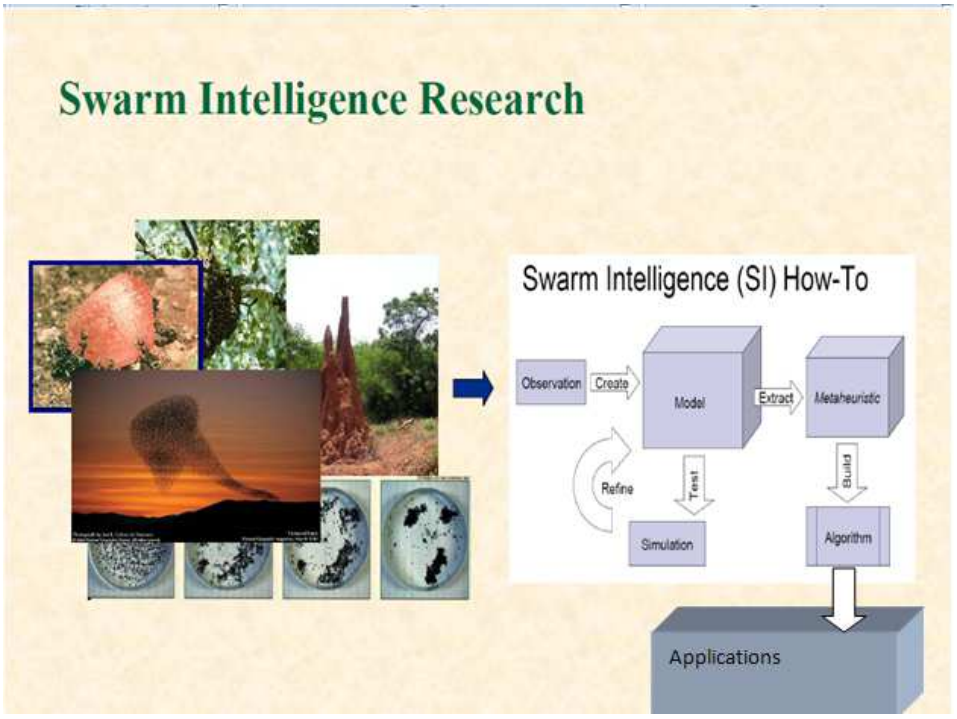


Figure 4.16: Swarm intelligence research

When material is dropped, cement pheromone is emitted inside it. This pheromone diffuses freely in the air and attracts other termites by stigmergy. This accumulation of material induces a strong emission of pheromone which attracts more and more termites. Material is called *active* if it still contains pheromone which have not completely diffused in the air.

The analytical model (a partial differential equational system) proposed by Deneubourg involves, for each location r and each time t:

- The density of laden termites, $C(r,t)$;
- The amount of active deposited material, $P(r,t)$;
- The concentration of pheromone emitted into the air, $H(r,t)$.

The first equation describes the evolution of the active deposited material:

$$\partial_t P = k_1 C - k_2 P. \tag{4.6}$$

where

- $k_2 P$ represents the production of pheromone emitted in the air by the material itself;
- $k_1 C$ represents the rate of pheromone deposited by the termite.

The second equation represents the evolution of the concentration of pheromone emitted into the air:

$$\partial_t H = k_2 P - k_4 H + D_H \nabla^2 H, \tag{4.7}$$

where

- $D_H \nabla^2 H$ is the term of diffusion (∇^2 denotes the Laplacien operator);
- $-k_4 H$ is the pheromone decay.

The third equation represents the evolution of the density of laden termites:

$$\partial_t C = \Phi - k_1 C + D_C \nabla^2 C - \gamma \nabla (C \nabla H), \tag{4.8}$$

where

- Φ is a flux of new loaded termites which is supposed to be constant;
- $\gamma \nabla (C \nabla H)$ describes the attractiveness of the pheromone gradient (∇ denotes the gradient operator) with $\gamma > 0$;
- $D_C \nabla^2 C$ describes the random component in individual motion.

The positive feedback generated by the pheromone diffusion at different sites in the building area gives rise to competition between different pillars which are close to one another. This leads to an 'inhibition' of pillar formation in the immediate neighborhood of a pillar and also facilitates the emergence of another pillar further away. Note that the present model is completely deterministic and therefore leads to a perfectly regular spatial distribution of pillars, where as in reality, this regularity is observed on average.

Deneubourg studied numerically the dynamics of a one dimensional system with γ close to $(\sqrt{k_4 D_C} + \sqrt{k_1 D_H})^2/\Phi$, and found that the present system converges to spatially periodic state (see figure 4.17). The same observation is true for a two-dimensional case (see figure 4.18).

This differential model gives an accurate physical model which describes the phenomenon itself by global laws (diffusion, attractiveness on gradient). The global behavior of the system is described through the three equations and there is no reference to local behavior of the termites involved in the building process. This model can be qualified of knowledge model, expressing the whole system functioning. From a practical point of view, additional information is needed to make it become a computable model. Like all partial differential equation systems, in order to be computed, this model needs some boundary conditions on a domain to be defined. These conditions are not easy to express.

From a completely different approach, we can model the phenomenon from the termites behavior expressions and model the stigmergic processes as indirect communications between them. Following the natural processes, we expect to obtain by simulation, the emergence of the system organization and building, from the entity behaviors and interactions. We describe such distributed algorithms in the following subsection.

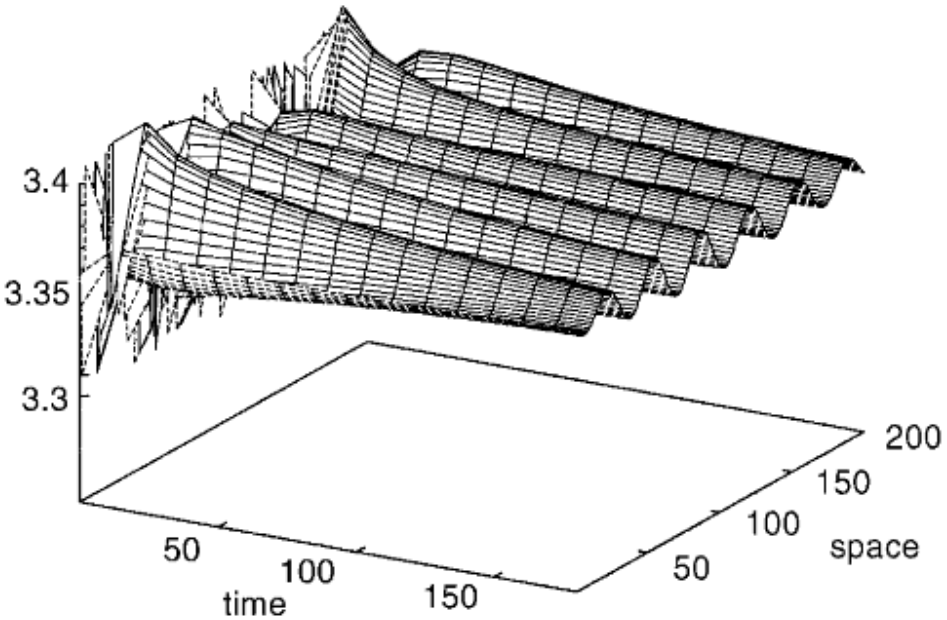


Figure 4.17: An example of temporal dynamics of the amount of active deposited material P for one dimensional system (from [21])

Wall Building Model: Implementation in Repast

A template probability p_t should be added to the probability of picking up and dropping.

Using this template function, we replace in the clustering algorithm, the two previous probabilities of picking up and depositing a grain of material by new values integrating this template function.

The new probability of picking up a grain of material is:

$$P'_p = P_p(1 - P_t) \tag{4.9}$$

where P_p is the previous probability given by equation (4.4).

The new probability of depositing a grain of material is:

$$P'_d = P_d P_t \tag{4.10}$$

where P_d is the previous probability given by equation (4.5).

On figure (4.19), we represent a template function adapted to the natural ant wall building and we represent the result of a simulation made on Repast. The material which has been deposited are here represented with blue color.

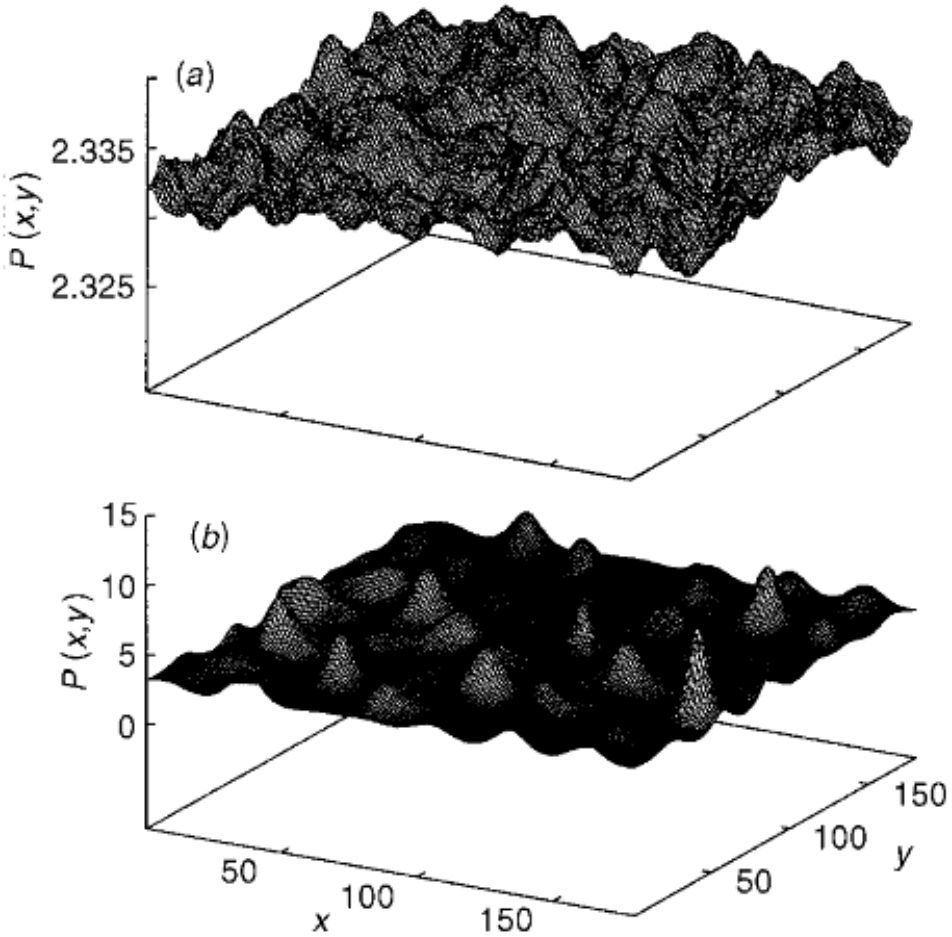


Figure 4.18: An example of spatial distribution of the amount of active deposited material P for a two dimensional system. The first figure is at $t = 4$ and the second figure is at $t = 100$

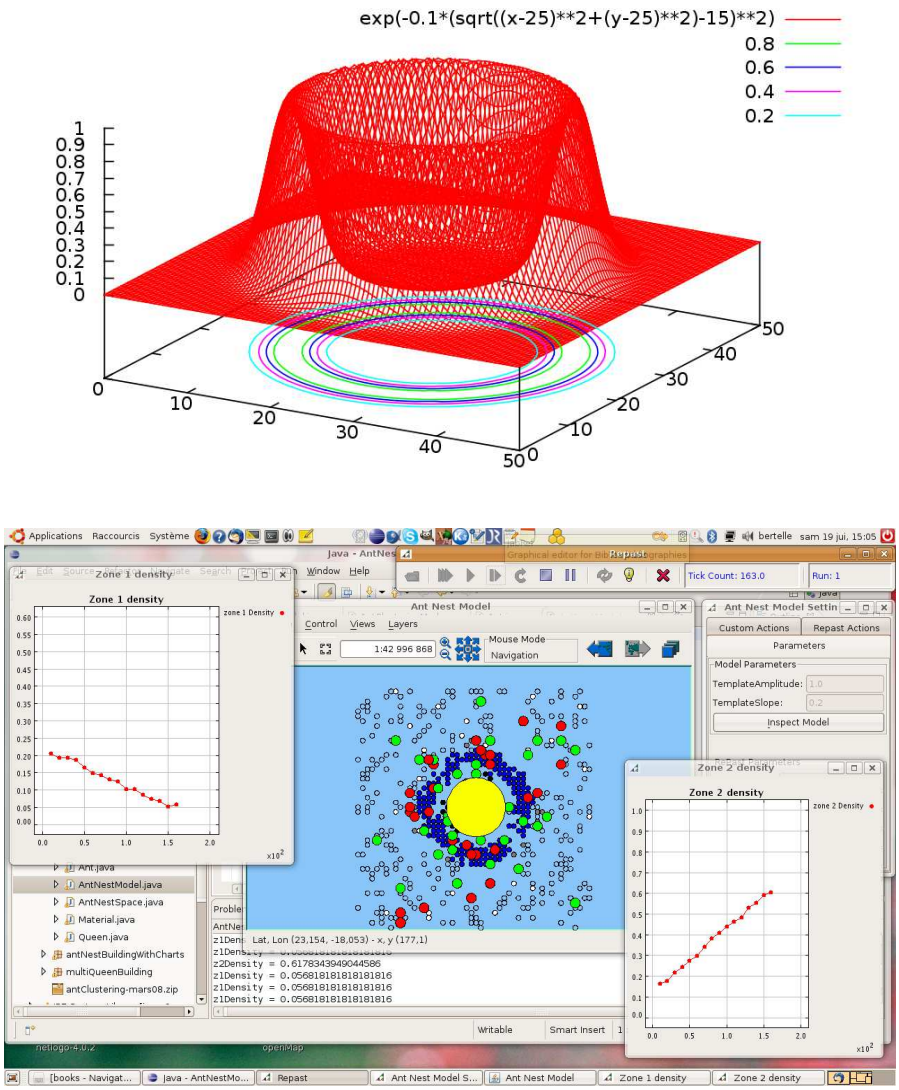


Figure 4.19: Template and associated ant nest building simulation in Repast

Adaptive Spatial Organization Feedback Implementation

As explained in section 2.2, complex systems deal not only with emergent organization processes from the interaction of its own entities, but also with the feedback processes of the organization over its own components. In the proposed model, we can take into account such feedback process and we present in figure 4.20 an adaptive process which makes the queen (describing the organization itself) modify the environment and the clustering processes itself. Following the template function, the queen locally defines around it two zones. The first zone is near itself and it is not expected to find material there. The second zone corresponds to the template maximum and it is expected to find a great concentration of material there. In the simulation, we count in a dynamical way the number of materials in these two zones and when these numbers reach some thresholds, we make the queen evolves by increasing its own size and so increasing the 2 associated zones. After this evolution, the ants have to move some material following the new template function attraction. The low part of the figure shows the evolution of the queen which has evolved 6 times since the simulation beginning. On this figure, we can see the red curves counting the zones density. Each gap in these density curves correspond to an evolution of the queen.

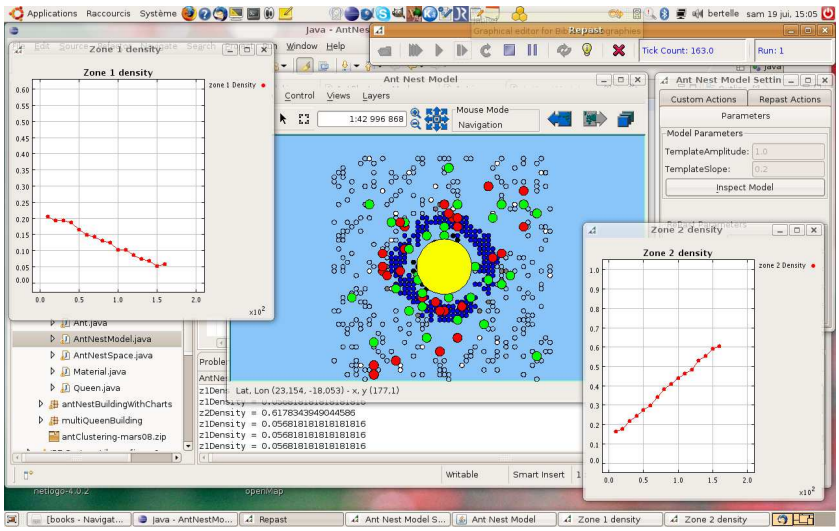
4.4.3 Application Examples

An Ant-Based Algorithm for Annular Sorting

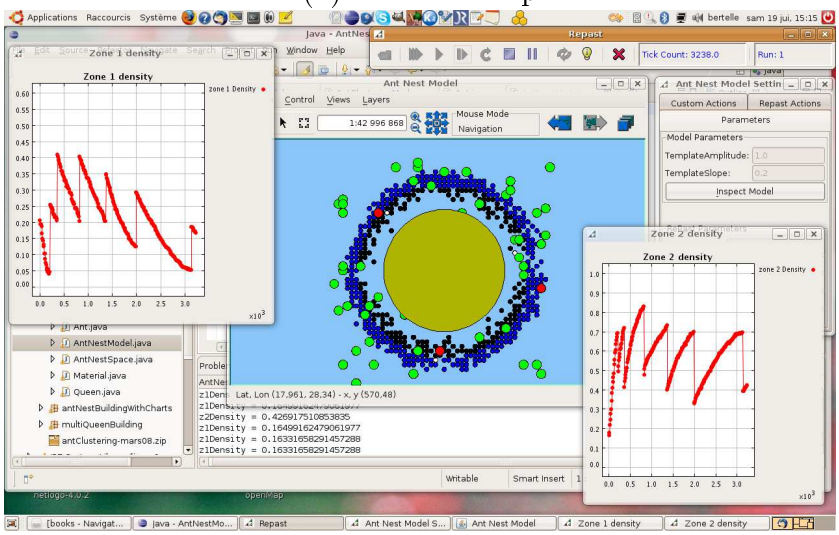
Swarm-based spatial sorting methods, inspired from brood sorting in spatially different areas (see sub-section 4.4.1), are swarm-based models that require only stochastic agent behavior coupled with a pheromone-inspired "attraction-repulsion" mechanism [2]. This algorithm is useful when one has objects that may change over time and require different amounts of separation. Wilson et al. in [132] create a physical implementation for the algorithm using mobile robots agents which are able to pull placed objects with weak probability out of the center of a cluster without disturbing other objects or risking collision, something that is hard to do with simple robotics. such kind of tasks had been done with a great environmental spatial stigmergic process which originally template inspired algorithms [63]

Emergent Structure Built by Robot

Another example that used swarm inspired template mechanism is the establishments of a structure around a light source as an environmental dynamical template by a set of autonomous robots. This work [119] uses simple rule robots agents and the information encoded in the environment by the light template. The intelligence which emerges from the swarm is the result of simple agent interaction with the complexity that they decode from their environment. Mason, in his paper [82], generalizes this mechanism to produce a swarm of agents that build complex compassable structure using phenomenal templates .



(a) after few step



(b) after queen adaptive development

Figure 4.20: Adaptive queen behavior modelling: according to its surround material spatial perception, the queen evolves

Self-Organized Data and Image Retrieval

One of the powerful points in using bio-inspired mechanisms are used by social insects is the creation of decentralized systems of simple interaction. The study of ant colonies behavior and of their self-organization capabilities is of interest to knowledge retrieval/management and decision support systems science because it provides distributed adaptive model which are useful to solve difficult optimization, classification, and distributed control problem. The application of ant systems has been used in digital image retrieval problems and unsupervised clustering [100].

DNA Chip Analysis

With the advanced technology at hand, the main trend in biological research is rapidly changing from structural DNA analysis to understanding cellular functions of the DNA sequences. DNA chips are now being used to perform experiments and DNA analysis processes are being used by researchers. Clustering is one of the important process used for grouping together similar entities. M. Lee et al. [75] propose an ant clustering algorithm that takes into account the features of biological data.

Web Documents Categorization

The self-organization behavior exhibited by ants are used to solve real world clustering problems like web document categorization [93].

The idea of this application is obtained from template matching mechanism with a Gaussian Probability Surface (GPS) to constrain the formation of the clusters in predefined areas. This work improves the existing results.

An Algorithm for Site Selection in GIS, Multi-Objective Resource Allocation

While GIS have been designed to handle general spatial analysis problems, most such spatial analysis problems are computationally inefficient when using conventional algorithms. In particular, it is the case when the problem involves searching large data sets and different conflict objective have to be optimized. Site selection or resource allocation problems are such problems.

Ajay Sharma et al. in [112] use swarm intelligence based algorithms inspired from termite nest building in order to propose an automatic computational tool for the site selection problem. They apply the algorithm on a set of spatial data and they provide some simulation results using object oriented discrete event simulation platform inside GRASS GIS software [55].

Part II

Model

Chapter 5

Adaptive Multi-Criteria Multi-Center Systems Dynamics

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5.4 Adaptive Processes in Ant Nest Building for Multi-Criteria Multi-Center Dynamics 116

In this part, we develop within two chapters, the core of the model proposed in this work. The first chapter develops an extension to social insect systems modeling and the second chapter develops an emerging computation in order to detect communities from automata based system representation.

In this chapter, we start in presenting our general methodology for swarm computation engineering. Then we describe the formalism based on an extension of nest building models. In the one hand, we present specifically the process of attraction phenomena, we give some simulation outputs illustrating the importance of the different components of the models and we give some conceptual tools to analyze the complexity of these model outputs. In the other hand, we present how we implement adaptive processes at this level of abstract modeling and later at the level of applicative case-studies developed in part 3.

5.1 Introduction

The swarm intelligence algorithms described in the previous part and chapter, are the direct formalization of natural social insects systems. As described in figure 5.1, they can be considered as the first stage of our modeling organization.

From these *elementary models*, we propose to combine different elements and we need to add other processes in order to model more sophisticated phenomena.

As extensions to the elementary models of the previous chapter, we add advances on spatial adaptive and self-organized systems by the integration of the following aspects:

- **Multi-center**: we will consider a spatial environment composed of several centers attracting ants and their carried material. The advantage of such an extension concerns the spatial repartition of the attraction phenomena, including concurrent aspects, and based on decentralized mechanisms.
- **Multi-criteria**: we need to progress from insect societies toward human societies which are characterized by the complex interactions of many services and expectations according to non homogeneous populations (various age, various social position, etc).
- **Adaptivity extension for multi-criteria**: we need to propose adaptive processes to manage the multi-criteria extension of the model. The feedback mechanisms become more complex and some of the negative feedbacks can be not the direct consequence of the positive feedback which leads the emergence of the system. In other words, some *hidden* criteria which are not directly involved in the systems building emergence can produce feedback and regulation.

Finally, as explained in figure 5.1, the final applicative usage of our model will consist in *plugging* the components of the abstract model with concrete features which have

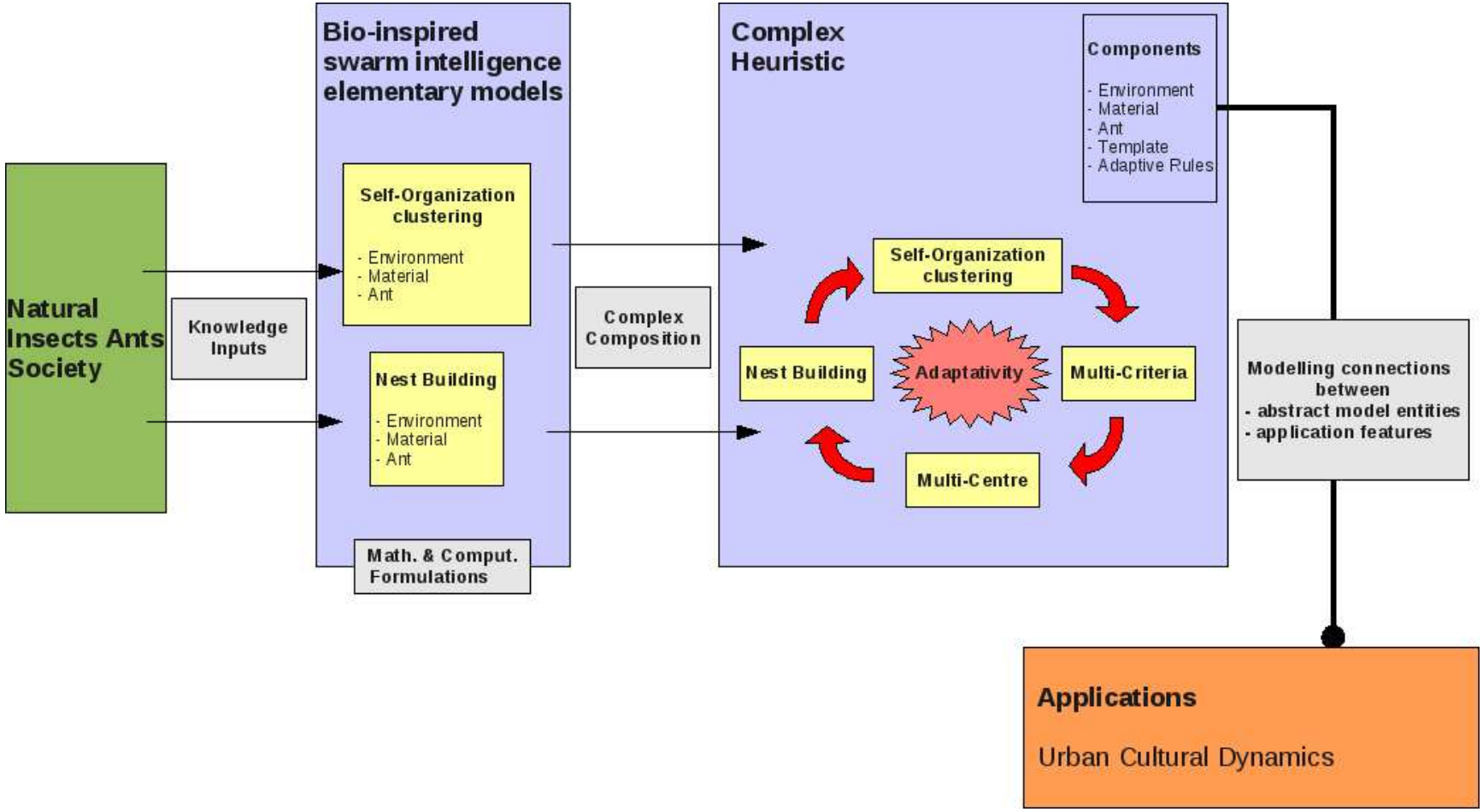


Figure 5.1: Conceptual modeling approach and engineering

meaning for the applicative system. The study of urban cultural system which will be the main aspect of the study-case developed in the following part of this document, will be managed in that way. We will come back to this figure and extend it in order to better highlight this *plugging* between abstract model and application features.

5.2 Ant Nest Building Extension for Multi-Criteria Multi-Center Dynamics for Attraction Phenomena

In this section, we extend the mechanism described in the previous section by multi queen spatial configuration. Such a spatial configuration, with many queens spread in all the space, is the core of a multi-center simulation where each criteria of each center is described by a queen.

5.2.1 Spatial Environment for Multi-Criteria Multi-Center Simulations

To introduce the concept of multi-criteria phenomena, we introduce different kinds of pheromones. Each kind of pheromone is represented by a specific color. We introduce the notion of center which is a specific spatial location. On each center, we are able to define many queens. Each queen, belonging to a center, is able to emit its own pheromone which is represented by a colored pheromone that is different from the other queen ones belonging to the same center. A queen, associated to a spatial center, describes a specific criterium linked to a colored pheromone. To represent the same criterium on different centers, we describe it by the same colored pheromone on these different spatial locations.

In order to force the ants to deposit their material only near the center, we have introduced the template function. Even if the pheromone function and the template function must have similarities in order to attract and make deposit the material at the same place, we have to separate these two functions. The template function must exhibit a close area of non null values near the center to link the material to the center. The pheromone function must attract ants with material on the same place but the attraction phenomena has to cover a widest area than the template function, in order to be able to attract materials and ants at some distance from the center.

Definition 5 *A spatial multi-criteria multi-center simulation is described by a set of n_p* ***centers****, $\{P_i; 1 \leq i \leq n_p\}$, and by a set of n_c* ***colors****, $\{c_j; 1 \leq j \leq n_c\}$.*
For each center P_i, we define a ***c_j-colored template function****, $\Phi_{ij} : S \rightarrow I\!R$, which gives the value of the c_j template intensity on each spatial position.*
For each center P_i, we can define a ***c_j-colored pheromone function****, $f_{ij} : S \rightarrow I\!R$, which gives the value of the c_j pheromone intensity on each spatial position.*

Remark 1 *We can define the c_j-colored template function of the P_i center by the following* **radial exponential function**

$$\Phi_{ij}(x,y) = \alpha_{ij} \exp(-\beta_{ij}(d((x,y),(x_{P_i},y_{P_i})) - r_{ij})^2) \tag{5.1}$$

where α_{ij} is the template amplitude, β_{ij} is the template slope, (x_{P_i}, y_{P_i}) are the P_i center coordinates.
We then define the c_j-colored pheromone function for the P_i center with a similar formula

$$f_{ij}(x,y) = a_{ij} \exp(-b_{ij}(d((x,y),(x_{P_i},y_{P_i})) - r_{ij})^2) \tag{5.2}$$

where a_{ij} is the template amplitude, b_{ij} is the template slope.

We have to remark that the radius r_{ij} is the same in the above two formulas and allows to define the same maximum value position, but the amplitude and slope are different. The slope of template function has to define close area of maximal value near the center. The slope of the pheromone function must not have maximal area too much close to the center in order to attract ants or materials which are located at some distance from the center.

Remark 2 *In the previous template function associated to a center, we can consider that some of the parameters are geometric parameters which can be associated to the center position and are independent of the pheromone color. Therefore, the parameters b_{ij} and rij can be considered, in such way, as b_i and r_i. In this case, the previous template function is then given by:*

$$\Phi_{ij}(x,y) = \alpha_{ij} \exp(-\beta_i(d((x,y),(x_{P_i},y_{P_i})) - r_i)^2) \tag{5.3}$$

The same remark can be applied to the pheromone function too.

Figure 5.2 is similar to figure 2, but we represent here, on the top of the figure, two centers and two colored pheromones. The template function used to represent the pheromone emission corresponds to the function defined in remark 2. On the bottom of the figure, we present the associated simulation in Repast.

We give in the following some definitions which allow to generalize the ant nest building algorithm for the multi-criteria multi-center simulation.

Definition 6 *A center P_i has the* ***dominant color*** *c_j if*

$$a_{ij} = \max\{a_{ik}; 1 \leq k \leq n_c\}.$$

Definition 7 *On each space location $Z = (x,y)$, we define the* ***c_j colored pheromone intensity*** *as the function* $\boldsymbol{F_j(Z)}$ *or* $\boldsymbol{F_j(x,y)}$ *defined by the formula:*

$$F_j(Z) = F_j(x,y) = \sum_{i=1}^{n_p} f_{ij}(x,y). \tag{5.4}$$

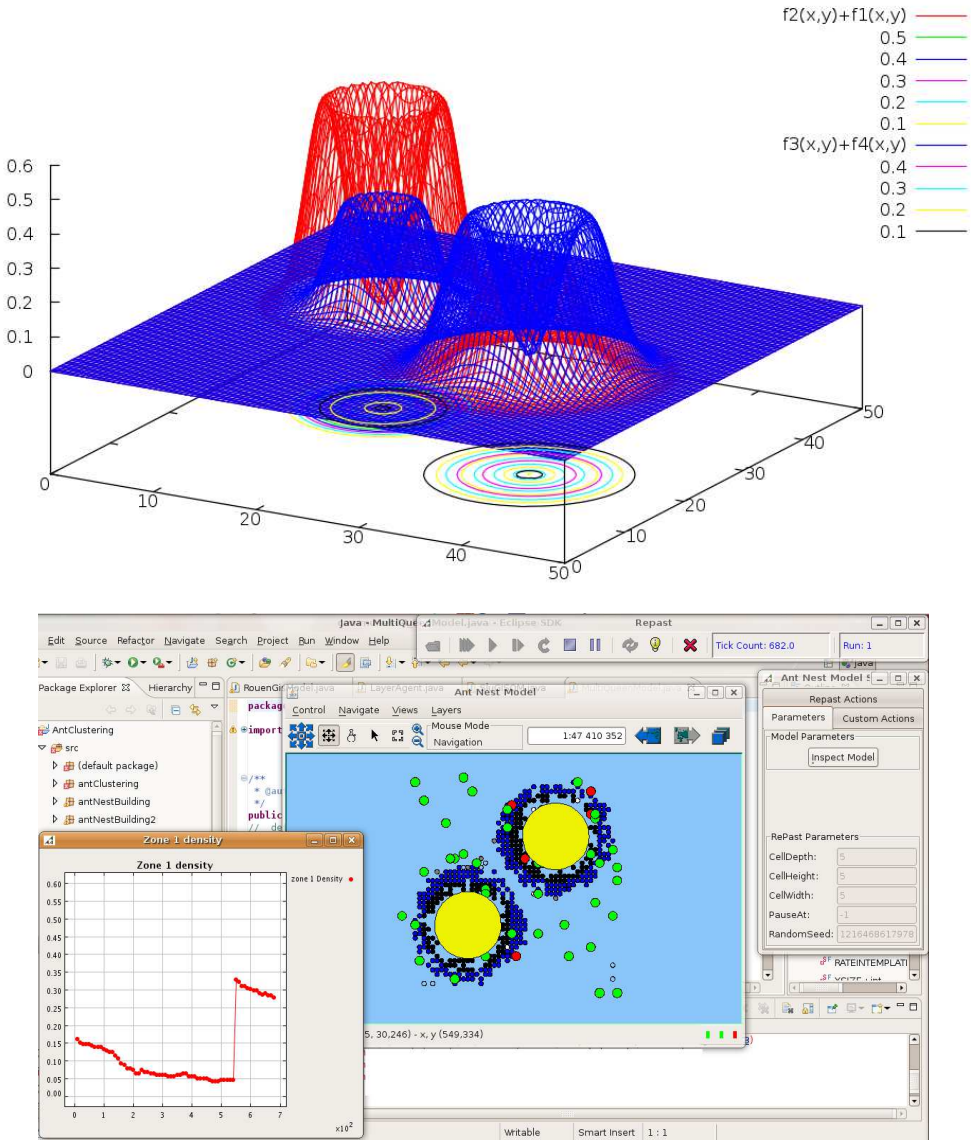


Figure 5.2: Multi-center multi-colored pheromone template represented by radial exponential functions and the associated ant nest building simulation in Repast

5.2.2 Spatial Objects and Agents for Multi-Criteria Multi-Center Simulations

The multi-criteria multi-center model proposed here, implement some spatial objects that are the material and spatial agents (which are the ants). The ants have to carry the material in order to achieve the spatial self-organization simulation. We describe in this section the objects and the agents and we will describe in the following section the mechanisms involved in the self-organization simulation.

Definition 8 *A material involved in a spatial multi-criteria multi-center simulation has to include a* ***characteristic color table*** *which corresponds to the only colors that the material is able to perceive and upon which it will be able to react.*

Definition 9 *An ant involved in a spatial multi-criteria multi-center simulation and which is carrying a material has to include a* ***characteristic color table*** *which corresponds to the material characteristic color table.*

5.2.3 Multi-Criteria Multi-Center Dynamics Algorithms for Attraction Phenomena

Definition 10 *Each ant of the simulation which is carrying some material M_l, has to implement a decision process which gives, as output, a color pheromone template c_j that is used for the material transportation by the ant. This selected color c_j is called* **the ant behavior**.

At each simulation step, a carried material M_l is associated to a color c_j, called the ant behavior in definition 10. The ant which is carrying this material will then move by searching in its neighboring position, the one with the highest value of the c_j colored pheromone.

We propose two ways to compute the ant behavior as described in the following.

Ant behavior computation based on dominant color

The first way to compute ant behavior consists in searching the highest value of the colored pheromone on the space position of the ant and to return the color of this highest value. The ant moves on the neighboring place which has the highest value of colored pheromone defined by its behavior. The algorithm is the following:

Ant behavior computation based on ranking

The second way to compute ant behavior is based on a specific ranking process which will evaluate the greatest ranking place between the neighboring place corresponding to some highest pheromone color rate. In the following, we define the notion of ranking and then describe the detailed algorithm of this second ant behavior computation.

Algorithm 1: Ant behavior algorithm based on dominant color

```
for each color c_j belonging to the ant characteristic color table do
    phRate ← Evaluation of the c_j colored pheromone rate in the space at the ant
    location
    if phRate is the maximum pheromone rate find until now then
        update the maximum pheromone rate with phRate;
        maxColor ← c_j;
    ant behavior ← maxColor;
    Move the ant on the neighboring place which has the higher rate of maxColor
    pheromone;
```

Definition 11 *For each material M (or the ant carrying it), we define the* $\boldsymbol{c_j}$ ***color attribute preference*** *as the rate, a real number* $\boldsymbol{s_{jM}} \in [0, 1]$.

Definition 12 *For each material M (or the ant carrying it) and each space location $Z = (x, y)$, we compute the* ***ranking,*** $\boldsymbol{\rho_{MZ}}$ *by the formula:*

$$\rho_{MZ} = \sum_{j=1}^{n_c} s_{jM} * F_j(Z) \tag{5.5}$$

where n_c is the number of pheromone colors, $F_j(Z)$ is the c_j colored pheromone intensity on the location Z, defined in definition 7 and s_{jM} is the c_j color attribute attribute preference for the material M defined in definition 11.

The algorithm 2 describes the ant behavior process as defined in definition 10, using the ranking computation.
The ranking computation provides more relevant computation according to the multi-criteria aspects of the model. With ranking, more complex behavior can be involved to manage the attraction phenomena, taking into account more information inside the whole system of individual characteristics. In the following, the computation are using the ranking algorithm better than the dominant color algorithm.

5.3 Attraction Phenomena Experiments

Simulation experiments are made using Repast on OpenMap for the specific configuration described in the next section. We describe in the following the experimental configuration, then the simulation output and finally an analysis in order to study the attraction phenomena.

5.3.1 Experimental Configuration

An experimental configuration is defined by the initial positions of all the components of the system: (i) the centers, (ii) the queens, (iii) the materials and (iv) the ants.

Algorithm 2: Ant behavior algorithm based on ranking computation

```
M ← material carried by the ant
rank_value ← 0
color_rank ← -1
x_rank ← 0; y_rank ← 0
for each color c_j belonging to the ant characteristic color table do
    (xp, yp) ← the neighboring place of (x, y) which have the highest pheromone
    intensity of color c_j
    rank ← Σ_{j=1}^{n_c} s_jM * F_j(x_p, y_p)
    if rank > rank_value then
        rank_value ← rank
        color_rank ← c_j
        x_rank ← x_p; y_rank ← y_p
if color_rank = -1 then
    move the ant in random way
else
    move the ant in (x_rank, y_rank)
```

In this section, we study a specific experimental configuration, composed of 6 centers and with random initial places for the materials and for the ants. The center positions are described on the left top sub-figure of figure 5.3. On each center, we put 8 queens, each one is associated to a colored pheromone labelled from 0 to 7. In figure 5.3, we also represent the amplitude of colored pheromone corresponding to the radial exponential templates as described in figure 5.2.

5.3.2 Simulation Output and General Analysis

In this sub-section, we implement the simulation following the first algorithm of the ant behavior, defined in the previous section.

On figure 5.4, we show the result of one simulation where ants progressively aggregate the material around the center, following pheromone trails and clustering algorithm. On the left top sub-figure, we see the initial distribution of materials and ants. In the three other sub-figures, we see three successive steps of the simulation. We can observe the formation of material affectation to each center in order to respect the attraction process, according to the material characteristics.

On figure 5.5, we make a zoom of the last step of the simulation shown on figure 5.4, removing the ant representation.

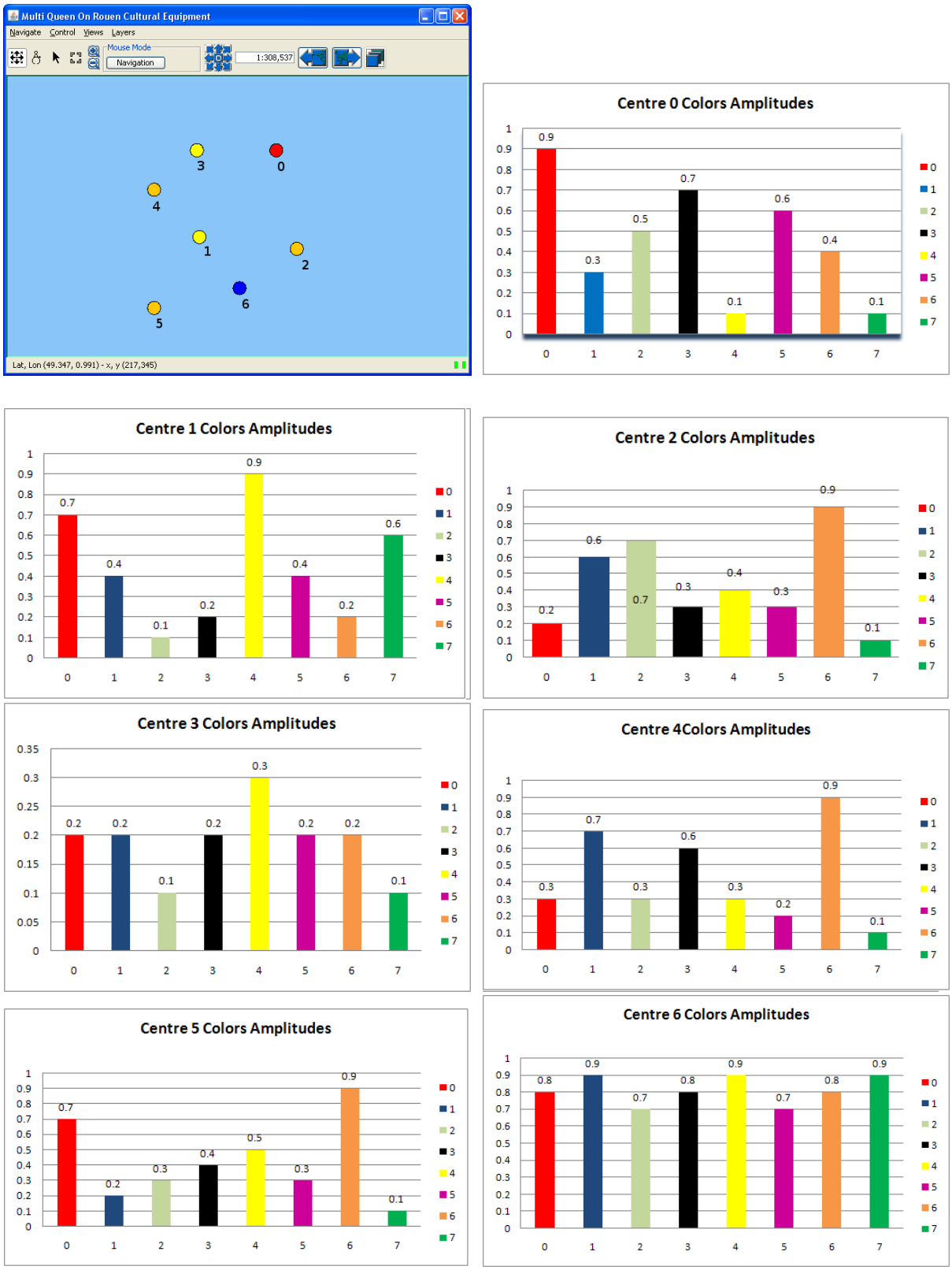


Figure 5.3: Experiment configuration

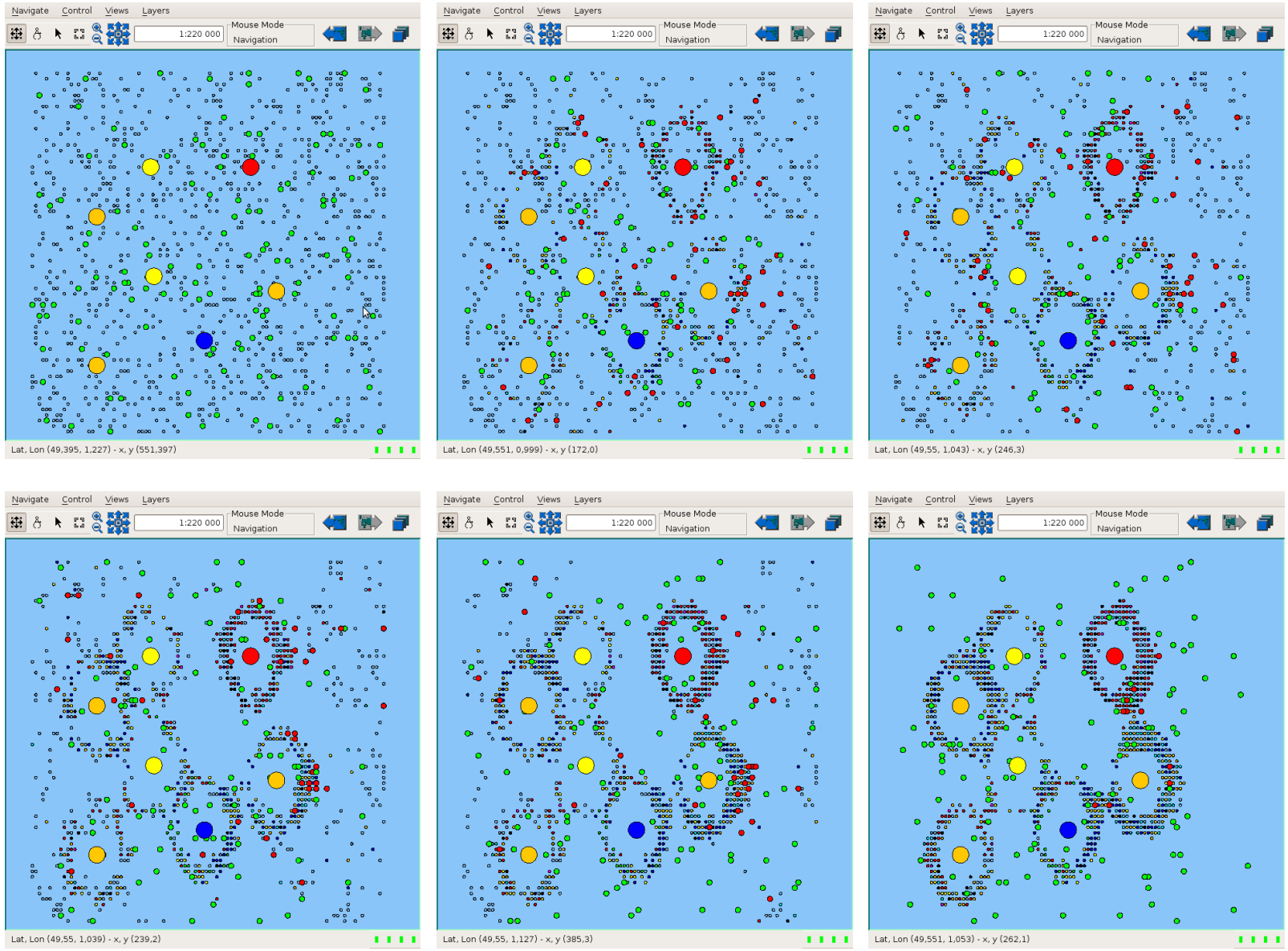


Figure 5.4: Simulation computation, at successive steps: iterations 0, 152, 250, 370, 601, 1601.

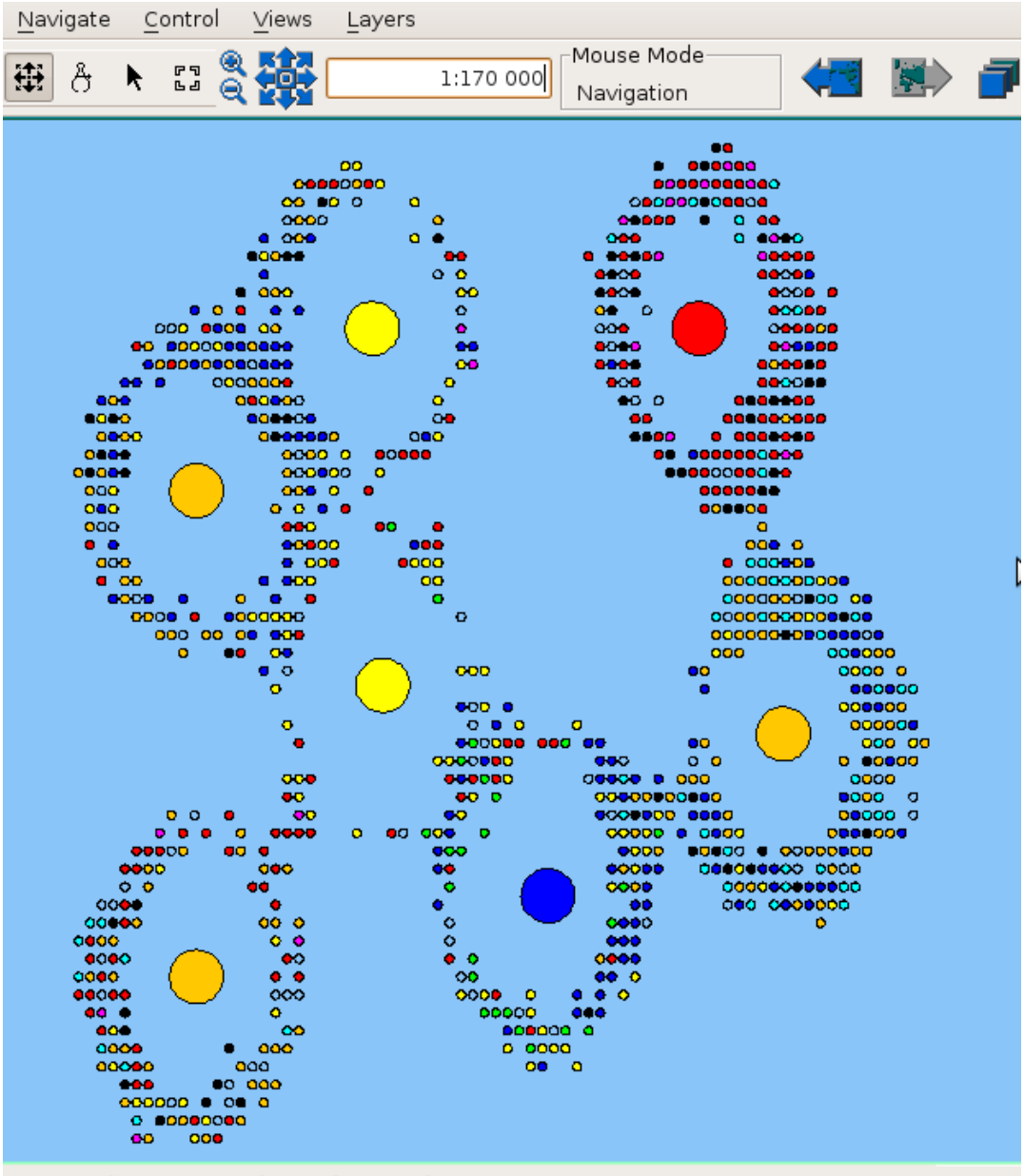


Figure 5.5: Simulation: zoom on final step

5.3.3 Attraction Analysis Based on Dominant Component

We need to exhibit some analysis to better understand how the computation produced, by self-organization, the distribution of the material over the centers system.

In the first part, the analysis is based on the dominant component for the material: a characteristic color table is associated to each material. The process of attraction is lead by the ant behavior defined previously. This ant behavior consists here to extract from the characteristic color table, a selected color corresponding to the colored pheromone which controls the ant in order to move to the places of highest values for this colored pheromone.

To better understand the mechanism of attraction, we have to focus on the selected color associated to each material which controls the ant displacement and to forget the other colors belonging to the characteristic color table of the material. In this part, we only associate to each material the dominant color and we study how these colored material are distributed over all the center system.

To analyze this distribution, we represent 3 graphs for each center. On each graph, we have a specific representation of the distribution of all attracted material according to his dominant selected color.

Before defining all these graphs, we have to define a zone of analysis for each center:

Definition 13 *For each center P_i and each color pheromone c_j corresponding to the template function f_{ij} defined in remark 1, we define the* **referential disk** *as*

$$D_{ij} = \{M = (x, y); f_{ij}(M) < ra_{ij}\}$$

where a_{ij} is the template amplitude of the function f_{ij} and $r \in [0, 1]$ is a real number whose value is generally equal to 0.5 *in the following*

According to this referential disk, we compute, by three ways, some indicators corresponding to the quantity of material of each color in this disk, or some relative quantity of material in function of the pheromone amplitude or in function of the neighborhood.

The three graphs used in our study are defined by

- The **material density** graph which computes the density of material of each color (its dominant selected color) in the referential disk. The material density of dominant color c_j for the center P_i is computed as follow:

  $$\rho(P_i, c_j) = \frac{\eta(D_{ij})}{\mathcal{A}(D_{ij})}$$

  where $\eta(D_{ij})$ is the number of materials of dominant color c_j inside the referential disk D_{ij} of the center P_i and $\mathcal{A}(D_{ij})$ is the area (e.g. number of material places) of the disk D_{ij}.

- The **pheromone efficiency** graph which computes the density of material of each color in the referential disk, relatively to the pheromone amplitude of its color for the corresponding center. The pheromone efficiency of dominant color c_j for the center P_i is computed as follow:

$$\rho_r(P_i, c_j) = \frac{\rho(P_i, c_j)}{a_{ij}}$$

- The **relative pheromone efficiency** graph which computes the queen efficiency relatively to the neigborhood network. This computation consists in changing the pheromone amplitude used in the previous graph by a relative pheromone amplitude a^r_{ij} defined by:

$$a^r_{ij} = \frac{a_{ij}}{\sum_{k \in \vartheta_i} a_{kj}}$$

  where ϑ_i is the set of centers belonging to the neighborhood of the center c_i on the center neighboring network. The relative pheromone efficiency of dominant color c_j for the center P_i is computed as follow:

$$\rho_{sr}(P_i, c_j) = \frac{\rho(P_i, c_j)}{a^r_{ij}}$$

The last graph exhibits a complex indicator which takes into account the interaction network of the center system.

On figure 5.6, we show the center neighboring network corresponding to the experimental configuration. On figure 5.7, we show the neighborhood of the center 0 and of the center 1 in this experimental configuration.

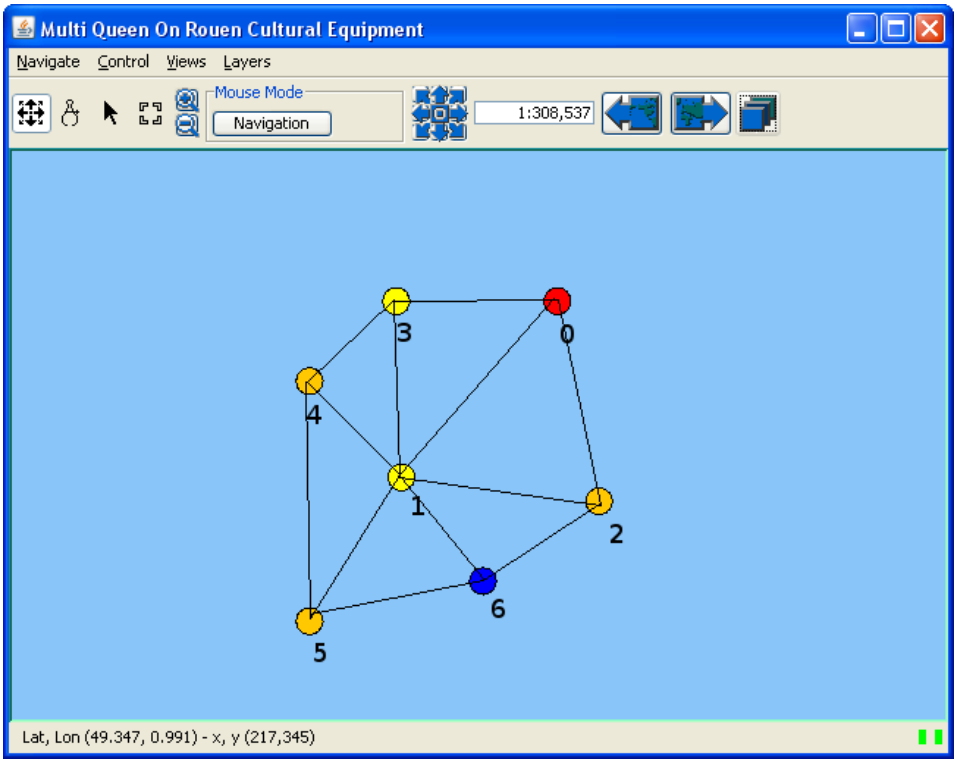


Figure 5.6: Center neighboring network

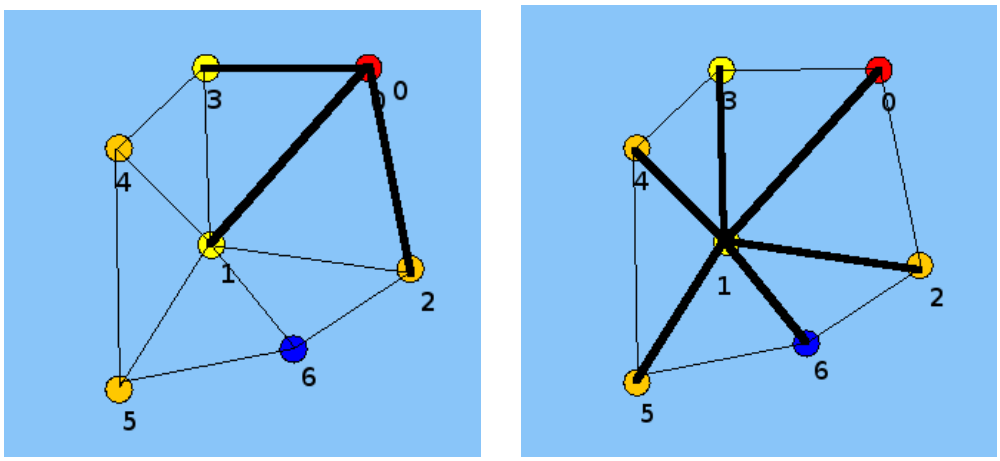
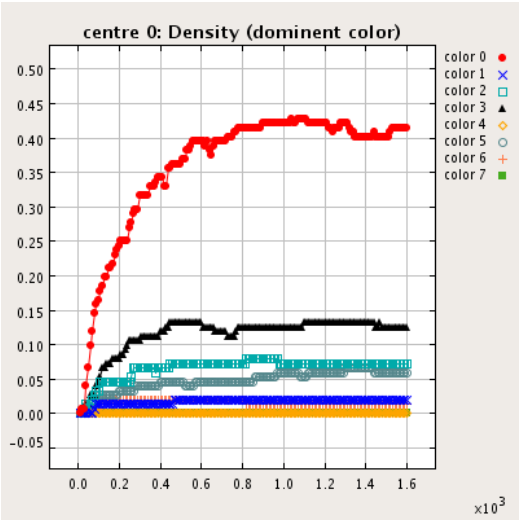
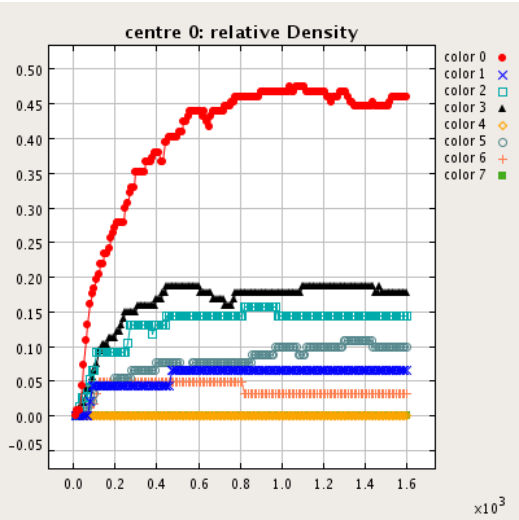


Figure 5.7: Neighborhood of center 0 and center 1 over the centers network

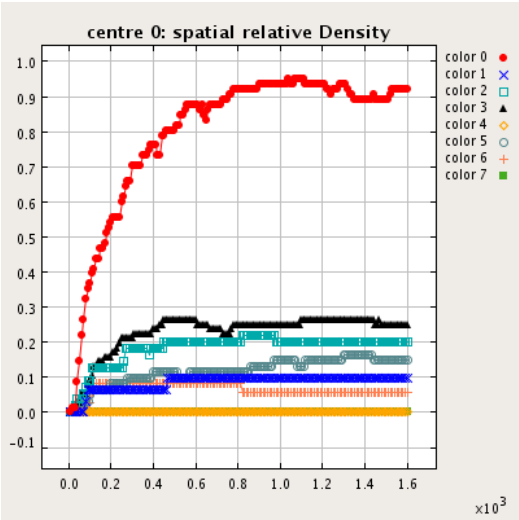
On figures 5.8 to 5.14, we represent for each center, the 3 graphs defined previously and we represent two additional graphs corresponding to the pheromone amplitude and to the relative pheromone amplitude according to the neighborhood, for each color.



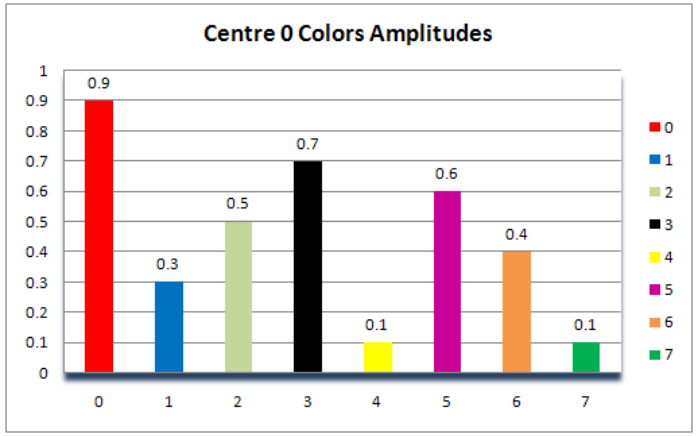
(1) material density



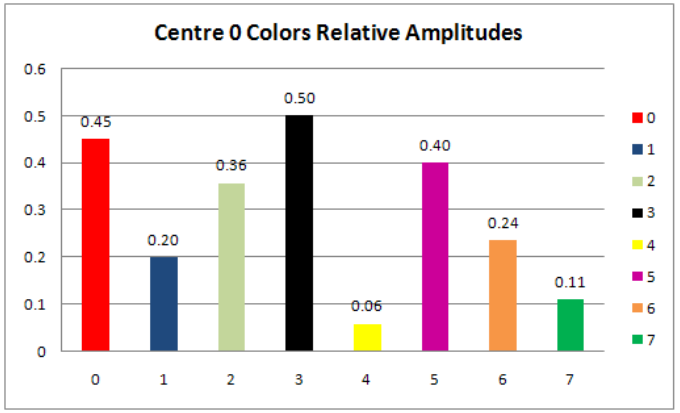
(2) pheromone efficiency



(3) relative pheromone efficiency

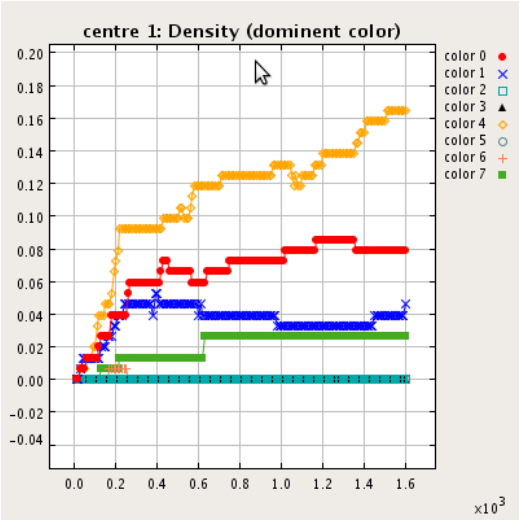


(4) pheromone amplitudes

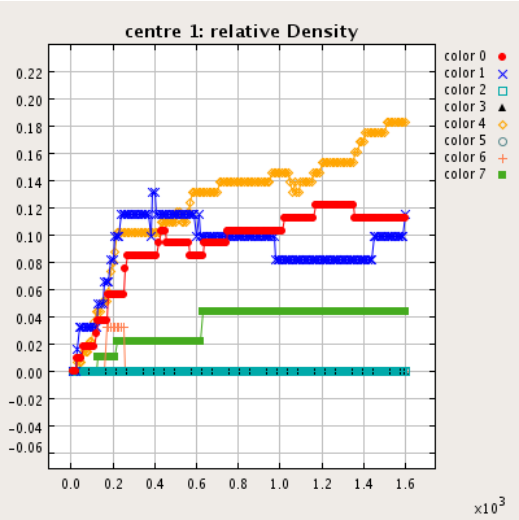


(5) relative pheromone amplitudes

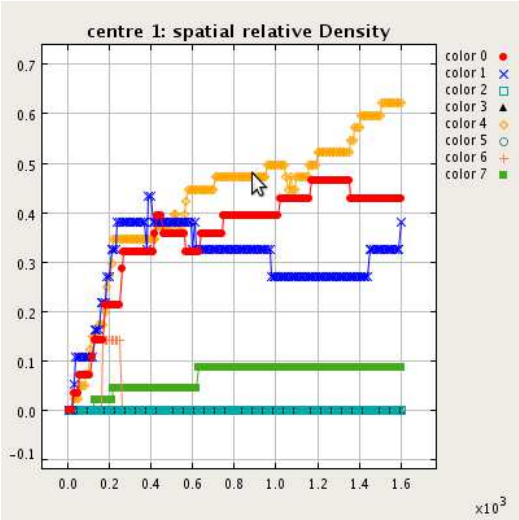
Figure 5.8: Attraction analysis for the center O



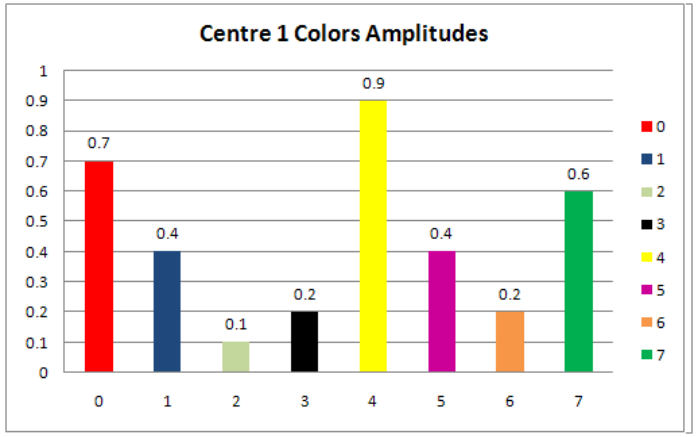
(1) material density



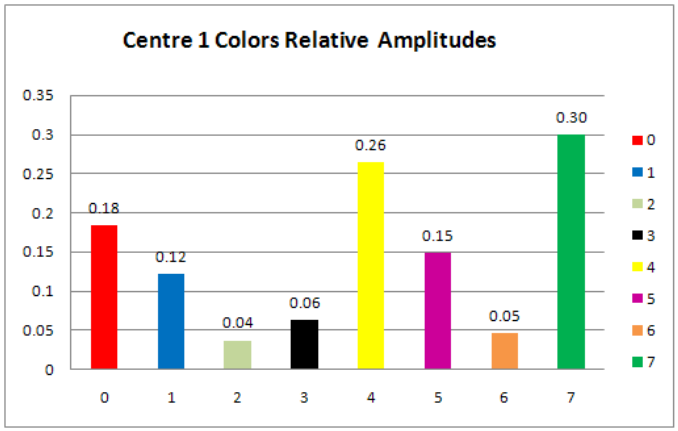
(2) pheromone efficiency



(3) relative pheromone efficiency

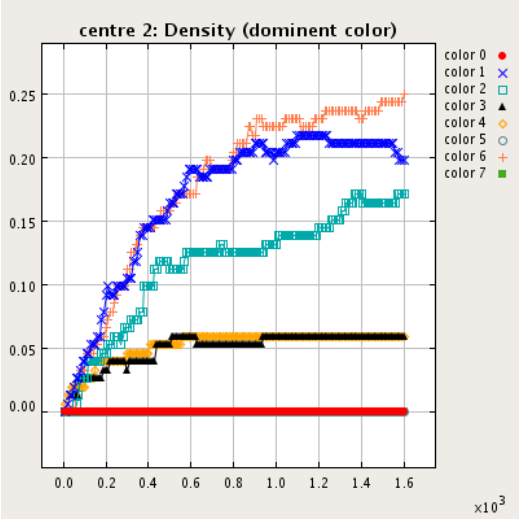


(4) pheromone amplitudes

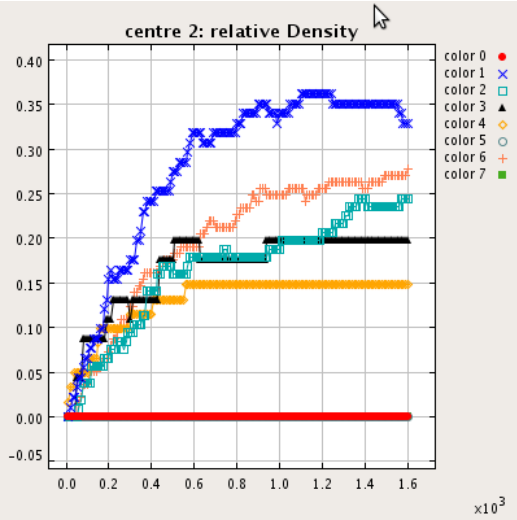


(5) relative pheromone amplitudes

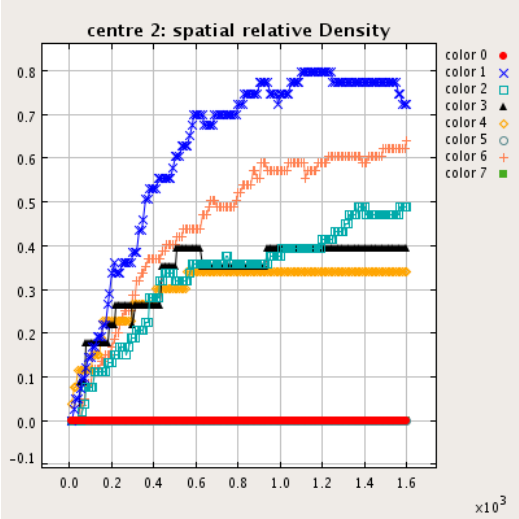
Figure 5.9: Attraction analysis for the center 1



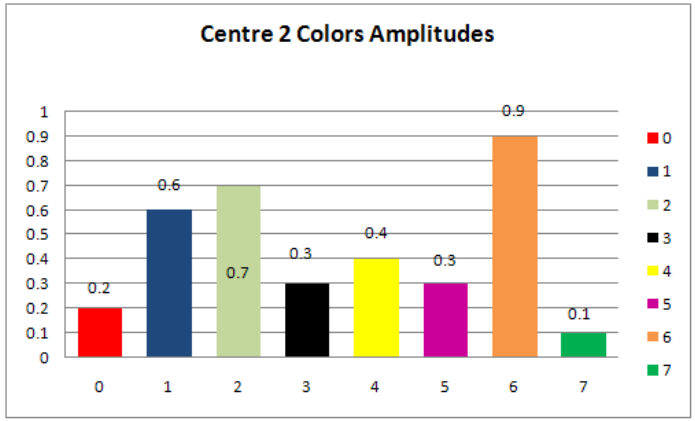
(1) material density



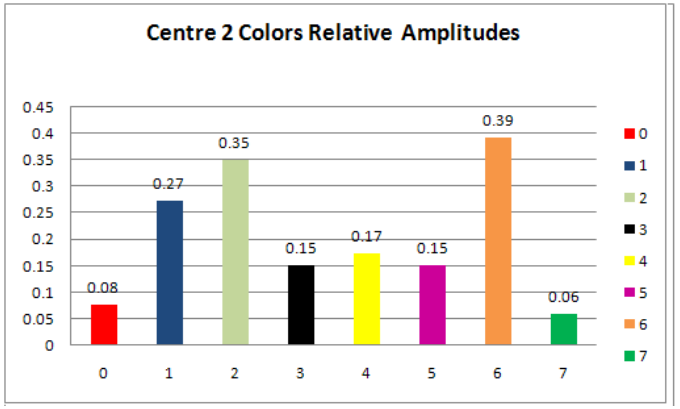
(2) pheromone efficiency



(3) relative pheromone efficiency

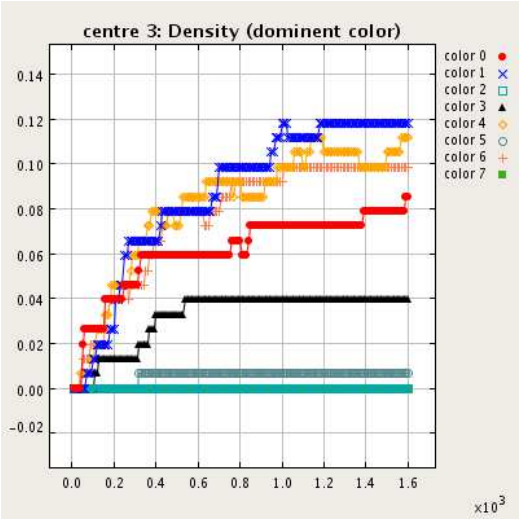


(4) pheromone amplitudes

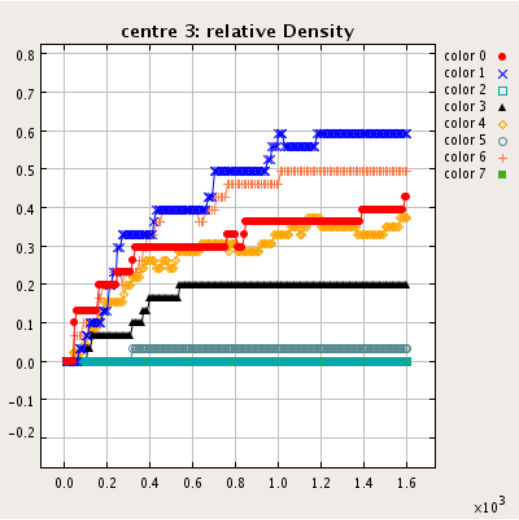


(5) relative pheromone amplitudes

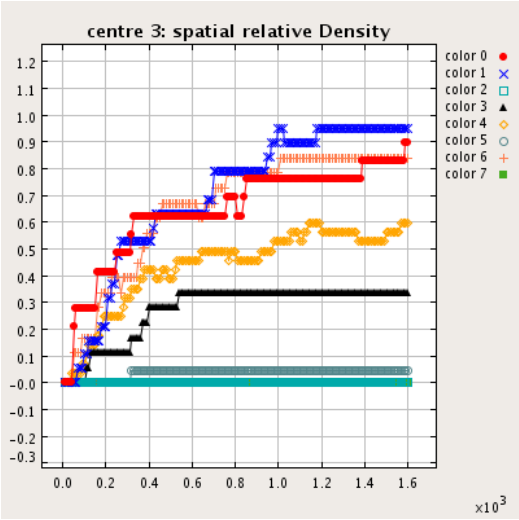
Figure 5.10: Attraction analysis for the center 2



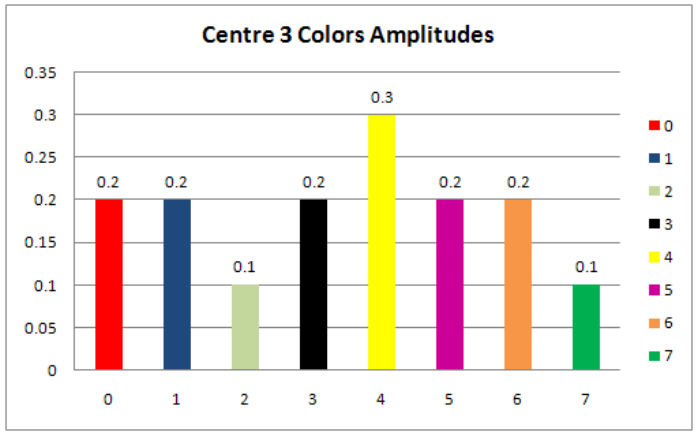
(1) material density



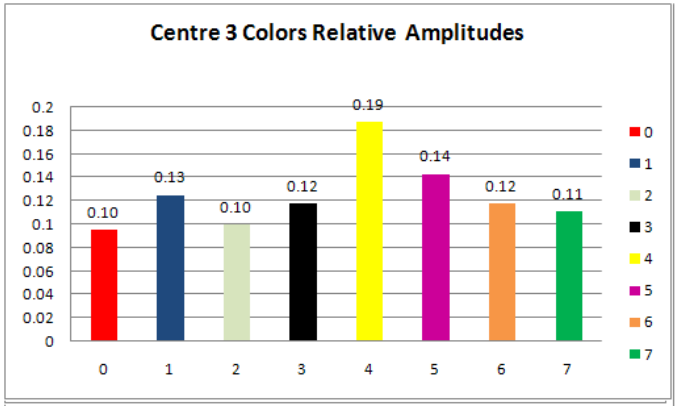
(2) pheromone efficiency



(3) relative pheromone efficiency

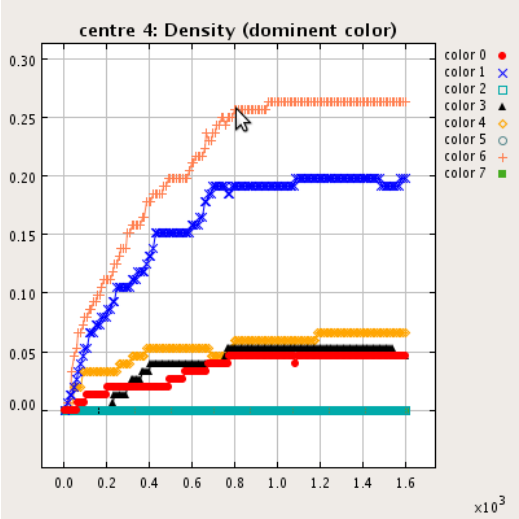


(4) pheromone amplitudes

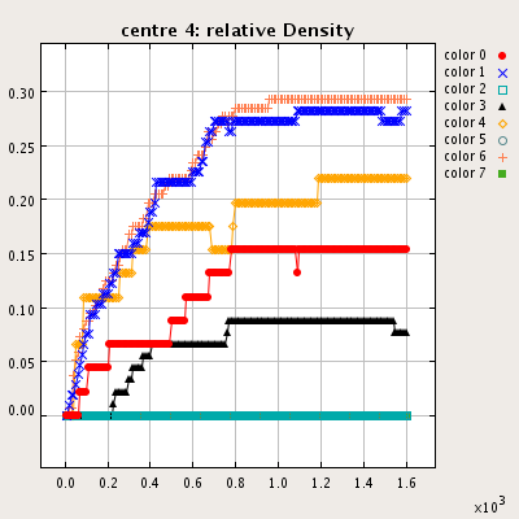


(5) relative pheromone amplitudes

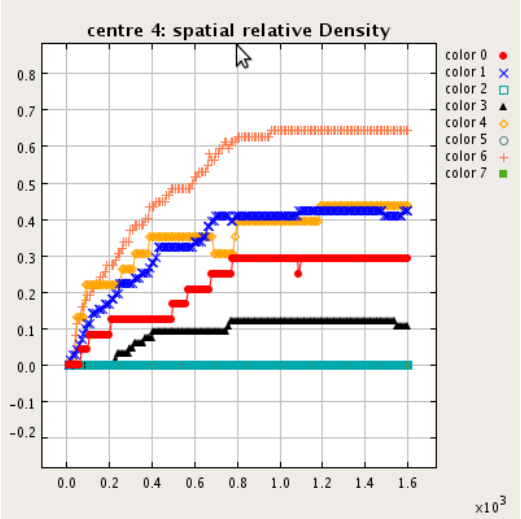
Figure 5.11: Attraction analysis for the center 3



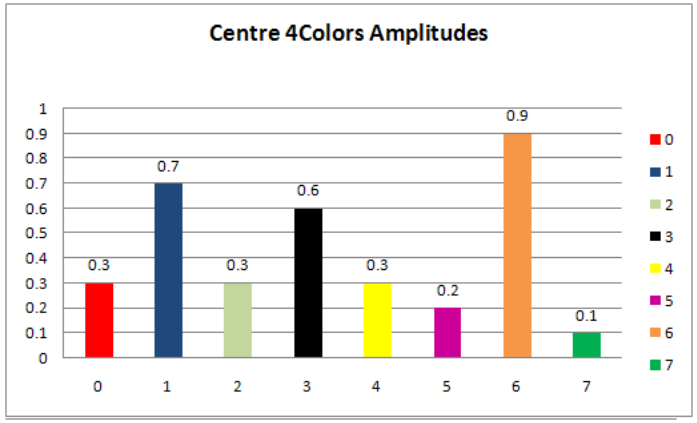
(1) material density



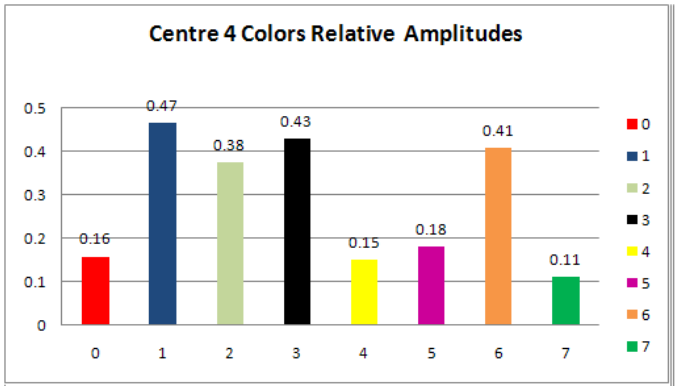
(2) pheromone efficiency



(3) relative pheromone efficiency

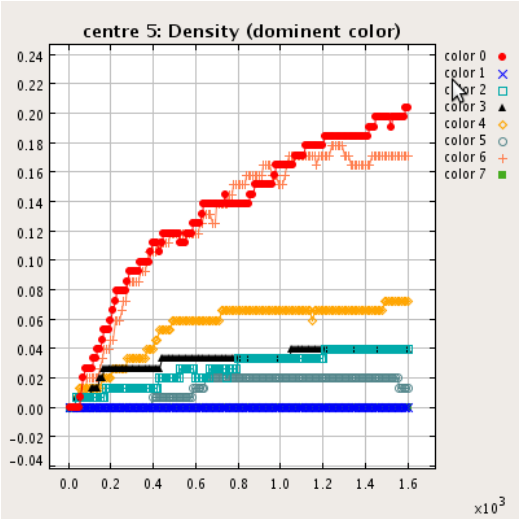


(4) pheromone amplitudes

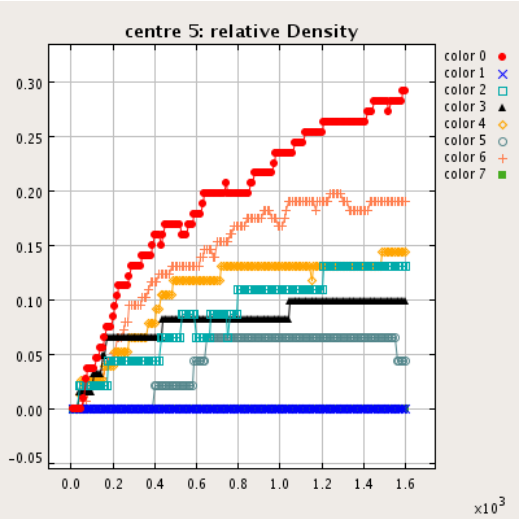


(5) relative pheromone amplitudes

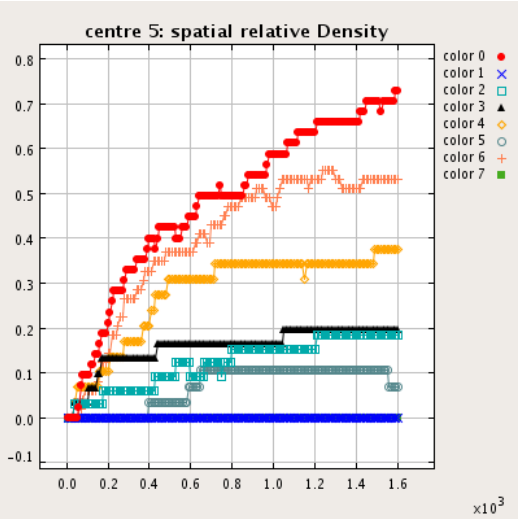
Figure 5.12: Attraction analysis for the center 4



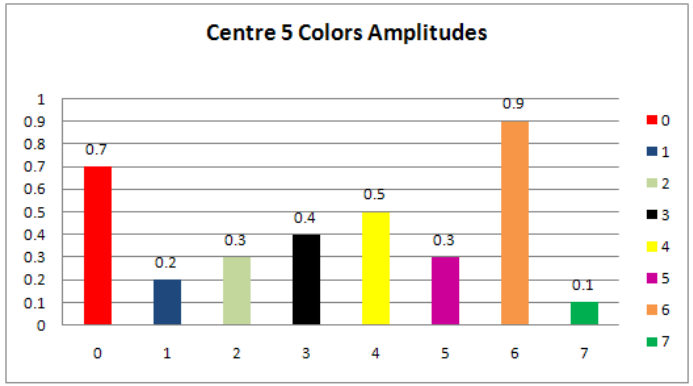
(1) material density



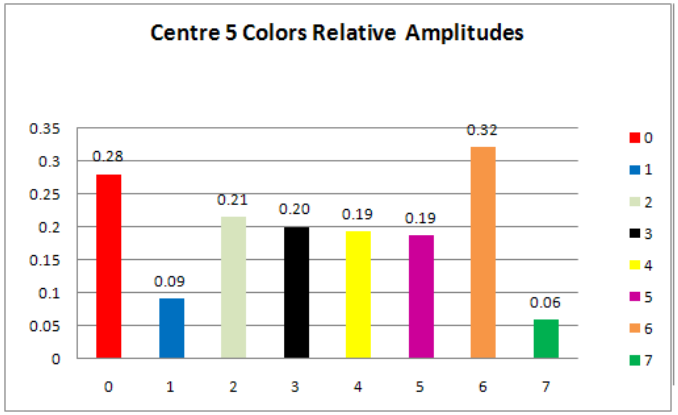
(2) pheromone efficiency



(3) relative pheromone efficiency

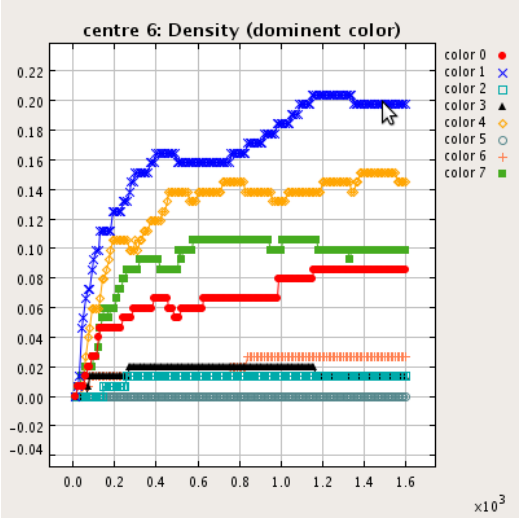


(4) pheromone amplitudes

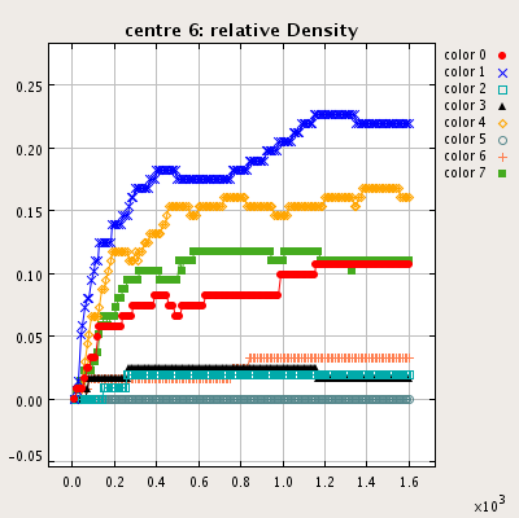


(5) relative pheromone amplitudes

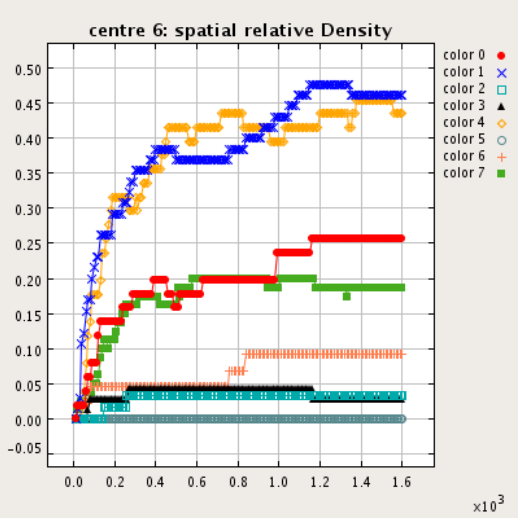
Figure 5.13: Attraction analysis for the center 5



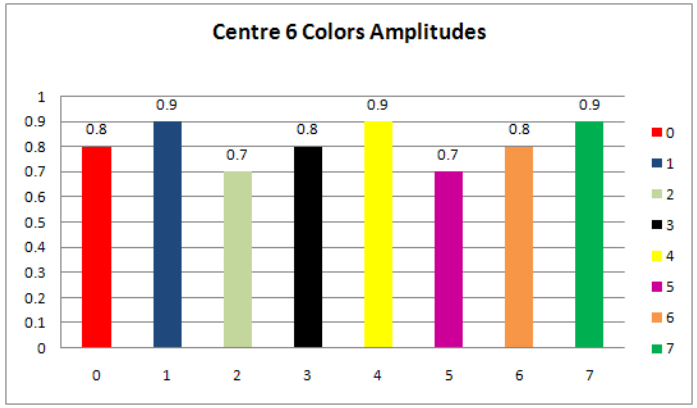
(1) material density



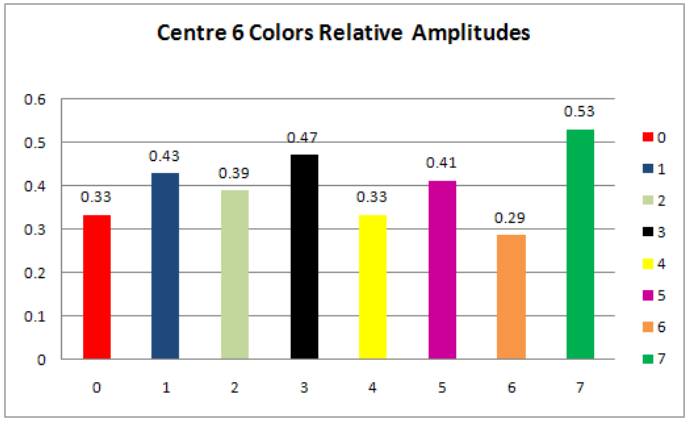
(2) pheromone efficiency



(3) relative pheromone efficiency



(4) pheromone amplitudes



(5) relative pheromone amplitudes

Figure 5.14: Attraction analysis for the center 6

Results Analysis

This attraction analysis with the three associated graphs: (i) material density graph, (ii) pheromone efficiency graph and (iii) relative pheromone efficiency graph, allows us to better understand the complexity of the phenomena according to the multi-criteria and to the spatial effects.

To illustrate this analysis, we will observe the results of the center 4, based on figure 5.12:

1. A first remark concerns the non linear properties of the attraction phenomenon which makes the color of the more important pheromone intensities attracting a great number of materials of this color and a few number of materials of color of lower pheromone intensities. There is no linear relation between the number of colored material and the corresponding colored pheromone intensity. Finally, the material of color of lower pheromone intensity are not significant. Concerning center 4 of our current experiment, we will focuss only on the material of the two dominant colors: orange (color number 6) and blue (color number 1).

2. On center 4, the first graph - material density - shows that the more attracted colored materials are, in order, the orange colored materials and then the blue colored materials. The predominance of the orange colored material over the blue is corrected on the second graph which consists in dividing the colored material number of each color by the corresponding colored pheromone intensity. As orange pheromone is greater than the blue one, we could expect that this center will attract more orange materials than blue ones. The pheromone efficiency graph shows this, making the orange and blue curve become close.

3. The second graph, the pheromone efficiency graph, takes into account only local information about the center and not spatial information. With the third graph, the spatial pheromone efficiency graph, we correct the importance of the pheromone intensity of each color on a specific center with respect to the same color pheromone intensity of the neighboring centers. On figure 5.6, we observe that the neighbors of center 4 are the centers 1, 3 and 5. For these three centers, the blue pheromone intensity is low and the orange intensity is high on center 5. And so, if we observe part (5) of figure 5.12, we can see that the relative orange intensity becomes lower than the relative blue pheromone intensity. The last graph - relative pheromone efficiency - gives a correction according to this relative pheromone intensity. But, finally, this graph shows that the orange material number is still greater than the blue one. That is an unpredictable event.

Of course, the complexity of the simulation is not completely predictable by nature and unpredictable phenomena appear as we finally observe in the previous example. There are mainly due to the complexity of the spatial configuration and the multi-criteria characteristics. These unpredictable charateristics of the result overtop our advanced analysis which integrate a spatial interaction correction of first order (e.g. only direct neighbors are considered in this analysis).

5.3.4 Material Distribution Analysis Using Non Dominant Components

In the previous section, we have studied and analyzed the simulation results, taking into account, for each material, only its dominant color (e.g. the color selected after the ranking process). This dominant color defines the behavior of the ant carrying the material: the ant will follow the attraction of the lonely colored pheromone corresponding to this dominant color. As described in figure 5.15, the attraction interaction with the center concerns only the dominant criterion/color.

Our goal is to go further on the analysis of the result with respect to its complexity. We want to observe all the color attribute contained in each material and follow, during the simulation, how "hidden" colors (e.g. colors which has not been selected as the dominant one in the process) are distributed and organized inside the spatial system of the simulation. For example, it could be possible that some "hidden" colors become high in some center and so be able to feed-back on the center during its adaptive process (which will be described later), as illustrated in figure 5.15.

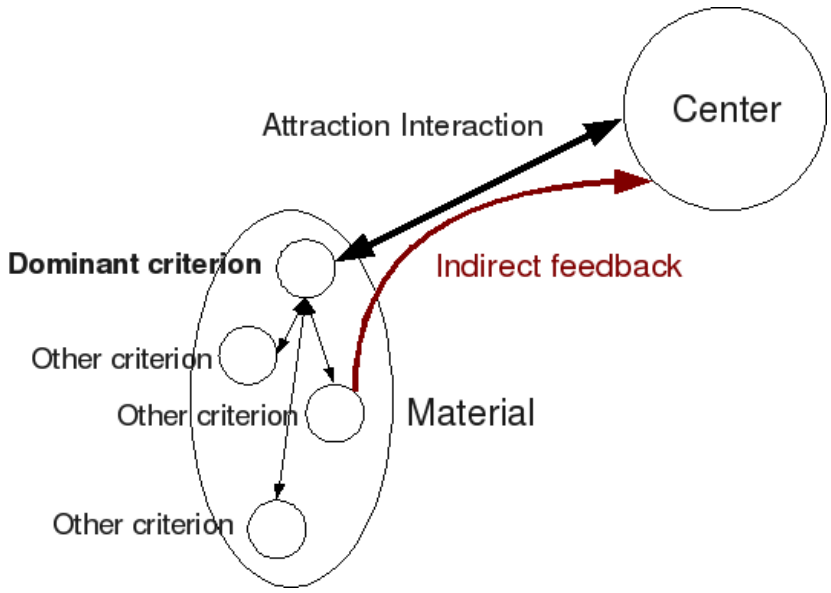


Figure 5.15: Material criteria indirect feedback on center

In the following, we give some experiments which highlight some possible effect of "hidden" colors/characteristics during the simulation.

The figures 5.16 to 5.22 represent, for each of the seven previous center, the dominant color repartition graph on the left side, versus the complete color repartition graph on the right side. In this right graph, all the colors contained in each material are computed in order to draw the right graph.

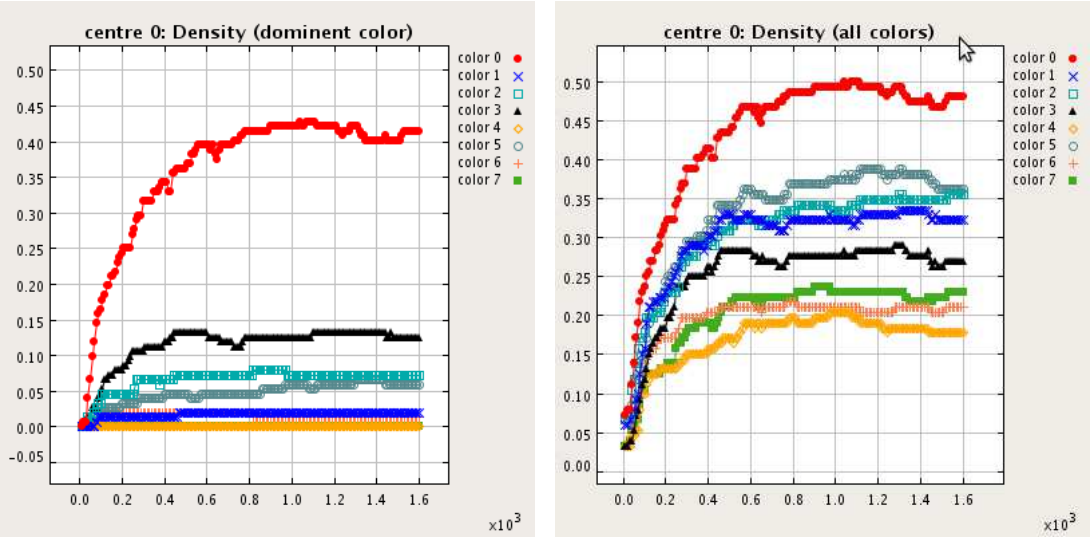


Figure 5.16: Material distribution analysis for the center 0: on the left figure, material density graph with respect to their dominant color; on the right figure, material density graph with respect to any color (dominant or not) belonging to some material

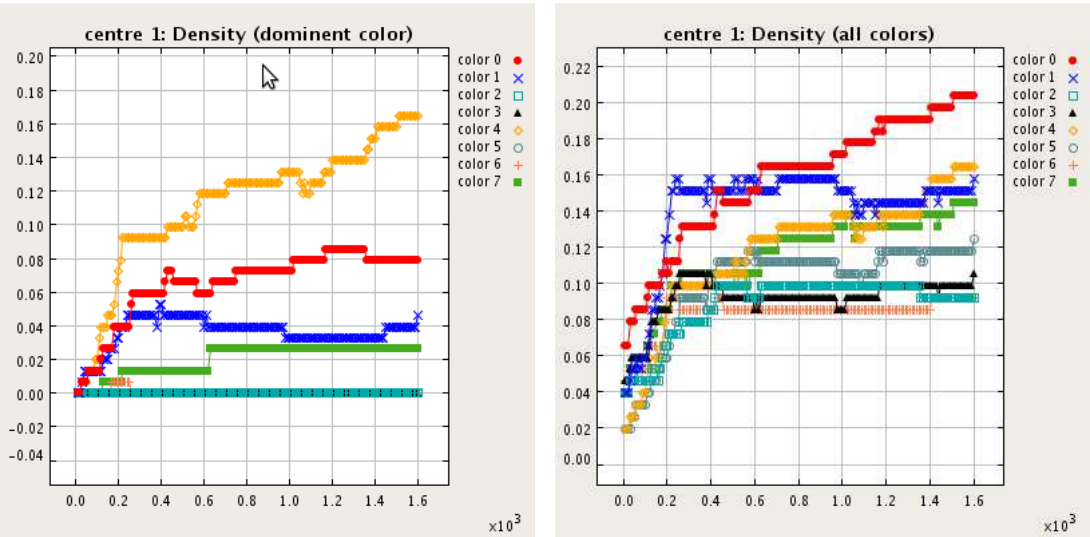


Figure 5.17: Material distribution analysis for the center 1: on the left figure, material density graph with respect to their dominant color; on the right figure, material density graph with respect to any color (dominant or not) belonging to some material

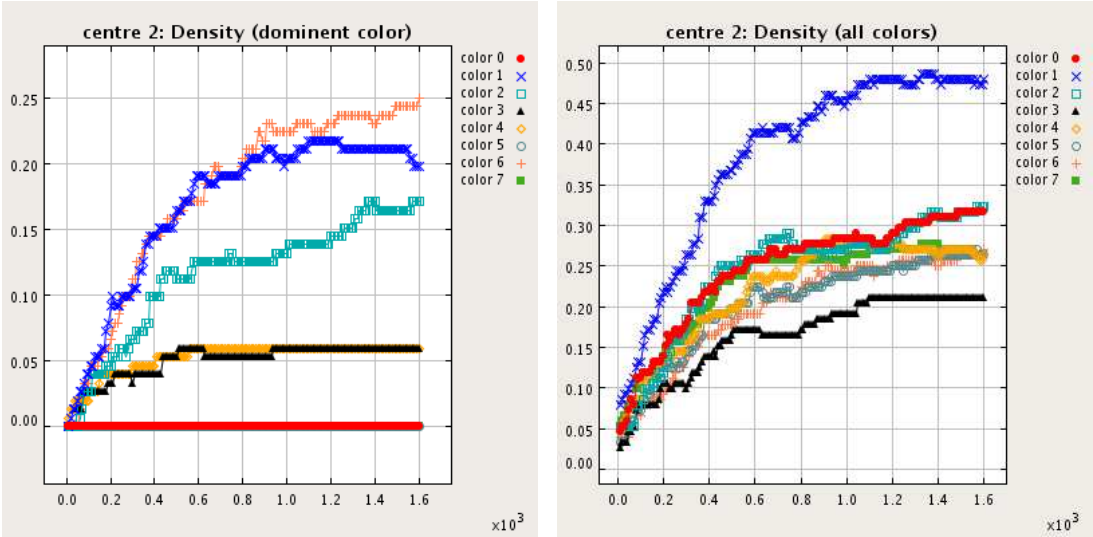


Figure 5.18: Material distribution analysis for the center 2: on the left figure, material density graph with respect to their dominant color; on the right figure, material density graph with respect to any color (dominant or not) belonging to some material

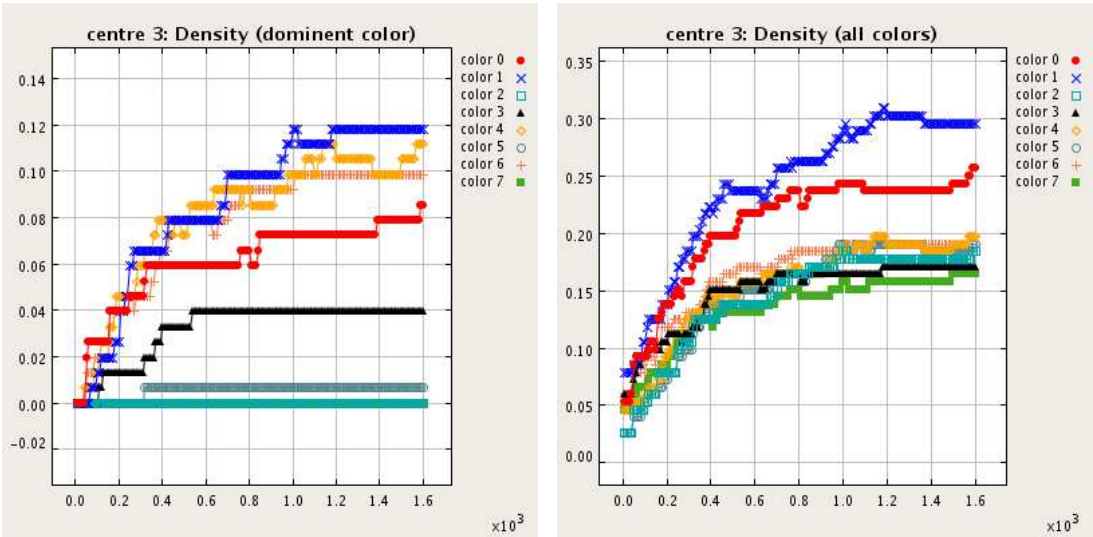


Figure 5.19: Material distribution analysis for the center 3: on the left figure, material density graph with respect to their dominant color; on the right figure, material density graph with respect to any color (dominant or not) belonging to some material

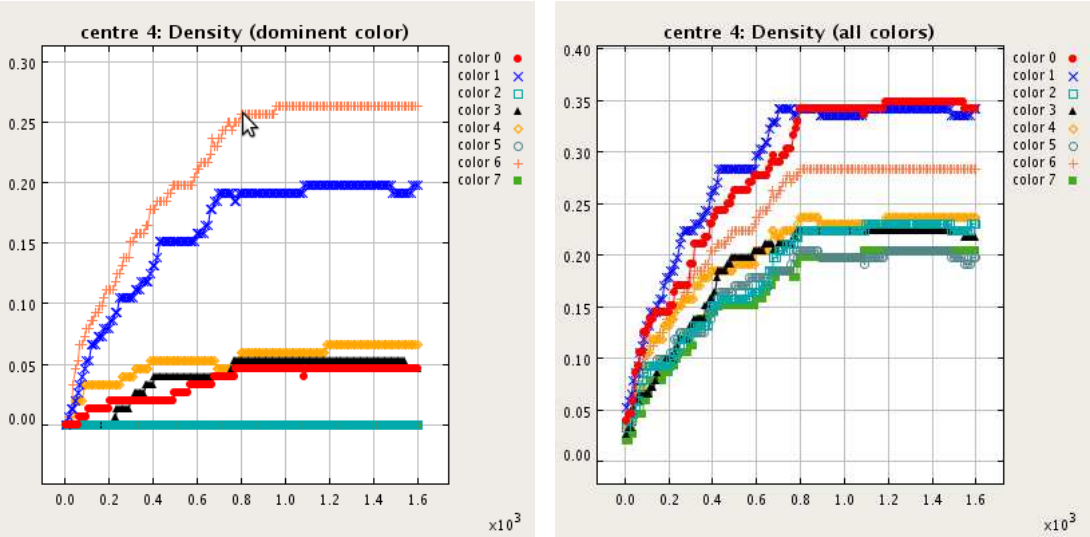


Figure 5.20: Material distribution analysis for the center 4: on the left figure, material density graph with respect to their dominant color; on the right figure, material density graph with respect to any color (dominant or not) belonging to some material

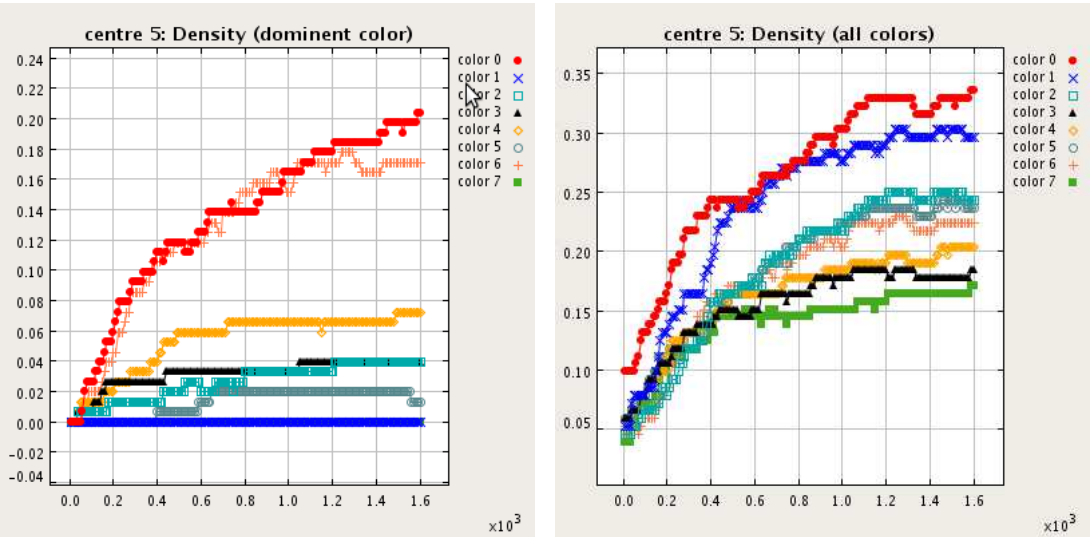


Figure 5.21: Material distribution analysis for the center 5: on the left figure, material density graph with respect to their dominant color; on the right figure, material density graph with respect to any color (dominant or not) belonging to some material

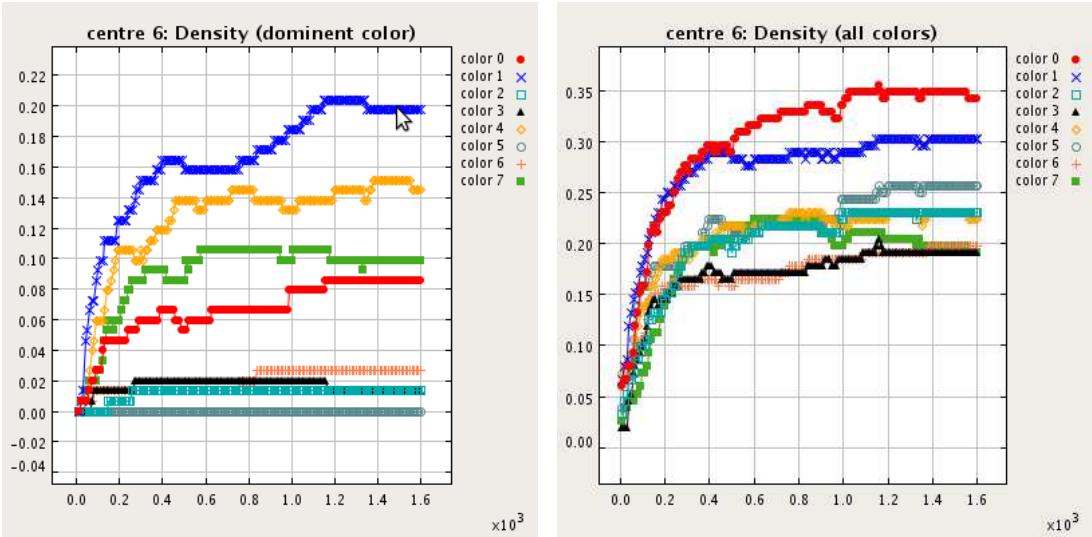


Figure 5.22: Material distribution analysis for the center 6: on the left figure, material density graph with respect to their dominant color; on the right figure, material density graph with respect to any color (dominant or not) belonging to some material

Result Analysis

In these result outputs, the complete color repartition graph - right part of each figure - cannot be predictable. In fact the "hidden" colors are transported like *blind* characteristics, by some ant moving with respect to the dominant color of their material.

To illustrate these comments, we will focus again on center 4 corresponding to figure 5.20. We only care of the red (color 0) color distribution and the blue (color 1) color distribution. To illustrate in a more concrete way, we consider (as it is really done in the simulation) that each material has only one of these two colors/characteristics. The interpretation is that these two colors represent gender: blue for man and red for woman. On figure 5.20, the left part means that the men are attracted by the center but not the women. On the right part of the figure, we observe a very different situation: the women are finally a little more numerous than the men. The explanation is that the women come to this center, not because they are women but because of one of their other characteristics, represented by another color (probably the orange one - color 6).

5.4 Adaptive Processes in Ant Nest Building for Multi-Criteria Multi-Center Dynamics

As we explained in the previous section, some color / material characteristics can have some important effect and it is expected that the simulation, while running, adapt to such situation.

The adaptation described here concerns some center evolution according to the mate-

rial usage. At this level of abstraction in our general model, it is difficult to propose a specific response to some adaptation suggestion. If we take inspiration from nature, in nest building, termite queen can adapt its size (by growing) when it feels safe inside protecting walls designed by its congeners. According to the application and case study in which our model will be applied, different adaptation mechanisms can be defined and different adaptive responses can be generated, like moving center, make them growing, make the pheromone intensity increase or decrease, etc.

At our level of method abstraction modeling, we can observe that the adaptive response from the center makes the centers become active entities during the simulation, instead of simple data information providers. To achieve this need of making such adaptive center active, we need to implement, in Repast, the centers as agents themselves. Moreover, because centers contain different colored-pheromone, and because some adaptive response can concern only changes on specific color, it seems better to define an agent to manage each colored pheromone associated to the center. For this purpose, we include the colored pheromone description in a class *queen*, keeping our inspiration from the natural mechanisms after which we build our model. As in the nature, the colored pheromones will be controlled by the queen. And finally, each queen will include a standard Repast method, called *step*, which will have finally the role of producing adaptive response from the center.

In this chapter which describes a general method, we will not go further in the description of the adaptive process. Chapter 8 will present a complete computation of adaptive processes which finds its meaning according to the case study.

Chapter 6

Community Swarm Optimization

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This chapter has been published as a book chapter in Springer series "Understanding Complex Systems" [138]

6.1 Commmunity Definition

In the following, we will present some of these modern methods concerning artificial swarm intelligence and we will propose a new one, called Community Swarm Optimization (CSO). This method is mainly based on the concept of spatial evolutive populations of behavioral entities. The concept of community is the basic property of this method.

Definition 14 (Community operational definition)
A community is a system or an organization which is characterized by a spatial property, a behavior property and the interaction between both.

Example 1 *In ecology, a community is a group of plants or animals living in a specific region and interacting with one another.*

Example 2 *The spatial patterns generated by Schelling's segregation models [107] are some examples of communities and these spatial patterns are linked with some elementary behavioral rules implemented for each grid case. These rules describe, for each step, the movement of each individual according to its neighborhood.*

In our method, we need to represent an efficient way to describe the behavior of each entity and we use algebraic structures called automata with multiplicities [109]. The main advantage of these automata is to be associated with algebraic operators leading to automatic computations. With these operators, we can define behavioral distances for the entities modelled with these automata. The behavioral distance is one of the major keys of this new method. Section 6.2 describes the algebraic basis for the automata management used in this method and in section 6.3, we describe the proposed method.

The method proposed in this chapter, is called Communities Swarm Optimization (CSO) and it consists in the co-evolving of both the spatial coordinates and the behavior of each individual of a virtual population of automata. The feed-back process of the whole system over the entities is modelled by a genetic algorithm based on this co-evolving. The automata behaviors allow to define for each individual, a set of arbitrary complex transition rules. We develop the formalism needed to describe this method and the associated algorithms in the two next sections.

6.2 Spatial Behavioral Automata

6.2.1 Behavior modelling using automata

An automaton with multiplicities is an automaton with output values belonging to a specific algebraic structure, a semiring, including real, complex, probabilistic, non commutative semantic outputs (transducers) [52, 116]. In this way, we are able to build effective operations on such automata, using the properties of the algebraic structures which belong to the output data. We are specifically able to describe automata by means of a matrix representation with all the power of the new (i.e. with semirings)

linear algebra.

Definition 15 (Automaton with multiplicities)
An automaton with multiplicities over an alphabet A and a semiring K is the 5-uple (A, Q, I, T, F) where

- $Q = \{S_1, S_2 \cdots S_n\}$ *is the (finite) set of states;*
- $I : Q \mapsto K$ *is a function on the set of states, which associates to each initial state a value in K, called entry cost, and to each non- initial state a zero value ;*
- $F : Q \mapsto K$ *is a function of set states, which associates to each final state a value of K, called final cost, and to each non-final state a zero value;*
- T *is the transition function, that is* $T : Q \times A \times Q \mapsto K$ *which to a state* S_i*, a letter a and a state* S_j *associates a value z of K (the cost of the transition) if it exist a transition labelled with a from the state* S_i *to the state* S_j *and zero otherwise.*

Remark 3 *We have not yet, on purpose, defined what a semiring is. Roughly it is the least structure which allows the matrix "calculus" with unit (one can think of a ring without the "minus" operation). The previous automata with multiplicities can be, equivalently, expressed by a matrix representation which is a triplet*

- $\lambda \in K^{1\times Q}$ *which is a row-vector which coefficients are* $\lambda_i = I(S_i)$*,*
- $\gamma \in K^{Q\times 1}$ *is a column-vector which coefficients are* $\gamma_i = F(S_i)$*,*
- $\mu : A^* \mapsto K^{Q\times Q}$ *is a morphism of monoids (indeed* $K^{Q\times Q}$ *is endowed with the product of matrices) such that the coefficient on the* q_i*th row and* q_j*th column of* $\mu(a)$ *is* $T(q_i, a, q_j)$

Figure 6.1 describes the linear representation of a probabilistic automaton which is a specific automaton where output values are probabilistic values. For these probabilistic automata, the sum of the coefficients of each matrix row is equal to 1 (being the sum of outgoing and loop probability).

Definition 16 (Automata-Based Agent Behavior)
We represent the agent behavior by automata with multiplicities (A, Q, I, T, F) *over a semiring K:*

- *The agent behavior is composed of a set of states Q and of rule-based transitions between them. These transitions are represented by T; I and F represent the initial and final costs;*
- *Alphabet A corresponds to the agent perceptions set;*
- *The semiring K is the set of agent actions, possibly associated to a probabilistic value which is the action realization probability (as defined in [140]).*

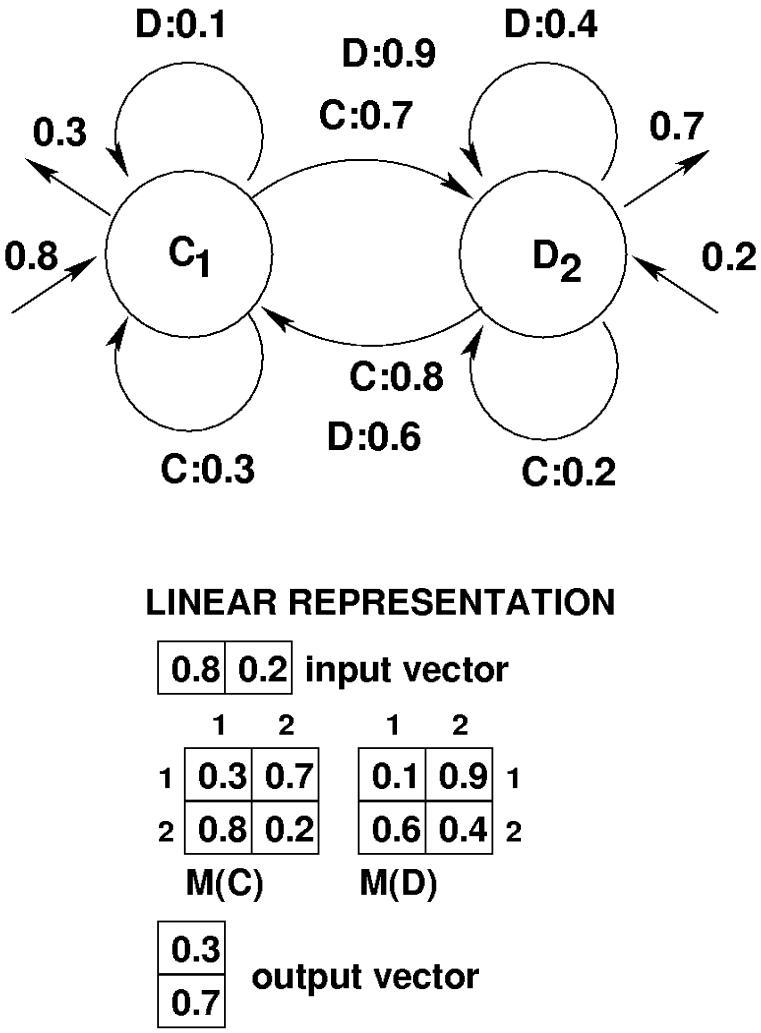

Figure 6.1: Probabilistic automaton over the alphabet {C,D} and its linear representation

6.2.2 Spatial Automata and associated spatial distance

Definition 17 (Spatial Automata-Based Agent)
A spatial automata-based agent is defined by its structural representation:

- *An automaton with multiplicities corresponding to its behavior as a whole process managing its perceptions and its actions over its environment. They include its communication capabilities and so its social behavior;*
- *A spatial location defined on some specific metric space.*

Remark 4 *According with this previous definition, we define two metrics on the spatial automata-based agent. The first one concerns a spatial distance which is directly induced by the metrics of the spatial location (from any standard Hölder norm). The second one*

is more innovative and concerns a behavioral distance or semi-distance. One of the major interest of the previous automata-based modelling is to be able to define such behavioral distance which leads to powerful automatic processes dealing with self-organization. We detail this definition in the next section.

6.2.3 Metric spaces for behavioral distances

The main advantage of automata-based agent modelling is their efficient operators. We deal in the following with an innovative way to define behavioral semi-distance as the essential key of the swarm algorithm proposed later.

Definition 18 (Evaluation function for automata-based behavior)
Let x be an agent whose behavior is defined by $\mathcal{A}$, an automaton with multiplicities over the semiring K. We define the evaluation function $e(x)$ by:

$$e(x) = V(\mathcal{A})$$

where $V(\mathcal{A})$ stands for the vector of all coefficients of (λ, μ, γ), the linear representation of $\mathcal{A}$, defined in remark 3.

Definition 19 (Behavioral distance)
Let x and y are two agents and $e(x)$ and $e(y)$ their respective evaluations as described in the previous definition 18. We define $d(x, y)$ a distance or a metric between the two agents x and y as

$$d(x, y) = ||e(x) - e(y)||$$

a vector norm of the difference of their evaluations.

6.2.4 Genetic operators on spatial automata-based agent

We consider in the following, a population of spatial automata-based agents, each of them is represented by a chromosome, following the genetic algorithm basis. We define the chromosome for each spatial automata-based agent as a couple of two sequences:

- the sequence of all the rows of the matrices of the linear representation of the automata. The matrices, associated to each letter from the alphabet of the agent perceptions, are linearly ordered by this alphabet and we order all the rows following these matrices order [16]. Figure 6.2 describes how this sequence is created from a linear representation of two matrices;
- the sequence of all its spatial coordinates.

In the following, genetic algorithms are going to generate new automata containing possibly new transitions from the ones included in the initial automata.

The genetic algorithm over the population of spatial automata-based agent follows an evolutive iteration composed of two main operators, as on adaptation of the classical genetic operators [53]:

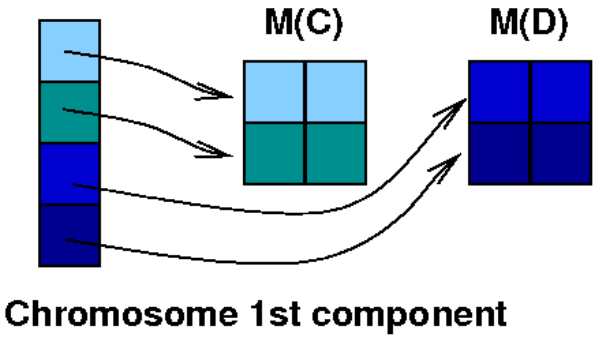

Figure 6.2: Chromosome first component building from the matrix rows of the linear representation of an automaton over the alphabet {C,D}

- *Reproduction (Duplication and Crossing-over)*: This operator is a combination of the standard duplication and crossing-over genetic operators. For each couple of spatial automata (called the parents), we generate two new spatial automata (called the children) as the result of the chromosome crossings and we keep, without change, the parent spatial automata. To operate for the crossing-over operation, we have to compute
  - the automata of the behaviors of the two children. For this purpose, we consider a sequence of rows for each matrix of the linear representation of one of the two parents and we make a permutation on these chosen sequences of rows between the analogue matrix rows of the other parent;
  - the spatial locations of the two children. These children locations can be chosen by many ways: on the linear segment defined by the parent locations or as the nodes of the square obtained with the parent and the children as describe in figure 6.3.
- *Mutation*: This operator deals only with the linear representation of the spatial automata-based agent. With a low probability, each matrix row from this linear representation is randomly chosen and a sequence of new values is given for this row (respecting some constraints if needed, like probabilistic values [16]).

6.3 Community Swarm Optimization Algorithm

6.3.1 Adaptive objective function for community-based swarm optimization

The community swarm optimization method is based on a genetic algorithm over a population of spatial automata-based agents. The formation of the community is the result of the population evolution, crossing by a selection process computed with the fitness

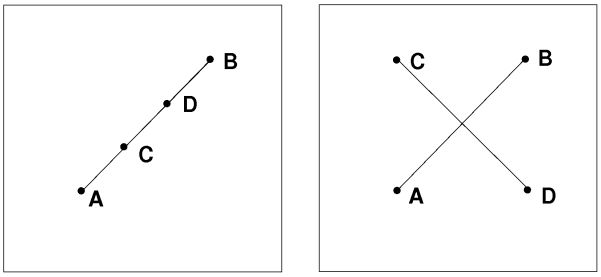

Figure 6.3: Spatial locations for the children C and D from the parents A and B, after a reproduction step. Two possible computations of locations are presented in the two sub-figures.

function defined in the following.

For this computation, we deal with two distances defined on agent sets. The first is the spatial distance associated with the agent spatial location and the second is the behavioral semi-distance defined in definition 19.

Definition 20 Community clustering and detection fitness
Let $\mathcal{V}_x$ be a neighborhood of the agent x, relative to its spatial location. We define $f(x)$ the agent fitness of the agent x as :

$$f(x) = \begin{cases} \dfrac{card(\mathcal{V}_x)}{\sum\limits_{y_i \in \mathcal{V}_x} d(x, y_i)^2} & if \sum\limits_{y_i \in \mathcal{V}_x} d(x, y_i)^2 \neq 0 \\ \infty & otherwise \end{cases}$$

where $d(x, y)$ is the behavioral distance between the two agents x and y.

This fitness allows to implement a co-evolution process which generates an emergent set of community swarms. These community swarm formation is the result of both the emergence of the spatial location of the generated communities and the adaptive behavior of the communities as the result of the homogenization of the behavioral automata of all agents which compose these emergent communities.

6.3.2 General CSO algorithm

CSO algorithm needs an initial step description which is the major step of the modelling process. The way of going from the problem formulation to the initial spatial automata-based agents must be realized accurately. The formal description of the methodology to use, for this initial step, is described in Algorithm 3.
The core of the CSO algorithm is described by the iterative scheme defined in algorithm 4.

Algorithm 3: Methodology to model the initial step of CSO

1. Problem formulation by the definition of a set of transition rules ;
2. Building of the behavioral automata based on the previous set of transition rules, describing the sequences and the context of their applications ;
3. Decrepitation of the spatial domain, according to its topological properties (Cellular automaton, network or graph, Geographical Information System) with the spatial location of the initial virtual population of spatial automata-based agents;

Algorithm 4: Iterative scheme of CSO

```
Building the initial virtual population of the spatial automata-based agents
(following the methodology of Algorithm (3)) ;
repeat
    for Each couple of individuals in the population do
        Reproduction step generating 2 new children as described in the section
        (6.2.4) ;
        Mutation step as described in the section (6.2.4) ;
    Selection of the half population of the individuals corresponding to the
    highest values of the agent fitness described in section (6.3.1) ;
until (the sum of the fitness values of the whole population reaches a threshold)
or (the maximum iteration number is reached) ;
```

An example of fitness function computation output is illustrated by figure 6.4 where we show, on the same population, a high level fitness individual which will be probably kept inside the population at the next iteration and a low level fitness individual which will be probably removed from the population at the next iteration. The used colors describe graphically the chromosome composition, allows to appreciate the similarity of the individuals.

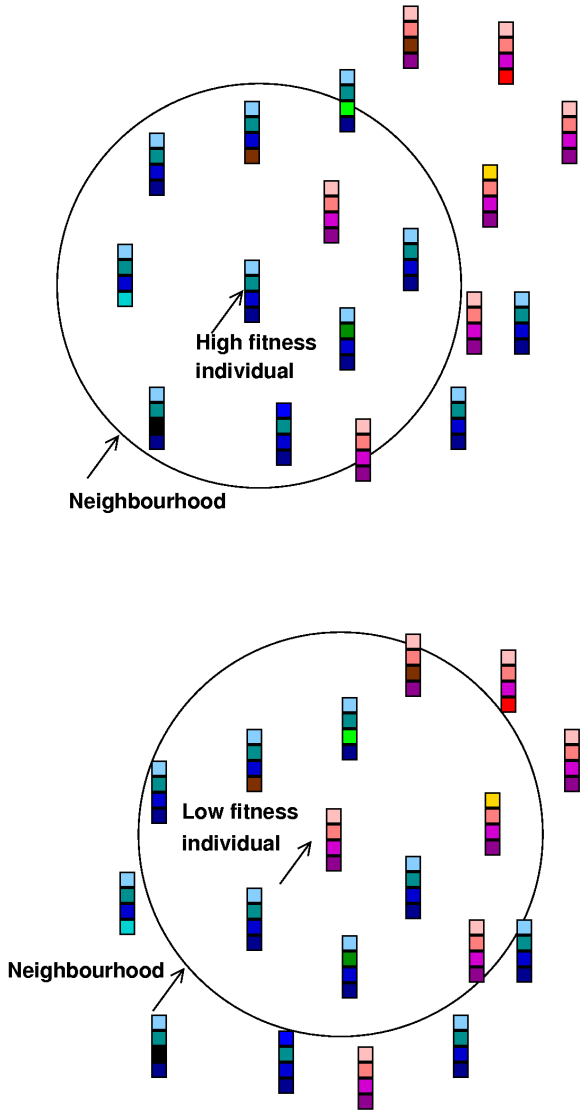

Figure 6.4: Two examples of the result of selection operators within the CSO algorithm

Part III

Case Study: Urban Service and Infrastructure Dynamics

Chapter 7

Organizations, Services and Planning for Urban Complexity

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Some parts of this chapter have been published in the international journal DCDIS-B [143]

7.1 Urban Dynamics Modelling

Social and human systems are typically complex systems. In urban development and dynamics we can find many examples for spatial emergence, self-organization and structural interaction between the system and its components.

In the following, we develop a classification of urban models. The first section presents the first class of models which are based on top-down approaches. Then, we present the bottom-up methods: diffusion on grids (cellular automata), agents on grids or spaces. The concept of mixing agents on grids or spaces allows also to involve dynamical processes carrying by these agents as presented in the following section. Then we develop these dynamical aspects through interaction networks and their hierarchical structures. We conclude finally by our own urban dynamics model, based on the swarm intelligence engineering method presented in chapter 5.

7.1.1 "Black-box" Macro-Modelling

The first models of urban systems have been developed in the end of 1960s and concerns mainly "stocks and flows" descriptions of socio-economic indicators [13]. The main first contributors are I.S. Lowry [77] and J.W. Forrester [46]. Lowry's model of urban systems, applied to the city of Pittsburg, proposed some "integrated" model, defining flow charts between the three main indicator classes: (i) the basic sector of industrial and business activities, (ii) the householder sector and (iii) the retail sector concerning the local population. This flow chart model already deals with a mile-square decomposition similar to spatial decomposition which will be used later as an adaptation of cellular automata grids to geographical real space. The final output of the modeling process led to a kind of socio-economic equilibrium state. This approach finds its limit because of its static description and, as a matter of fact, dynamical models are essential to understand the city evolution. Forrester proposed a dynamical modeling based on the application of industrial dynamics to urban dynamics. His model is based on non spatial stocks and flows models. Stocks are exchanged within a three income levels decomposition into housing, jobs and population. This model, based on a simple urban description, aims to generate simulation and Forrester boasted, at that time, the benefit of computer simulation to understand the city evolution and how we can predict its evolution by the modification of guiding policies within the system.

The "stocks and flows" model continues to be improved and to give more and more details, including transportation subsystem or land market, for example. One of the most complete model, called Integrated Urban Model (IUM) was proposed in 1994, by Bertuglia et al. [17]. The computational complexity increases with the accuracy of the description and finally allows to avoid obtaining reasonable estimates of the parameters. These models are more representational tools than simulation ones [13].

To build efficient simulation models, the idea was to simplify the description, using a more global one facilitating the analytical description. Based on population dynamics

theory, some researchers proposed to build urban dynamic models originated from ecological modeling. The paradigm of prey-predators systems is then used to give efficient simulation tools to investigate the main feature allowing to understand the global dynamics. For example, Dendrinos and Mulally [37] use a prey-predator model, assuming that the increase of city population makes the economic status decreasing. The predators represent the urban population and the preys, the per capita income.

7.1.2 Micro-modelling and Bottom-up Approaches

All the previously described models are based on top-down approaches to model the system dynamics. We first consider the whole phenomenon and propose a way to split it in many sub-problems and then in stocks and flows or in different terms constituting the equational system. Another class of modelling is based on micro-modelling and bottom-up representation of the city as a collection of individual-based description, behavioral rule-based description and interaction systems. From this constructive approach, we want to obtain an emergent description of the whole system or of some sub-systems included in a hierarchical process. This methodology consists in generating a simulation where all the components, behavioral and rule-based ones, interact over an environment, perceiving and acting on it. The environment evolving is the support of emergent properties. In the following, we describe such methods based on cellular automata and agent-based modelling.

7.1.3 Grids, Automata and Agents

As explained in section 2.4.3, cellular automata modeling used a bottom-up approach based on rule-based system. Using cellular automata for urban or regional modeling consists in the decomposition of the city, region or any geographical area in a lattice of cells. Each cell is in some state which belongs to a finite set S. At each time step, the cells change their own state according to some transition rules, based on its previous state and its neighbor cells. Many works based on cellular automata, have been developed for geographical systems and urban dynamics [10, 42]. Extensions on environmental problems, like water streaming, are using these models as an efficient tool [73]. Cellular automata can be seen mainly as distributed tools to model diffusive phenomena using rule-based systems. One of the first researchers in human sciences who proposes models based on diffusive rule-based systems is T. Hägerstrand in very early period, during 50's [58]. But his work itself began to be diffused over the science community more than 15 years later when the computer development became able to implement his model for realistic studies.

SpaCelle and the Simulation of Urban Dynamics of Rouen Agglomeration

In order to model Rouen agglomeration development, E. Dubos-Paillard et al. [42] have developped a multi-layer cellular automaton allowing to decribe the land-use. A land-

use cell can have until 12 states according to the usage (forest, river, industrial area, household area, etc.). Three families of transition rules have been defined (i) land-use development shape rules, (ii) spatial coherence rules to avoid, for example, that a firm being created inside housing area, (iii) hazard rules to include stochastic dimensions.

On figure 7.1, we represent the result of SpaCelle simulation of land-use development of Rouen agglomeration in 1994, starting from the initial situation of this land in 1950. A comparison can be done with the real land-use.

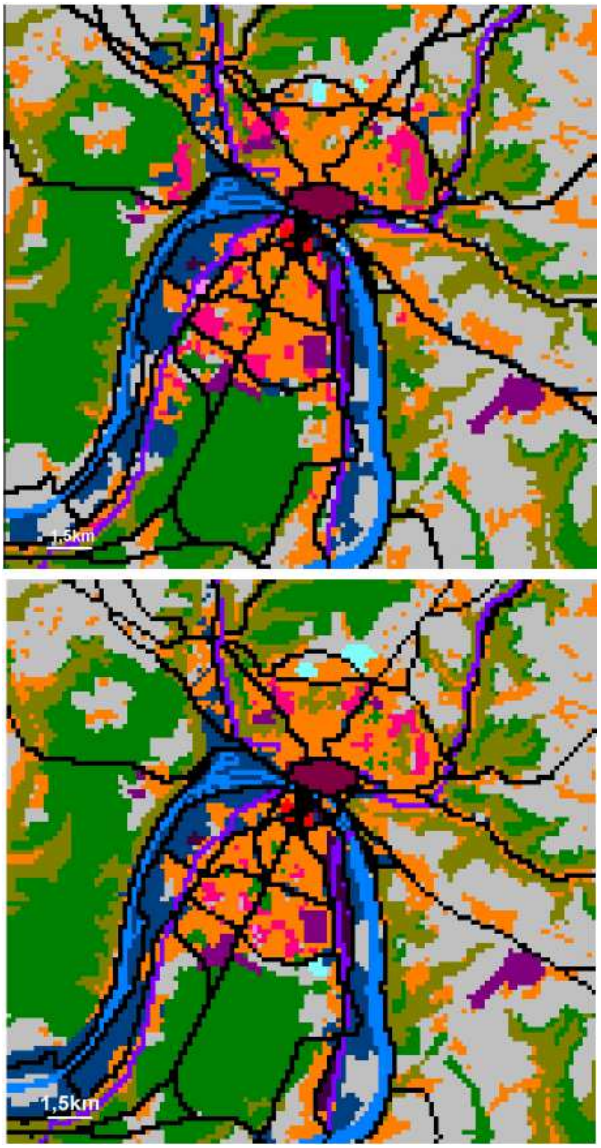


Figure 7.1: Rouen agglomeration land-use in 1994: reality on the top and simulation with SpaCelle from an initial situation in 1950 below (from [42]).

From Cellular Automata to Agent-Based Modeling

As we said in section 2.4.3, grid rules systems are generally not sufficient to model the complexity of many phenomena. We need to add on these grids or spaces, agents in order to move, to act on this space and interact with each others and with the environment. A classical example of the need of extending cellular-based model with agents come from T. Schelling's model describing the segregation process [107]. For this model, already presented in section 3.6, we face an important extension to cellular automata where we need to represent moving individuals from a simple deliberative process. The mixing of spatial data and cellular automata with autonomous entities, like agents, is here needed [35].

In the following section which develops the dynamics of cities, we present such modelling, mixing spaces (grid or GIS) and agents, in order to simulate the mobility of users.

7.1.4 Multi-Scale Dynamics for Urban Development

We can consider urban systems on two scales of dynamics. The first scale studies urban area expanding of the city observed during long time intervals equal to decades or to centuries. In this scale of representation, many studies have been made, showing how the urban growth depends on the urban topology. Some studies try to analyze this topology by the introduction of fractal coefficients for example [11]. The complex link between the land use and the city dynamics at this scale clearly appears in such studies. The second scale studies the urban dynamics through the people mobility during a time interval like, for example, one day, one week or one month. At this time scale, the city growth is not taken into account and we observe the city area as catalytic of the people usage. Clearly, urban infrastructures lead to specific services which induce specific usages. The city activities are very often compared to a swarming process, similar to the swarming activities of social insects, where urban space considered as a stigmergical environment.

Urban Growth and Spatial Epidemy

Urban growth modeling is generally based on a differential system, called *aggregate model*, which is inspired by epidemic phenomena [11]. In such models, we divide the studied area in three constitutive parts at any time t:

- the undeveloped land area, $A(t)$;
- the newly developped land area, $N(t)$;
- the etablished developped land area, $P(t)$.

The dynamics is similar to epidemiological models where $A(t)$ represents the number of population which is susceptible to be infected, $N(t)$ is the number of infected population and $P(t)$ is the number of removals of infected population. A compartmental

model describing the interaction of this 3 components population allows to model disease epidemies [89] or highly aggregate urban evolution [37]. The basic formulation of this model corresponding to the urban growth phenomenon is as follows:

$$\begin{cases} \dfrac{dA(t)}{dt} &= -\alpha N(t)A(t) \\ \dfrac{dN(t)}{dt} &= \alpha N(t)A(t) - \gamma N(t) \\ \dfrac{dP(t)}{dt} &= \gamma N(t) \end{cases} \tag{7.1}$$

where α is the interaction coefficient leading to the propagation of newly developed lands from undeveloped lands and γ is the coefficient leading to the transformation of newly developed lands to established developed lands.

From this global differential model and in order to study spatial diffusion, we have to build spatially disaggregated models which consist in projecting the differential equations on cellular automata grids and adding a diffusive term for each component of the population. For example, the equation describing the evolution of the newly developed area can be transform in the following way:

$$\frac{\partial N(x,y,t)}{\partial t} = \alpha N(x,y,t)A(x,y,t) - \gamma N(x,y,t) + \xi \Delta N(x,y,t) \tag{7.2}$$

where $\Delta N(x,y,t) = \frac{\partial^2 N(x,y,t)}{\partial x^2} + \frac{\partial^2 N(x,y,t)}{\partial y^2}$ is the classical laplacien operator.

Some graphical results of such simulations are given in [11]. Figure 7.2 is extracted from these studies with some variant from the previous basic model:

- light grey colored cells represent $P(x,y,t)$ cells;
- dark grey colored cells represent $N(x,y,t)$ cells;
- dark colored cells represent $A(x,y,t)$ cells which is here not all the undeveloped land area but only a part of this land available for urban development.

These models can be completed by introducing a threshold which controls the ability and the speed of newly developed land spreading. Another additional threshold can be introduced in order to allow the *redevelopment* usage of land which consists in demolishing buildings and making new usage of the new free land.

Spatial urban structure and city morphology generate typical development evolutions. Some studies about the possibility to classify urban growth with respect to their morphology have been developed in the last decades [47, 9].

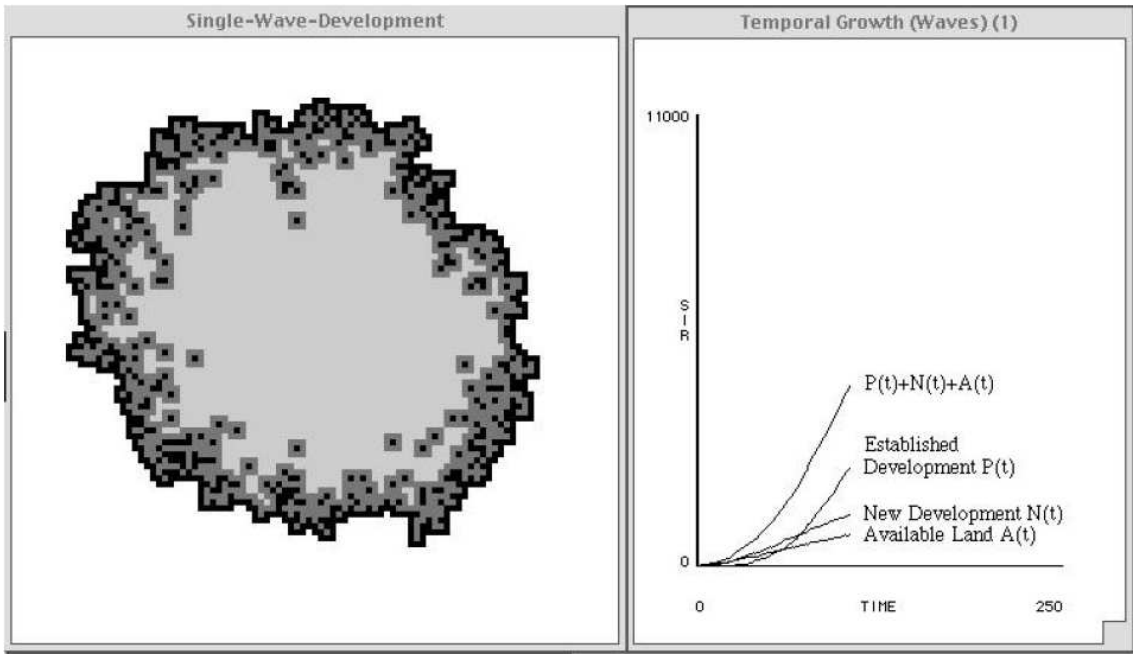


Figure 7.2: Urban Sprawl Modeling from [11]

Urban Mobility and Usage

Car transportation or pedestrian movement have been studied since many years. For both, two scales of modeling are used. At a global scale, the description is based on car or pedestrian flows [131] and the typical model is fluid dynamic equations.

To simulate detailed interaction of pedestrians, we need to change the scale of description and we have to work with behavioral model of pedestrians [65]. These behavioral models have to involve various constraints or concepts like avoiding collisions, finding path close to the shortest one, changing displacement direction not too rapidly.

Modeling each pedestrian behavior leads to an important computational complexity and global forces allow to mix individual agents with collective behaviors. Social forces, repulsive forces, potential energy are some conceptual models which have been developed in new models of pedestrians individual movement inside accurate spatial configuration [61, 51]. Using such models, crowd simulation involving collective behavior have been developed and applied to urban simulation recently [76].

Household Preferences

Urban multi-agent modeling has to deal with several kinds of interactions, adaptations to infrastructure environment and also with choice heuristics and decision making [14].

The development of household preferences shows how decision making can be taken

into account in urban dynamics [125]. Economical based models have been transposed to individual behavior [113] and lead to an optimization problem involving various parameters: benefits at a current location, cost of moving, jobs attraction, etc. A *stress-resistance* approach, also called *dissatisfaction utility*, has been proposed, describing the final decision of moving from the result of a kind of stress potential threshold reaching [95, 115].

Interaction Networks and Hierarchical Organizational Systems

Complex systems theory leads to explain system behavior with respect to their entities interaction. Urban systems are characterized by two scales interaction system: the interaction system inside cities and the interaction system between cities [98]. This hierarchical aspect and the interaction between these two scales are major elements in order to understand urban dynamics.

The city development is generally the result of land use and cost, spatial cooperation and competition between citizens. After the building of cities, the urban system itself leads to global constraints which are, for example, essential for firm development. Municipalities have, therefore, to define some global management leading to public equipments for sport or culture, for example. All these global urban management and constraints react on citizen preferences and behaviors.

At the governmental level, territorial management leads to increase cities interaction and some co-evolution phenomena exist between urban development of different cities. Paulus [94] shows how French cities between 1962 and 1992 co-evolved from industrial activities to tertiary activities in a similar way. Denise Pumain et al. [98] show how American urban systems and urban growths are qualitatively different from European urban growth and development with respect to the fact that the communication network involved during their respective growth period in their respective area were different for these two continents.

7.1.5 A Methodological Approach for Spatial Organization Dynamics

In this section, we propose our way of describing and modelling the spatial organizations in urban dynamics, based on the swarm intelligence engineering methodology developed in chapter 5. Our methodology deals with emergent computation from micro-modelling in order to detect and manage emergent systems and organizations. Our goal is then to re-introduce these emergent systems or organizations inside the simulation and manage their evolutions and their interactions with the components of the system. The re-integration of the emergent systems, during the simulation, can be explicitly expressed like in the multi-scale fluid flow simulation proposed by P. Tranouez [123] or like the process described in chapter 5. It can be also implicitly computed using a self-controlled process as described in the following, using genetic algorithms like the process described

in chapter 6.

In figure 7.3, we focus on the emergence of organizational systems from geographical systems. The continuous dynamic development of the organization feed-backs on the geographical system which contains the organization components and their environment. The lower part of this figure explains our analysis methodology. It consists in describing many applicative problems by dynamical graphs or environments in order to detect organizations over these dynamical environment. For the organization detection, we use swarm intelligence processes. We model the feed-back process of this emergent organization on the system constituents and its environment. To analyze or simulate urban dynamics, nowadays, we can use the great amount of geographical databases directly available for computational treatment within Geographical Information Systems. On the organizational level description, the development of multi-agent systems (MAS) allows to develop suitable models and efficient simulations.

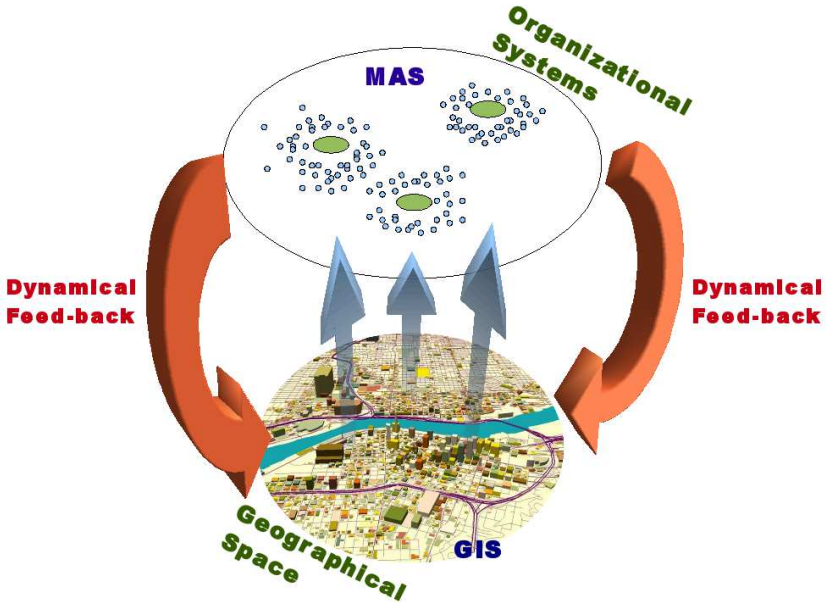
The applications we focus on, in the proposed models, concern specifically the multi-center phenomena inside urban development. The city development has to deal with many challenges, economical, social and environmental aspects in order to achieve the goal of sustainable development. The proposed decentralized methodology allows to deal with multi-criteria problems, leading to give a decision making assistance, based on simulation analysis.

Gentrification phenomena can be modeled using such a methodology. It is typically a multi-criteria self-organization process where emergent incomings of new population appear inside urban or territorial areas. This new population firstly attracted by some criteria, brings some other characteristics which are able to modify and feedback over the environment.

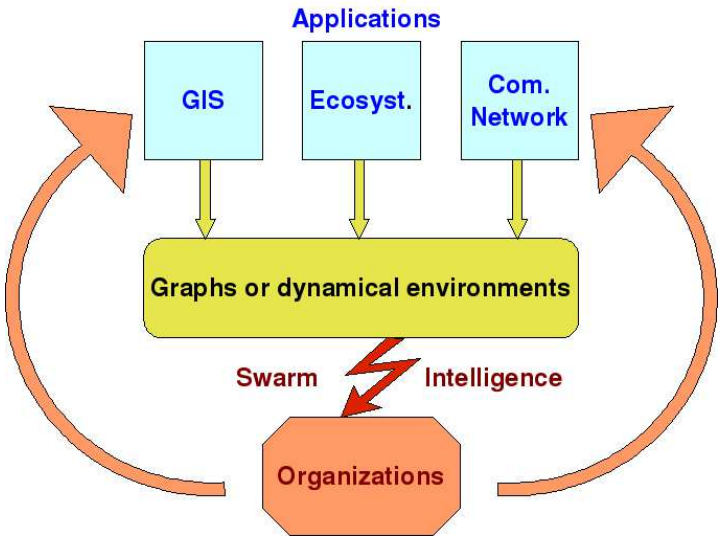
Cultural dynamics processes in urban areas are also such complex systems where multi-criteria must be taken into account. A modelling of these dynamics is presented later in this thesis.

7.2 Users, Services and Decision in Urban Dynamics

In the previous section, we have developed urban dynamics modeling in general aspects and we have concluded with our conceptual approach in order to model more specifically the complex urban system of services and users. We present in this section, some specific aspects of users and services in urban dynamics. Location Based Service is an innovative technology dealing with spatial complexity using GIS and GPS in order to propose individual decision. We will discuss in the final section on multi-scale decision making, from individual level to service management level and urban planning level.



(a) Complexity of geographical space with respect of emergent organizations



(b) Modelling the organization detection using swarm intelligence over dynamical environments

Figure 7.3: Spatial organization complexity description and the conceptual generic model based on swarm intelligence

7.2.1 Location Based Services

Location Based Services (LBS) is one of the aspects of what is called today Urban Computing. Urban Computing studies interactions between pervasive technologies (mobile, wireless, sensors), urban environment and infrastructures in order to improve people's lives [69].

Following Virrantaus [127], we define LBS as information services that are accessible with mobile devices, through the mobile network, and the ability to use the geographical portion of the mobile device.

Location Based Services assist people in their decision-making during the performance of tasks in a given space and time [101]. Users reach Location Based Services with mobile devices like phones or personal assistants (see figure 7.4). The first LBS services have been commercialized in Japan by DoCoMo, in July 2001.

Figure 7.4: ArcPad desktop emulation on Pocket PC with GIS information, on the left part and with the definition of relative importance criteria weights by user, on the right part (from [101])

Location Based Services are designed to be used in a great variety of contexts such personal life, health, emergency, urban localization and transportation planning, weather services, etc. Location Based Services include services to identify location of persons, objects and services at given time: bank cash machines, friends, employees, etc. They can include commercial applications with adaptive advertising to customers according

to their current location. LBS is an example of both services and technologies fusion.

Different technologies and infrastructures interact to define Location Based Services, as described in figure 7.5:

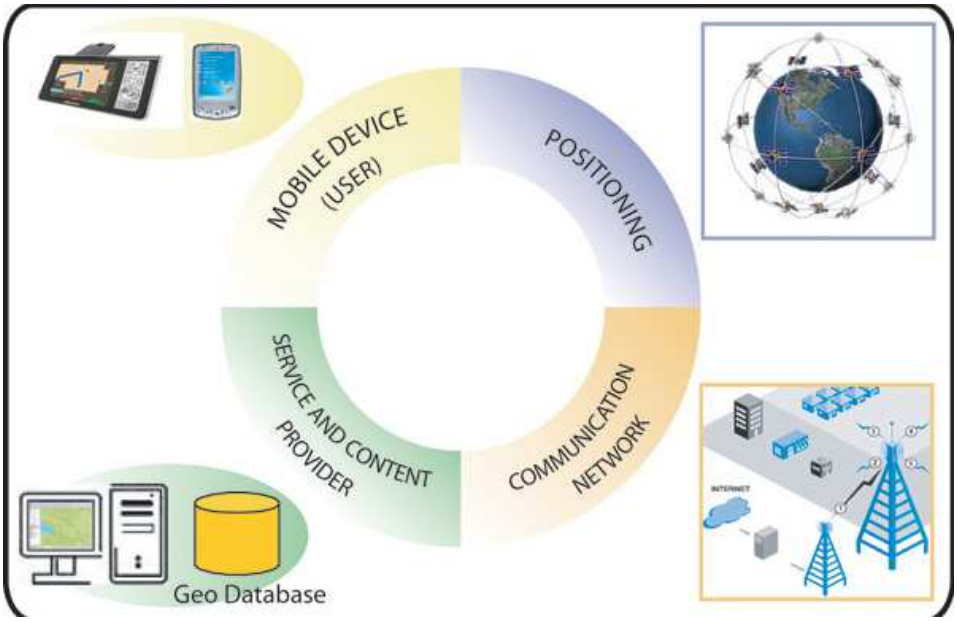


Figure 7.5: LBS infrastructures and environment

- Mobile devices for end users;
- Positionning components, based on Global Positionning System (GPS);
- A communication network, as information transport system for the users' devices;
- GIS and geospatial databases to manage the request and to give the relevent and appropriate answer.

As explained in [117], one of the important aspects of location based services development is to produce adaptive systems to answer to requests. This adaptation, as explained in figure 7.6, consists in managing huge geographical databases accessible through the communication network in order to filter it and produce relevant information for the user. The user interface and visualization must select the significant information for the user. The answer information must be selected according to space and time.

M. Raubal and C. Rinner proposes a multi-criteria decision analysis for Location based services [101]. They integrate the user preferences in a qualitative way in order to have more advanced computation in location based services. They implement a prototype in ESRI ArcPad (see the right part of figure 7.4).

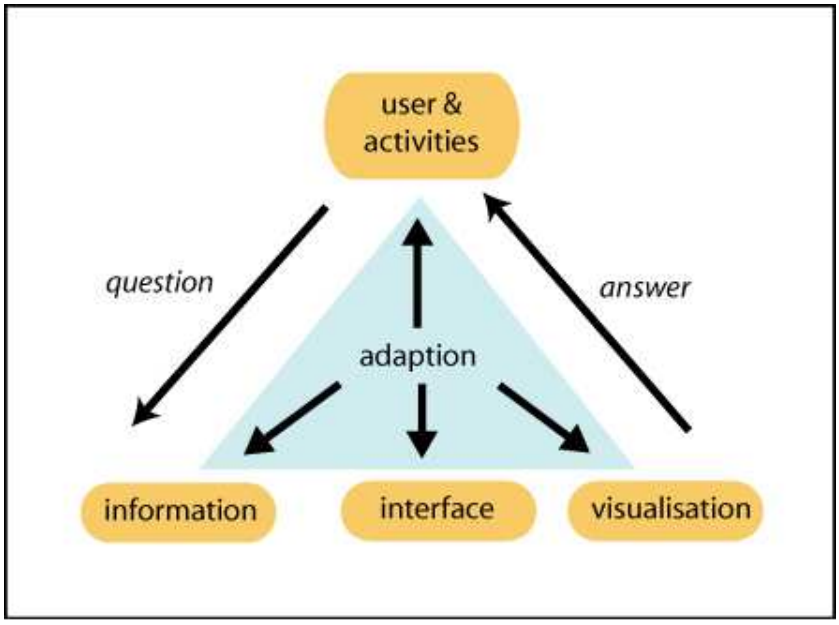


Figure 7.6: Levels of adaptation for LBS mobile after [102]

Multi-criteria aspects are an important factor for urban services users. European Union provides today supports to develop LBS, as an emerging technology in pervasive computing [41]. These studies deal today to propose individual decision-making in complex environments.

The models proposed in our work integrate such individual decision-making analysis by implementing a ranking process which taking into account qualitative preferences of the user. Furthermore, our models implement swarm intelligence processes that lead to analyze the collective usage of urban centers. Also our models implement service adaptive processes. These adaptive processes are the results of the interaction between individual behaviors, preferences and decisions.

7.2.2 Multi-Scale Decision Making

Urban or regional planning and management are based on generic problem solving within a complex set of data and phenomena. As mentioned in section 3.4.2, we can observe that urban understanding needs three levels of decision making analysis: (i) the individual decision for service usages, (ii) the service management which has to adapt to their users, (iii) the global urban or regional planning. In order to have the right decisions for each level, we need to take into account the interaction between these levels. In other words, we need a multi-scale representation to model micro-macro interaction.

Individual Decision Level

The individual decision level is typically what has been presented in the section "Location Based Services". We have to face multi-criteria decisions according to the user preferences. LBS or other equivalent treatments has to adapt a global service selection process in given space and time.

Services Management Level

According to the users preferences and characteristics, each service has to adapt its offer in order to improve it to face the dynamical user demand.

For example, banks need to improve their service qualities and adapt them for the users, in competition with other banks. Major environmental changes (like 2008 crisis) need them to adapt their services characteristics in order to face the customers changing demands.

Another example, a system of restaurant services has to deal with customers of different ages and social positions. Some restaurants, attractive because of its accessibility, can involve young population and low social level population to become its customers. This restaurant will have benefit to adapt its prices and to propose for example, lower price food to continue attracting this population instead of repulse it.

The service management decision making is in that way, linked with the individual decision level by a feedback loop of adaptation.

Urban Planning Level

Urban planning decision makers have to deal with different kinds of planning decision problems like site selection for different services (hospital, school, shops, etc). Another important decision problem is the territorial management in intelligent way to achieve the goal of sustainable development.

Using modelling and simulation like the models proposed in the previous chapters, we can simulate and predict the future placement of given services in the space and their complex interactions with other previous services and users in order to take the right decision after this simulation and prediction.

Modelling and simulation are important aspects in urban planning and developments because it can be used as a tool for understanding and analyzing the complexity of the dynamic interactions between the different parts of the systems like, for example, services and users interactions.

Chapter 8

Application to Urban Cultural Center Dynamics

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8.5 Perspectives and future works 173

This chapter describes a work which has been supported by "Région Haute Normandie" within the project [157]. Moreover, the chapter has been partially published in [155].

This chapter deals with the understanding of collective cultural facilities dynamics within urban area.

This study has been supported (for a total fund of 65000 euros on 3 years) by "Région Haute Normandie" with the CPER project "MCDCU - Modeling the Complexity of the Urban Cultural Dynamics" as a part of the Great Research Network called GRR TLTI. Our contribution consists in GIS survey and engineering and in swarm intelligence modeling. We have developed the core of this swarm intelligence model which is described in the following.

The cultural facilities inside the city are various and follow complex spatial mecanisms. Both geographical aspects and social factors are major in these dynamics, leading to specific equipment. The complexity of these phenomena which are the basis of the cultural development, needs some specific modeling techniques. In a first step, we propose some analysis and description of the cultural activity distribution based on a specific geographical information system (GIS). A case study is developed for the French city of Rouen in Normandy. In a second step, and respecting the complexity of the studied systems, we propose to use swarm intelligence methods over GIS to model the urban cultural dynamics. The goal is to better understand the relevant interactions within multi-criteria interactions. We will focus on the adaptive processes to implement and to analyze the simulation in order to produce elements of decision making. Mixing the swarm simulation with GIS will end this chapter.

8.1 Urban Cultural Development Analysis Based on GIS - A Case Study for the Rouen Urban Area

Our goal is to study the diffusion of cultural facilities and propagation during time, inside the urban area of Rouen. A graphical approach is proposed in order to understand the spatial dynamics of cultural infrastructures development. We want to better understand what are the relevant interactions within heterogeneous phenomena.

8.1.1 Data Support

We design the cultural mechanism in a social and territorial context. The cultural activities and equipment are particularly all services present in French city [78], where the majority of the population is located in, considering the general urbanization of the French society. Like other French cities, Rouen proposes a large diversity of cultural activities in the hopes of educating, entertaining and satisfying inhabitants and also for self-promotion.

The data from the city of Rouen concern urban environment and public or private cultural equipments within wide vision of culture. There are composed of academic sites (museums, operas, theaters, libraries, etc.) and popular ones (musical pubs, concert

places, festivals, cinemas, etc.). These data have been obtained from the agglomeration population composed of 400,000 inhabitants. We plan to study the various logic of geographical repartition and the motivation to create and build cultural equipment, including strategies for municipalities or commercial exploitations.

On figure 8.1, the cultural facilities development on Rouen agglomeration are described from 1744 to 2004.

At this local level we wish to understand two mechanisms. The first one is the conditions that conduct people or private and public institutions to create new cultural structures and how the new locations are chosen. The second one is to better know the circulation of the inhabitants during time in these cultural places which have different levels of attraction. Because, in addition to the problem of geographical distances, other parameters play an equal role in accessing culture: social, educational and economic selection constitute another restraint for the cultural practices of citizens [24].

8.1.2 First Graphical Analysis Using GIS

Urban environment is based on land use of Rouen from IGN topographical maps. Various GIS have been developed from these maps, integrating communication networks and cultural facilities or integrating land use and cultural equipments. The mixing with the municipality administration and service attraction is also planned to be studied.

Comparison between Communication Networks and Cultural Facilities Development

Figures 8.2 and 8.3 describe the location of the major roads (in red lines), the secondary roads (in blue lines) and the railways (in grey) in 1994. In the two figures, we show the development of cultural facilities from 1951 to 1970 and from 1970 to 1994, in order to identify some possible links between them. Black points represent the cultural facilities.

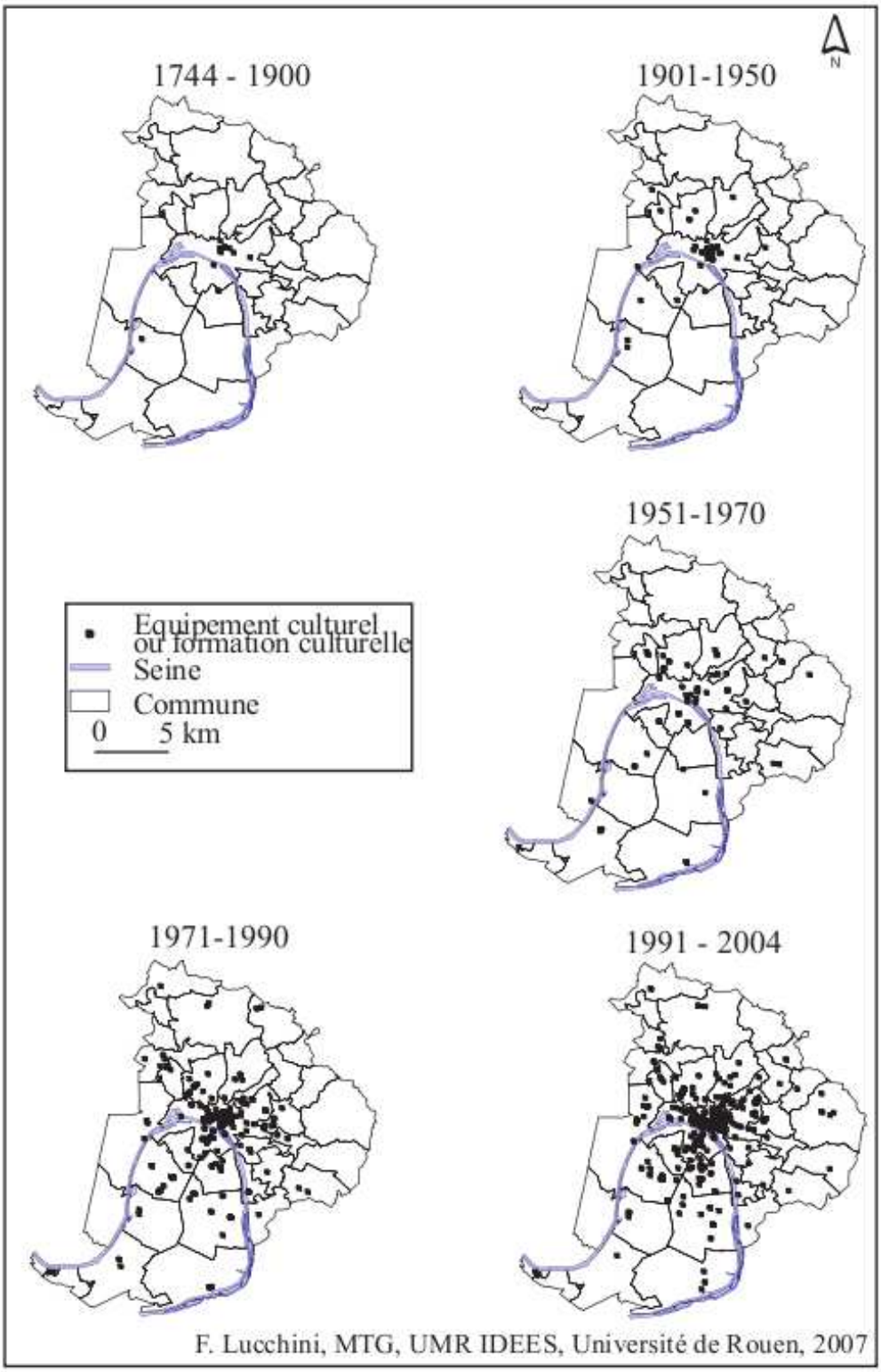


Figure 8.1: Cultural facilities development in Rouen agglomeration

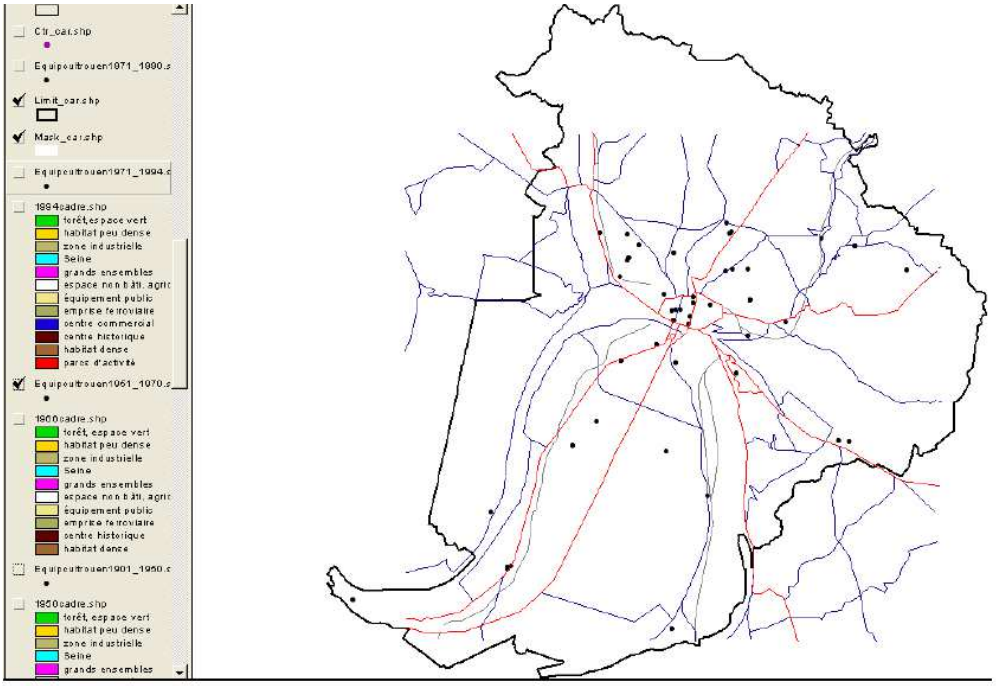


Figure 8.2: Communication networks (roads and railways) in 1994 and cultural equipment development between 1951 and 1970

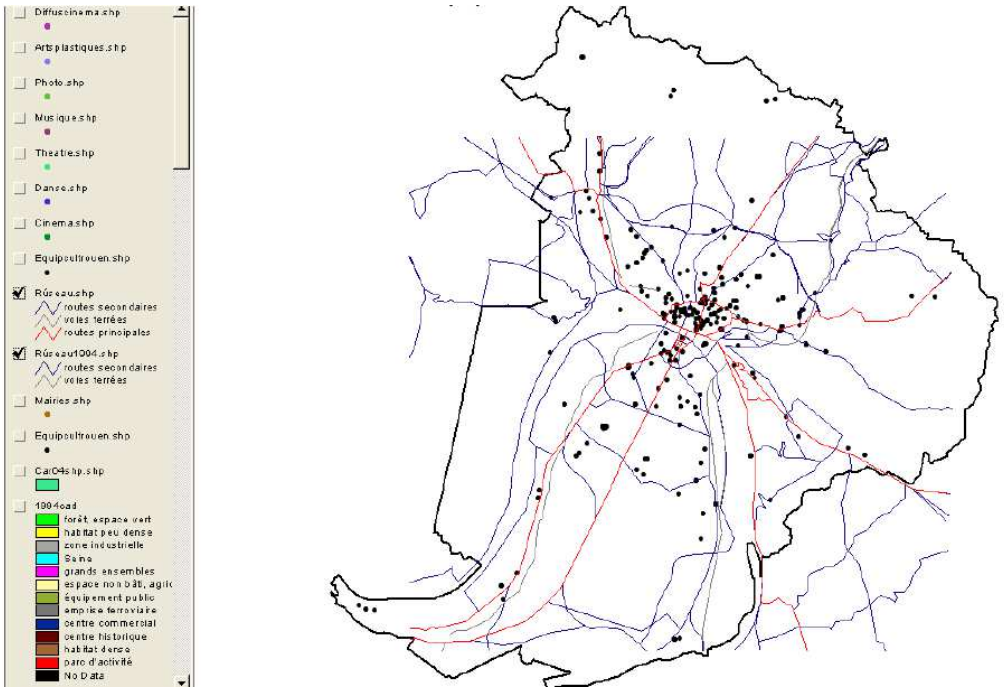


Figure 8.3: Communication networks (roads and railways) in 1994 and cultural equipment development between 1970 and 1994

Comparison between Land Use and Cultural Facilities Development

Figures 8.4, 8.5 and 8.6 describe the land use development and in parallel the cultural facilities development. The land use is characterized by colors which are described by the caption on the left side of the figure. The main colors are green for forests and areas without buildings, yellow for non dense urban areas, pink for dense buildings areas; the brown part characterizes the historical center of Rouen.

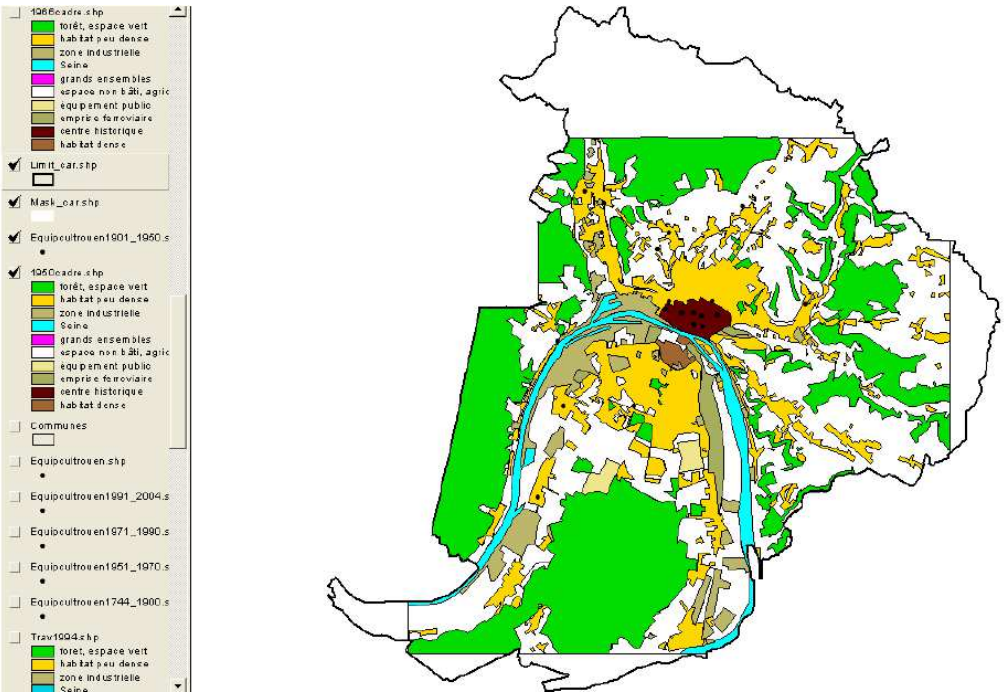


Figure 8.4: Land usage in 1950 and cultural equipment development between 1901 and 1950

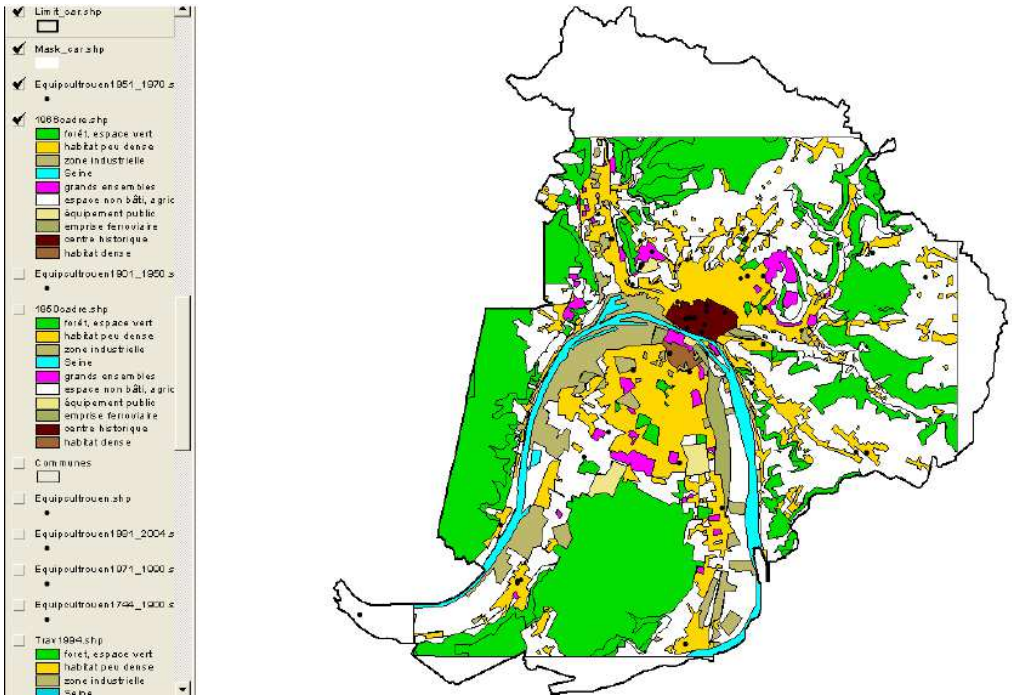


Figure 8.5: Land usage in 1966 and cultural equipment development between 1951 and 1970

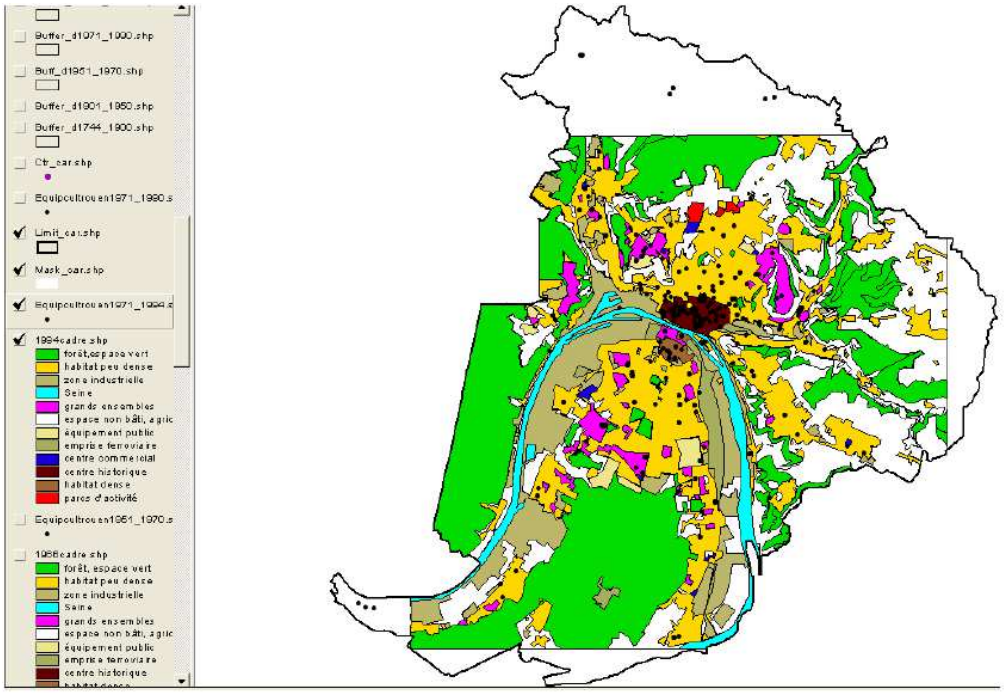


Figure 8.6: Land usage in 1994 and cultural equipment development between 1971 and 1994

Attraction of Municipalities Location on Cultural Facilities Dynamics

The last figure series and graphical analysis concerns a spatial visualization of the municipality centers on the cultural facilities development. Historically, on the beginning of the 20th century, the first cultural equipments like public libraries, were mostly near the city municipality and even sometimes, inside the municipality building. The development of important housing buildings in the suburbs of the city, after the mid of the 20th century, has generated the benefit for the population living there, to have cultural equipments near their home. This evolution makes the cultural facilities located far from the municipality center. Figures 8.7, 8.8 and 8.9 describe some circles around the municipality, whom radius correspond to the maximal distance between the municipality and their cultural facilities. The increase of these circle radius from 1900 until 2004, is following the development of dense suburban housing area.

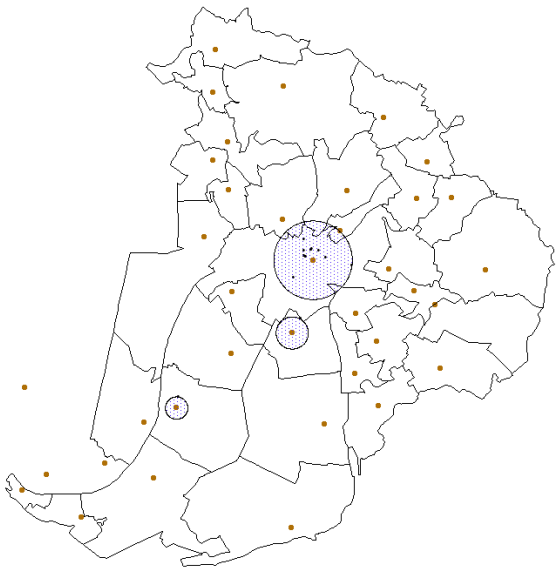


Figure 8.7: Circles of maximal distance between municipality centers and their cultural facilities, during the period 1744 to 1900

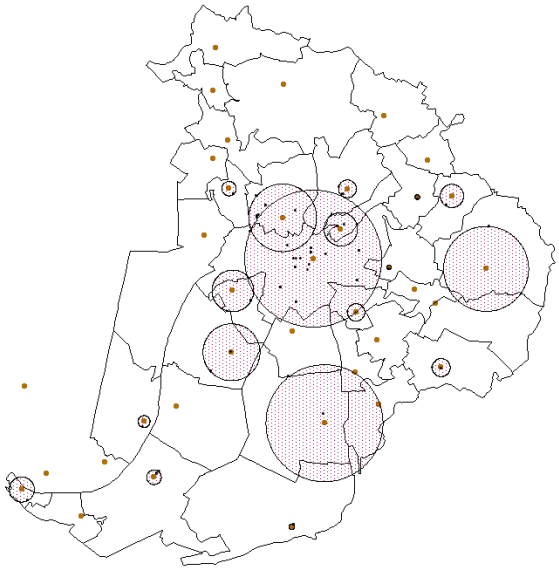


Figure 8.8: Circles of maximal distance between municipality centers and their cultural facilities, during the period 1951 to 1970

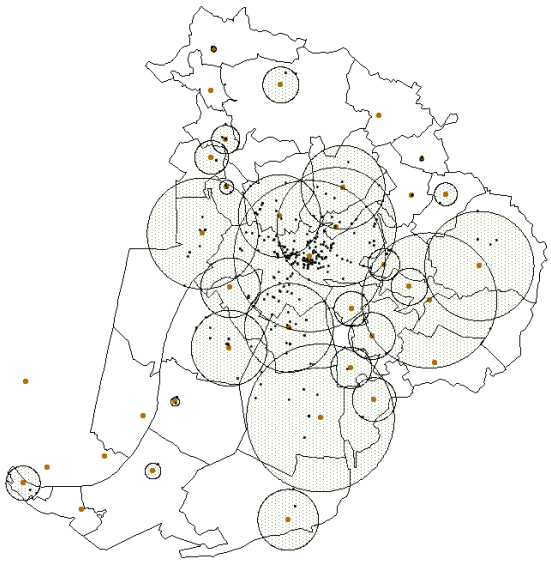


Figure 8.9: Circles of maximal distance between municipality centers and their cultural facilities, during the period 1991 to 2004

8.1.3 Processes Analysis

Cultural equipment repartition within city does not follow stochastic distribution [124]. This implies that the geography of these activities call on other dynamics than that of chance. This repartition is very different from sports equipment development, for example, as we can see from figure 8.10. The sports development follows the public school development that the cultural equipment does not follow.

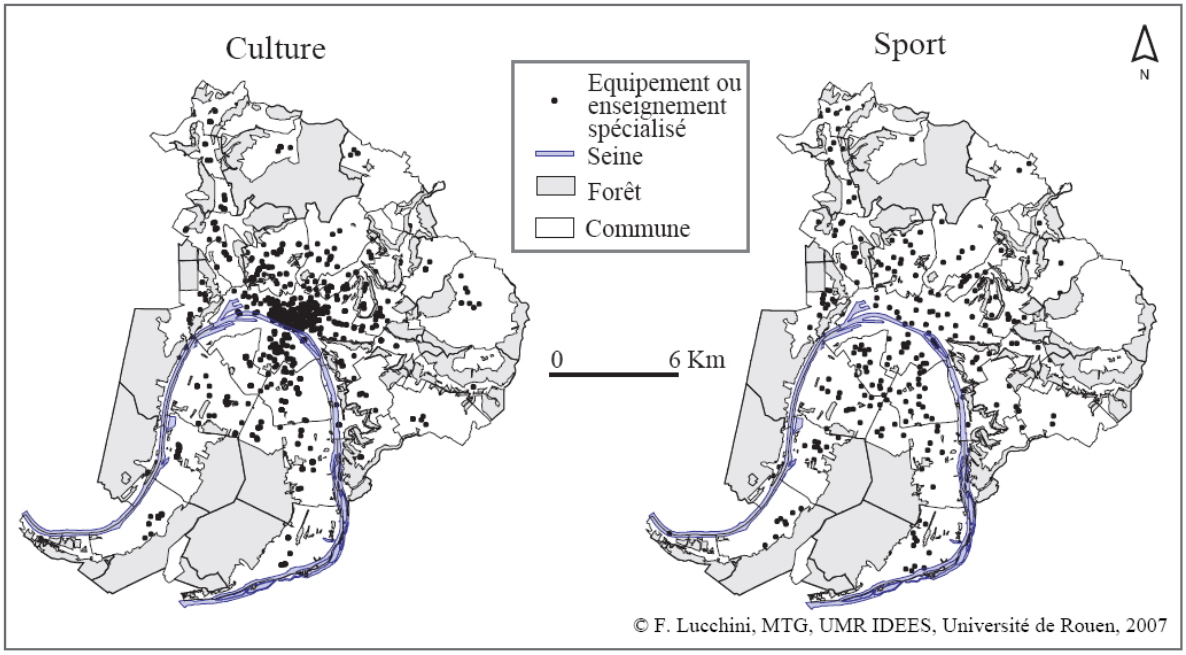


Figure 8.10: Sports equipments and cultural equipments development within Rouen city agglomeration

These observations lead us to better understand what are the mechanisms involved in cultural facilities dynamics. We have to study first the specific spatial constraints: river separation for the city of Rouen, industrial and housing proximity and municipalities service location. Spatial constraints are so a major aspect within the development dynamics, including heterogeneous factors. To model such a complexity, we propose a swarm intelligence method based on ant systems as detailed in the next section.

As explained previously, the aim of this project is studying Rouen cultural dynamics during 3 years (from 2007 until 2010). During the first year, graphical analysis with GIS as shown in this section, has been developed in order to identify some characteristics of these dynamics. The second year mainly focuses on the development of a swarm intelligence method able to simulate the phenomena which has been mainly described with attraction process and adaptive usage by citizens with respect to a complex set of criteria. Our goal during this modeling stage, was to be able to propose adaptive processes of the cultural center with respect to their usage by citizens. The third year will

be devoted to the application of this swarm intelligence method on Rouen configuration, linking GIS data with intelligent processes.

In the following, we will describe the work of the second year (which is now ending at the date of this document writing). The first steps of the mixing of this method with Rouen GIS is described at the end of this chapter. The complete integration of the algorithms on the whole cultural system of Rouen agglomeration is out of the aim of this research work, developed in this PhD, even if our objective is to show that we produce all the ingredients to be able to finish this technical engineering work.

8.2 Modelling Cultural Dynamics with Swarm Models

Cultural equipment development within urban dynamics must be understood through two aspects: the specific mechanisms which control the creation of cultural infrastructures and the use of attraction phenomena for these cultural equipments to follow their development. Emergent systems and organization simulation must be implemented to analyze the cultural dynamics and we will propose swarm intelligence technologies to model these phenomena.

The service-user dynamics is the core of the project problem. As we explain, this project recovers many aspects, from data analysis to accurate modeling over Rouen agglomeration. Morover, understanding the evolution of the service-user system is needed and the analysis of the phenomena through the simulation must lead to appropriate tools. Inside this huge work which will have a complete development during 3 years, we propose to implement the core of the model concerning this service-user systems, in order to be able to describe adaptive processes.

The swarm intelligence engineering model developed in chapter 5, is able to study how cultural equipments can attract users and the global self-organized system is able to give a decentralized solution of cultural centers users repartitions. In this case, the solution emerges from a specific spatial configuration composed of a set of cultural centers and a set of individuals localized initially at some resident places (ilots).

In chapter 5, we have defined a model composed of different components which are classified in two main classes: *environment* and *objects or agents*.

The environment's components are:

- $\{P_i; 1 \leq i \leq n_p\}$ is the set of centers;
- $\{c_j; 1 \leq j \leq n_c\}$ is the set of colors;
- $\phi_{ij}(x, y)$ is the template function of the color c_j, associated to the center P_i;
- $f_{ij}(x, y)$ is the pheromone of color c_j, associated to the center P_i;

- a_{ij} is the intensity of the pheromone function f_{ij};
- if $a_{ij} = max\{a_{ik}; 1 \leq k \leq n_c\}$, then c_j is the dominant color of the center P_i;

The objects and agents components are:

- A set of materials. Each material contains a table of characteristic colors.
- A set of ants. Each ant has a behavior method which gives the color c_j that makes it moves according to the c_j-pheromone function intensity. Each ant implements a decision process which consists in computing this behavioral color. In chapter 5, we give two kinds of decison processes: dominant color strategy and ranking strategy.

In this chapter and according to the application of urban cultural dynamics, we have to specify the connections between the previous abstract model entities with the application features, as we explain in the conceptual modelling approach described in figure 5.1. These connections have been developed in a more detailed way in figure 8.11 and are detailed in the following sections.

8.2.1 Environment Modeling

The centers are modelling the cultural equipments.

The colors are modelling individual user characteristics. These characteristics are of two kinds: **static characteristics** and **dynamic characteristics**.

The static characteristics are belonging to several classes:

- *gender class* has two characteristic values: man or woman;
- *age classe* has different characteristic values corresponding to age interval values: (i) under 15 years old, (ii) between 15 and 30 years old, (iii) between 31 and 50 years old, etc.;
- *education level class* has different characteritic values corresponding to the highest diploma obtained until now by the individual;
- *social level class* has different characteristic values corresponding to a standard classification;
- etc.

The dynamic characteristics corresponds to some **users preferences**. These characteristics are generally more complex features which can be, for example, the user preference to lower price services, the user preference to high quality services or the user preference to easily accessible services, etc. Because these dynamic characteristics play a major role in the adaptive processes proposed here, we will develop them in an accurate way

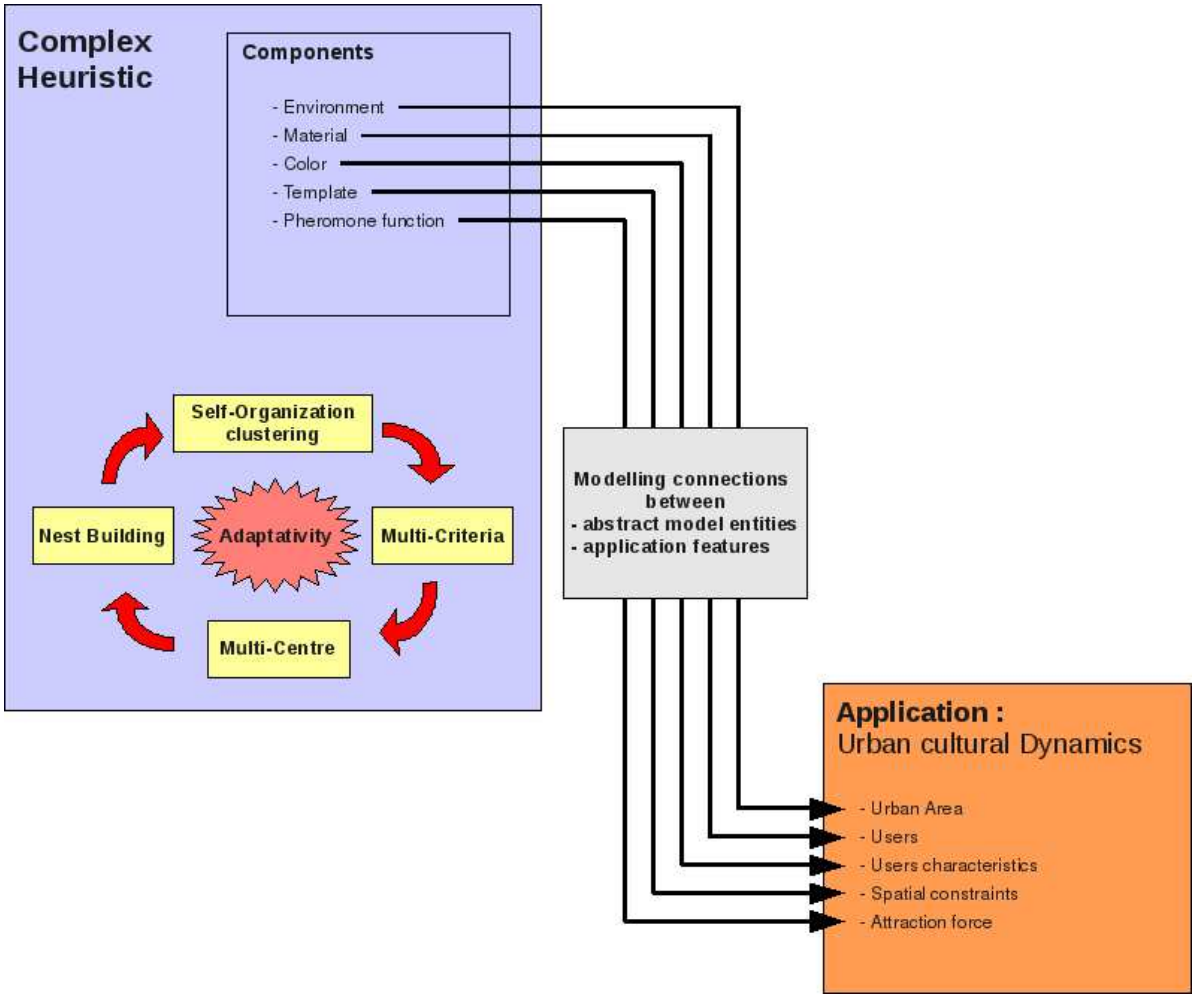


Figure 8.11: Specialisation of the general model to urban cultural dynamics application

in section 8.3.

Finally we associate a color to each possible characteristic, whatever is its kind belonging (static or dynamic) and whatever is its class belonging (gender, age, education level, etc.). So we have a color identifier associated for all the characteristics:

- Male;
- Female;
- age before 15;
- age between 15 and 30;
- age between 31 and 50;
- age after 50;
- primary school diploma education level;
- undergraduated diploma education level;
- preference to lower price services;
- preference to high quality services;
- etc.

As defined in definition 11, for each material M and each color c_j, we associate a color attribute preference belonging to $[0, 1]$. With respect to the two kinds of characteristics (static and dynamic), we can complete the previous definition 11.

Definition 21 *For each material M (or the ant carrying it), we define the c_j color attribute preference as the rate, a real number $s_{jM} \in [0, 1]$. If the color attribute is associated to a static characteristic which belongs to the material, this rate s_{jM} equal 1. If the color attribute is associated to a static characteristic which does not belong to the material, the rate s_{jM} equal 0. If the color attribute is associated to a dynamic characteristic, the color attribute preference can take any value in $[0, 1]$.*

The colored pheromone functions allow to model the attraction capacity of each center, according to a specific characteristic. The more the cultural center is attractive for a specific characteristic, for example of color c_k, the more the amplitude of the c_k-pheromone function must be high. On the first part of figure 8.12, we represent an example of a two centers system with two characteristics and so two associated pheromone functions.

8.2.2 Objects and Agents Modeling

In the urban cultural dynamics phenomenon, the materials are modelling the individual users. Each material/user has a table of characteristic colors which corresponds to the meaning described previously. Each user has only one *static* characteristic item for each class: man or woman, only one age value characteristic, only one social level characteristic, etc. Each material/user has all the *dynamic* characteristics and a percentage is associated to each dynamic characteristics. For example, one individual has a preference to lower prices cultural services corresponding to 70% and a preference to high quality cultural services corresponding to 30%, etc.

The ants are not associated to application feature meaning because each of them contributes to be a decentralized solver in the swarm intelligence process. In this cultural services-users modeling, they will manage the materials/users which are initially located on their resident housing and they have the goal to make them move in abstract way to a cultural center according to the great number of criteria involved, according to the spatial organization of the cultural center systems and according to their mutual interaction together and with the environment. The users allocation to cultural centers is abstract and the ant moving is only a spatial solving moving which is not now connected to any meaning of concrete mobility. But the swarm intelligence engineering model is composed of easy connectable modules, because of its conception which is based on complex composition. Ant java class includes methods corresponding to the ant moving and these methods could be connected to more sophisticated and realistic processes which are not the goal of our model process in this work.

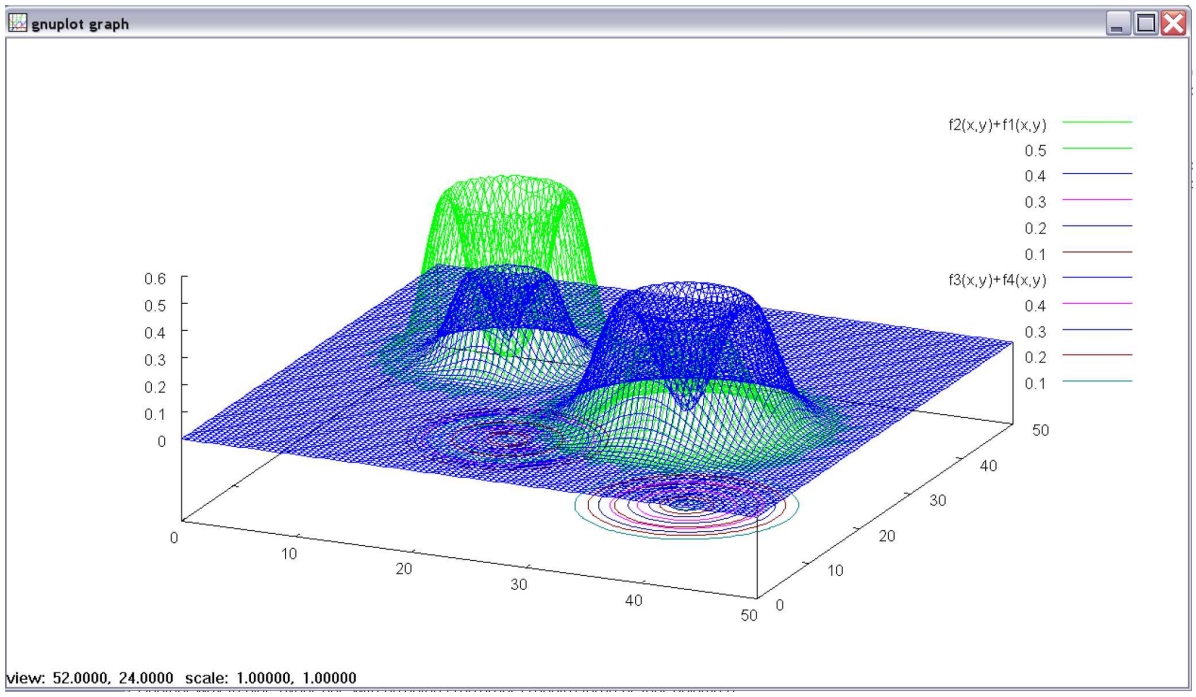
We give in figure 8.12, a schematic representation of an easy-to-understand simulation composed of two cultural centers, a cinema and a theater. We represent the pheromone/attraction functions as circles around the centers and we label them with the associated characteristic/color. Materials represent here users which will be carried and moved by ants, following the complex spatial system of attraction functions.

8.3 Adaptive Processes Modeling

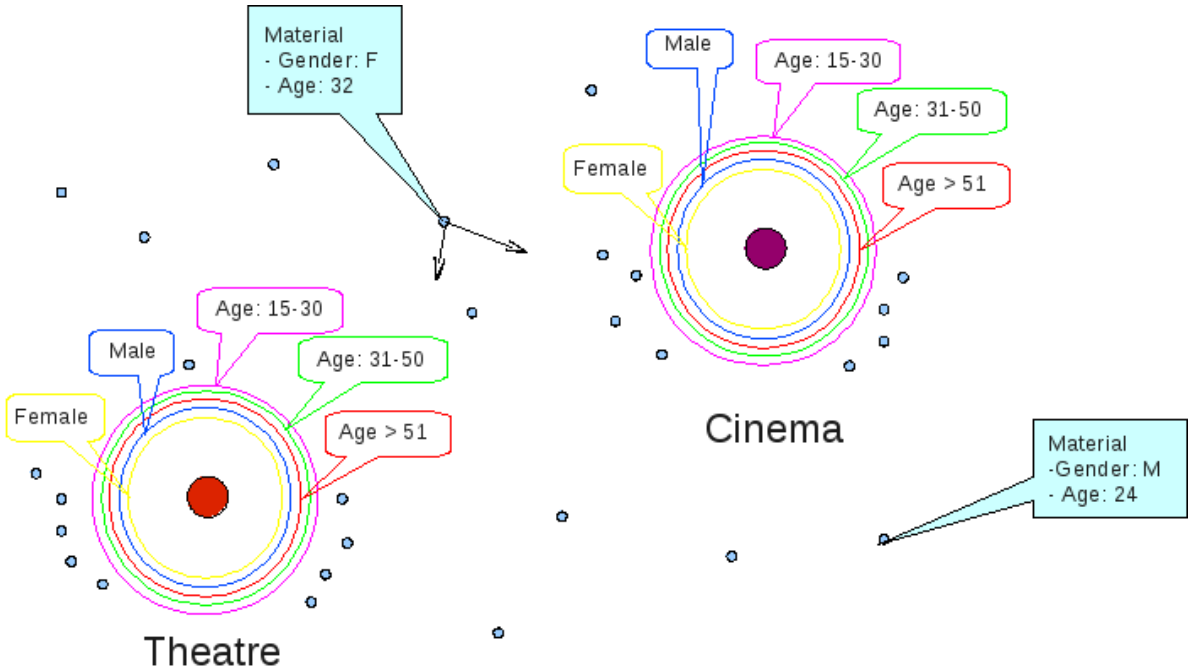
In this section, we develop the implementation of the adaptive mechanism for the case-study of urban cultural center dynamics.

As described in section 5.4, the adaptive mecanism has to be implemented as the *step* method of the agents *queens* or *centers* in our general model.

The queens are the manager devices for the colored pheromones. The cultural services are associated to these colored pheromones which represent their ability to attract users. The goal of the adaptive process is to be able to act on the system by acting on the individual behavior as the result of the modification of the pheromones intensity. This



(a) Example of two pheromone functions corresponding to two attraction forces for two centers



(b) Example of two cultural centers with several attraction forces corresponding to different user characteristics

Figure 8.12: Cultural equipment dynamics modelling

modification of the pheromone intensity represents the service adaptation from their own usage by the individuals.

The color themselves are modelling individual user characteristics. As explained in the previous section, characteristics are of two kinds: the static characteristics and the dynamic characteristics.

The first kind corresponds to static users descriptions and the attraction force are defined by statistics data. It is not possible to modify them and the adaptive process is not expected to act on them.

The second kind of characteristic, the dynamics ones, are defined from the user preferences. For example, as already explained, a user preference can be his preference for lower prices of cultural services. The colored pheromone associated to this preference represents, for a service, its capability to attract people according to its practice of lower prices. The adaptive process is expected to act on such services characteristics. For example, if a specific service successes to attract people who have a great value of preference for lower prices or people who are from low social level, so who are only able to use low cost services, this service will have benefit to adapt to its users by increasing the pheromone intensity corresponding to lower prices practice.

To define the whole process of the adaptive process, we need first to explain in the next section, how the individual preferences are modelled, then in the following section, we will explain the practical computation of services adaptation, based on a rule-based process.

8.3.1 Individual Preference Model

The dynamic characteristics of users are specific values according to the problem that we want to model. In the application developed in this case study, we propose a model of computation which allows to evaluate the preference rate (percentage) of a dynamic individual characteristic from a product of values associated to some static characteristics. The values of this product can evolve dynamically, according to the whole adaptive process. This mechanism introduces a link between dynamic and some static characteristics. These links are motivated because, using a symmetric process, we will propose an adaptive behavior for the associated dynamic characteristic on the center/services: its colored pheromone amplitude evolves with respect to the users number that contains the static characteristics associated to the computation of the weighted average.

For example, if we consider the dynamic user characteristic corresponding to their preferences for lower price services, we will propose to compute it from the following static user characteristic: the gender, the age and the social level. The gender class has 2 values: M (male) of F (female). In order to simplify the explanations, we consider that the age class has only 3 values: Y (young), A (Adult) or O (Old). The social level has also 3 values: S1 (low level), S2 (middle level) or S3 (high level). To compute the

preference percentage for this dynamic characteristic (lower prices service preference), we propose a product of values associated to these static characteristics.

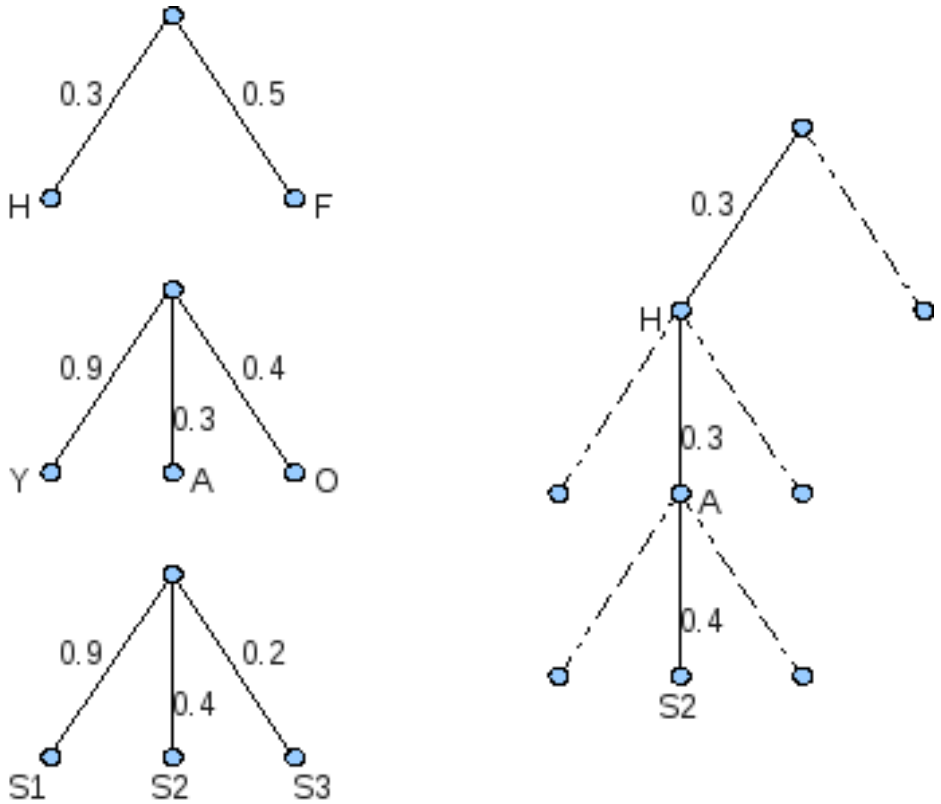


Figure 8.13: Preference tree computation based on 3 classes: Gender (M-man or F-female), Age (Y-Young, A-adult or O-Old) and Social Level (S1-low level, S2-middle level or s3-high level). On the left side, one level trees for each of the 3 classes are drawn, with preference rate on each edge. On the right side, a complete preference tree with the 3 levels is drawn.

On figure 8.13, we represent on the left part, 3 elementary trees for each static characteristic (gender, age and social level). On these elementary trees, we put some weights on the edge according to the importance of the value of this characteristic in order to evaluate the dynamic preference. For example, a young user will be more attracted by a lower price service (0.8 is the associated value) than an adult (0.4 is the associated value). The right part of the figure, shows that the final computation of the preference rate of "lower price services" is obtained from an arborescent computation, as the product of the values of the individual static characteristics involved in the process.

To "normalize" this product computation, we propose the following definition and formula.

Definition 22 *Preference rate computation for a dynamic characteristic.*
If n is the number of the static characteristics involved in the dynamic characteristic evaluation and $\{v_i; 1 \leq i \leq n\}$ are their associated values, with $v_i \in [0, 1]$, the preference rate for the dynamic characteristic is computed by

$$p = \left(\prod_{i=1}^{n} v_i \right)^{1/n}$$

Remark 5 *The previous computation proposed for the preference rate for a dynamic characteristic supposes that the values associated to each static characteristic are independent. This hypothesis could be felt as important and so it is still possible to use more advanced computation based on the principles of conditional probabilities. We do not consider this possible extension in this work.*

8.3.2 Rule-Based Processes Model for Center Adaptation

The principle of centers/services adaptation to their usage proposed in this work is computed with rule-based system which consists of two steps:

- Define the conditions from the users dynamics;
- Define center response with respect of the previous conditions evaluation.

On figure 8.14, we explain this adaptive process. From the simulation while running, we compute statistics according to the users number of each category (e.g. corresponding to specific characteristics). These statistics are the inputs of the adaptive process and according to a rule-based system, we produce some outputs. These outputs describe the colored pheromone amplitude that we have to modify in order to adapt the attraction phenomena according to the users behavior.

The statistics on users number of specific characteristic is based on the following definition using definition 13 of *referential disk* associated to a center/service.

Definition 23 *The density of materials containing the characteristic i near one center/service is defined according to Z, the referential disk associated to this center, with the formula*

$$p_i = \frac{\sum_{M \in Z} s_{iM}}{\mathcal{A}(Z)}$$

where $\mathcal{A}(Z)$ is the area of the referential disk Z and s_{iM} is the c_i color attribute preference for the material M as given in definition 11.

In a formal way, the adaptive process is based on a rule system to be implemented by each center/service. Each adaptive rule is describe by the standard formula as follows:

$$\text{if } C \text{ then } R \tag{8.1}$$

where C is the *condition* of the adaptive rule and R is the *response* of the adaptive rule.

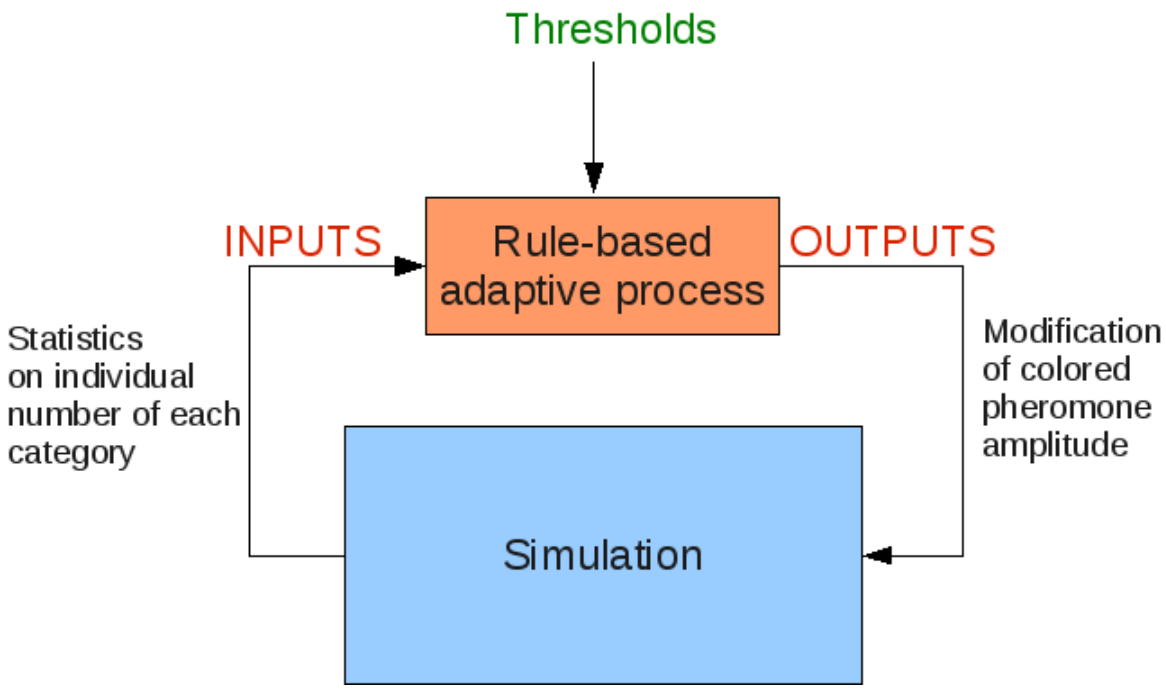


Figure 8.14: Concept of adaptive process

Definition 24 *The adaptive condition C from 8.1 is described with a set of n threshold conditions: $\{(i, r_i, b); 1 \leq i \leq n\}$ where i is a characteristic identifier, r_i is a threshold and b can have the values 0 or 1. The threshold is qualified as following:*

- *if $b = 0$ then r_i is a minimal threshold and the elementary condition consists to evaluate if p_i, the density of material containing the characteristic i near the center/services, is less than the threshold:*

$$p_i < r_i$$

- *if $b = 1$ then r_i is a maximal threshold and the elementary condition consists to evaluate if p_i, the density of material containing the characteristic i near the center/services, is greater than the threshold:*

$$p_i > r_i$$

Finally, to obtain the adaptive condition C, we have to compose a logical expression combining all the threshold conditions.

Definition 25 *The adaptive response R from 8.1 is described with a set of m pheromone modifications: $\{(j, \Delta_j); 1 \leq j \leq n\}$, where j is the pheromone c_j color identifier, Δ_j is the modification to compute on the pheromone intensity:*

$$a_{ij} \leftarrow a_{ij} + \Delta_j$$

where i is the center/service identifier when the adaptive rule is currently applied.

Example 3 *The adaptive process concerning the "lower price preference" can be computed as follows. We consider that the individual characteristics affected by this preference are being young (represented by Y in figure 8.13) and being of low social level (represented by S1 in the same figure). If we associate for example the characteristic identifier 2 to being young and the characteristic identifier 5 to being of low social level, we have to define 2 threshold conditions like*

- *(2, r_1, 1), where r_1 is an arbitrary minimal threshold;*
- *(5, r_2, 1), where r_2 is another arbitrary minimal threshold.*

The response will have a unique pheromone modification like (8, Δ_k), if 8 is the pheromone color identifier associated to the preference "lower price preference" and Δ_k is an arbitrary pheromone intensity modification to apply.

8.3.3 Experiments

This section concerns experiments illustrating the adaptive mechanism involved by the rule-based process described in the previous section.

To implement the process, we have to define (i) the static characteristics, (ii) the dynamic characteristics involved in the individuals and we have to implement them as material colors.

The static characteristics of this experiment correspond to the 3 classes defined in figure 8.13: gender (male or female), age (young, adult and old) and social level (low level, middle level and high level).

The dynamic characteristics correspond to the preference which are defined by the preference tree computation of the same figure 8.13. We implement the example developed previously concerning the "lower price services". This preference rate is computed following definition 22 and using the values given in this computation tree. The new color number associated to this preference is the number 8.

We have to define the adaptive process composed of (i) the adaptive conditions as defined in definition 24 and (ii) the adaptive responses as defined in definition 25. The experiment implements exactly the adaptive process given in example 3 with the values: $r_1 = 0.2$, $r_2 = 0.2$ and $\Delta_k = 0.2$. The adaptive process is implemented over centers 0 and 2. Initial pheromone function amplitudes are initiated respectively by the values 0.9 and 0.2 to the centers 0 and 2. According to the adaptive process, these amplitudes will increase during the simulation.

Figures 8.15 and 8.17 show the simulation output after 351 iterations and 843 iterations, respectively. Between this two steps, the adaptive process will be released making the pheromone corresponding to the preference "lower price services" increased for the two centers 0 and 2. We can observe this phenomenon by the increasing number of materials

of color associated to the preference (light red) around these two centers.

Figures 8.16 and 8.19 describe the material distribution around the center 0 after 351 iterations and 843 iterations. We can identify the release of the adaptive process by the fast increase of the 8-color (brown) curve on the figures part (a). The adaptive response characterized by the increase of the pheromone of the same color can be detect on the figure parts (b) with the decrease of the 8-color curve, describing that this amplitude increasing makes the associated pheromone efficiency decreasing.

On part (c) of the same figures 8.16 and 8.19, we observe the relative pheromone efficiency associated to the studied preference. During a short period these curve evolutions follow similar decreasing that in the corresponding curves of the figure part (b). Then, we observe that these curves increase. This fact means that, in the neighboring centers, this colored pheromone amplitude is increasing also: it is the consequence of the release of the adaptive process over center 2. Our analysis allows to follow the spatial effects and the dynamic interactions between the centers of the simulation.

Figure 8.19 describes the material distribution around center 2 after 843 iterations. We can observe the adaptive process release on part (a). We can observe the increasing step of the pheromone efficiency on part (b) due to the fact that the initial pheromone amplitude for the preference is low (0.2) and make this attraction phenomenon being efficient. After few time, the increase of the pheromone amplitude becomes high and makes the efficiency decreasing. Part (d) of Figure 8.19 shows that the relative pheromone efficiency curve for the preference pheromone has the same evolution that the pheromone efficiency curve on part (c) because there is no significants evolution modification on this preference pheromone on the neighboring centers.

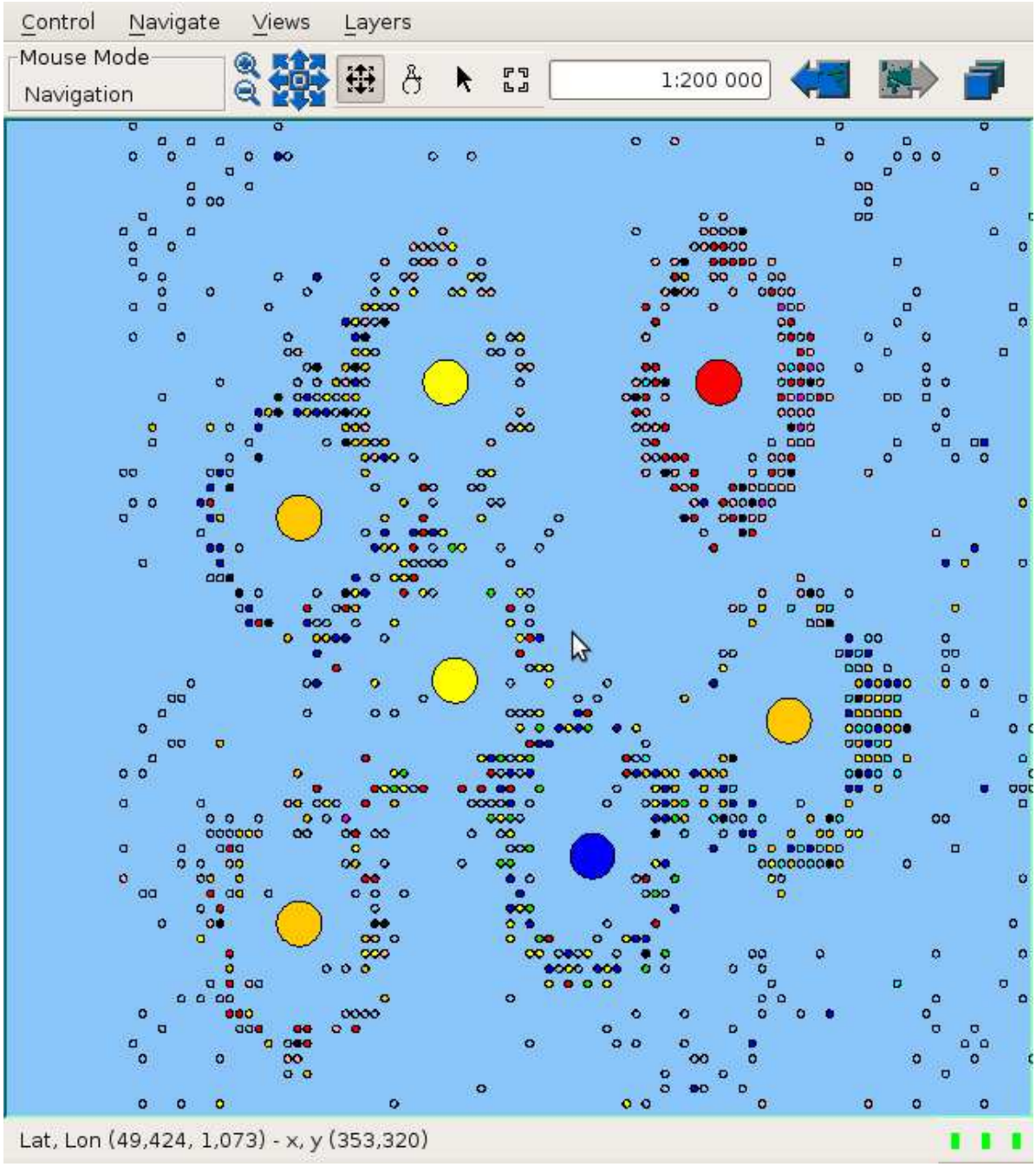
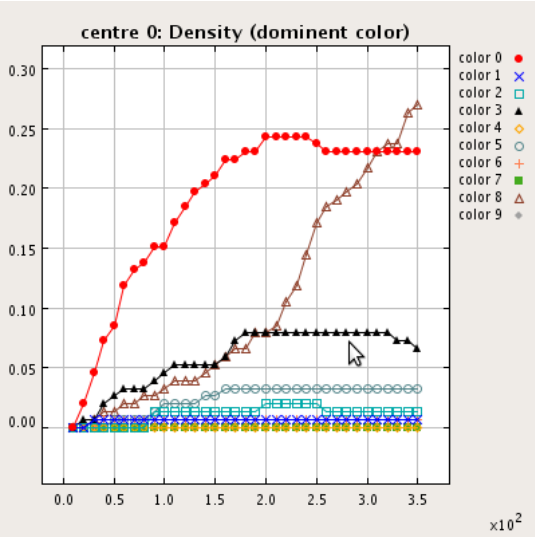
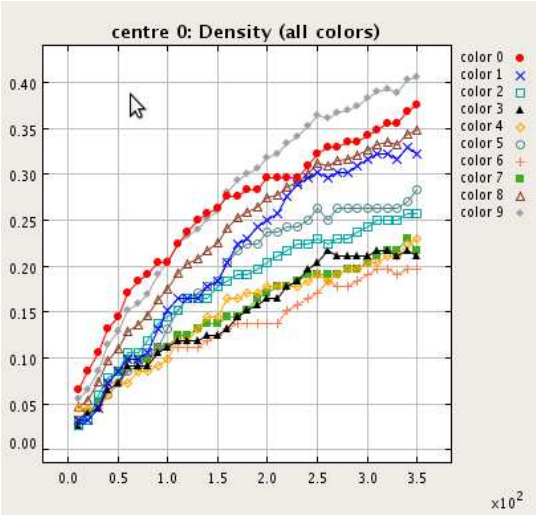


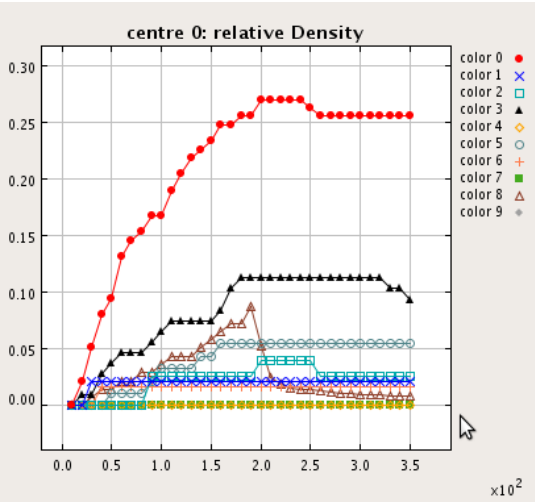
Figure 8.15: Center adaptation experiment: configuration at iteration 351



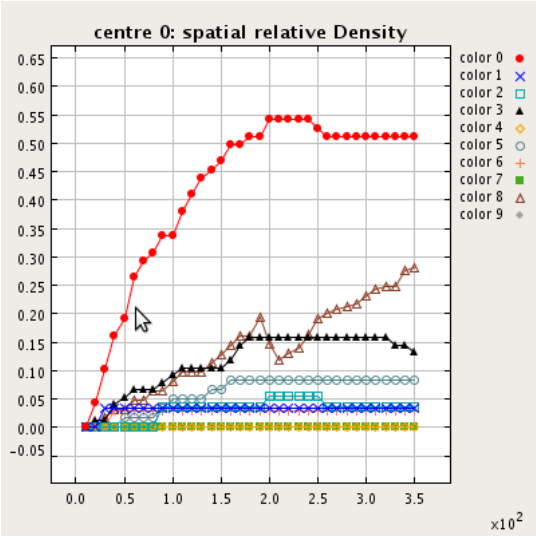
(a) material dominant color density



(b) material color density



(c) pheromone efficiency



(d) relative pheromone efficiency

Figure 8.16: Center adaptation experiment analysis: center 0 material distribution until iteration 351

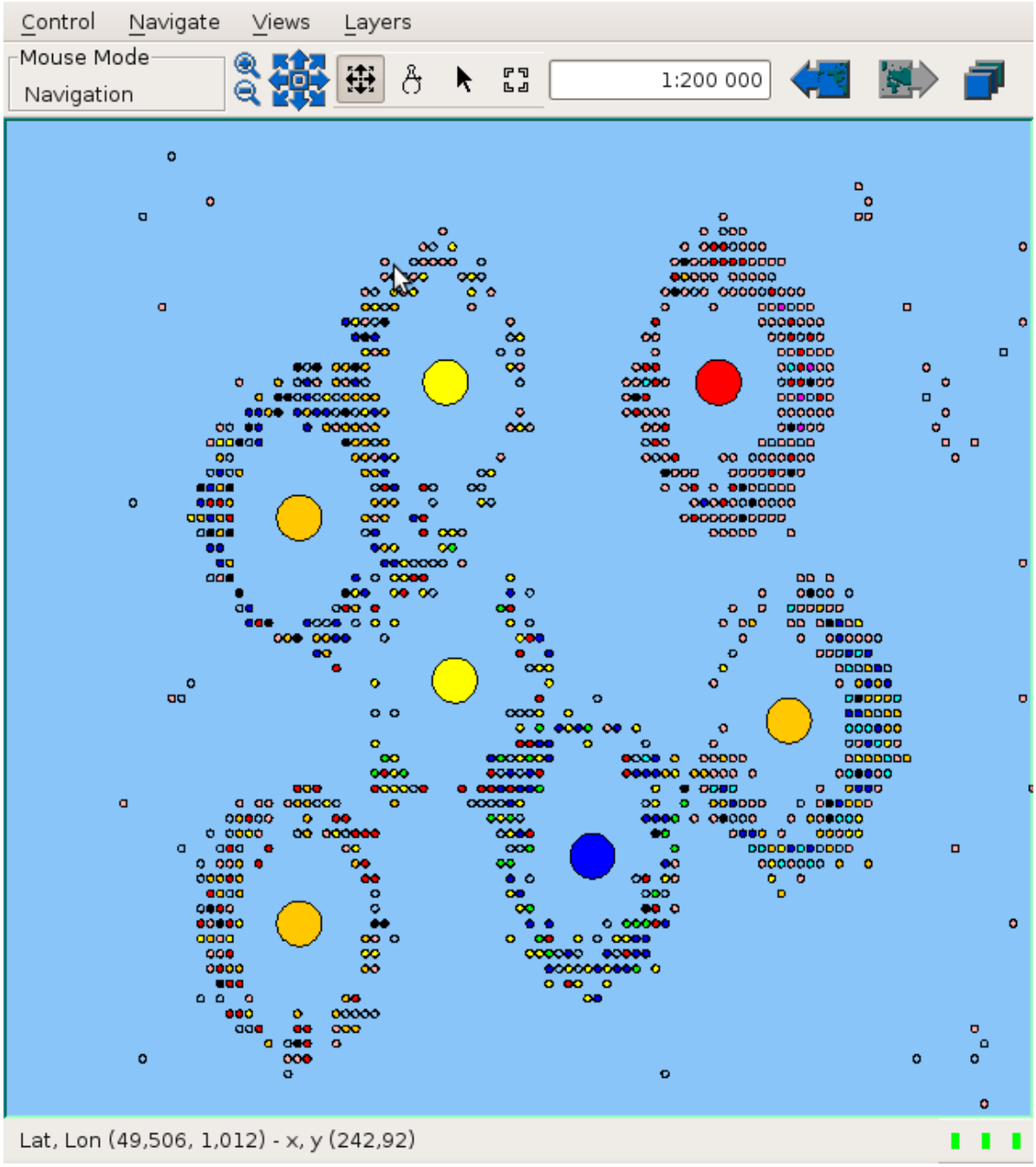
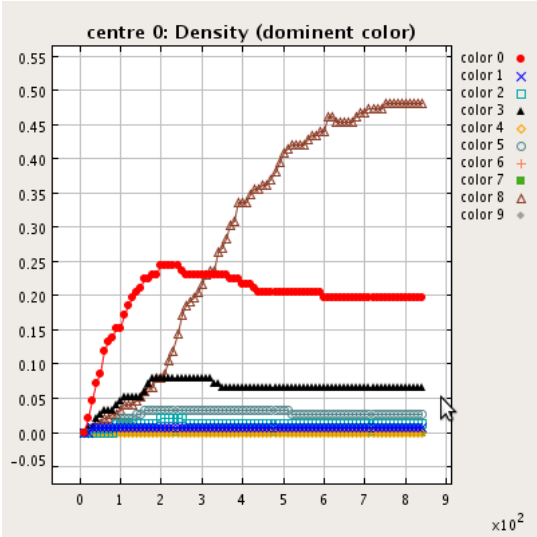
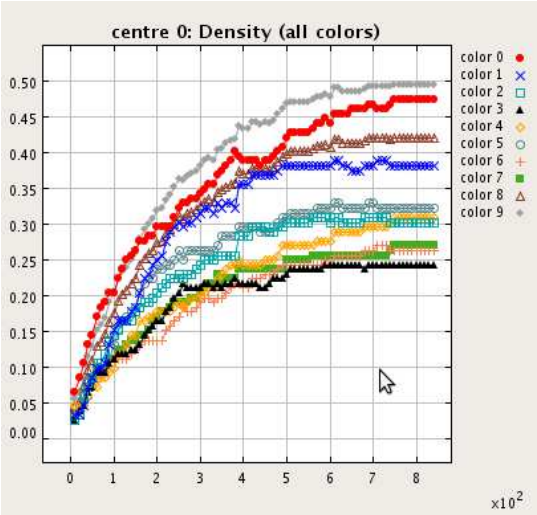


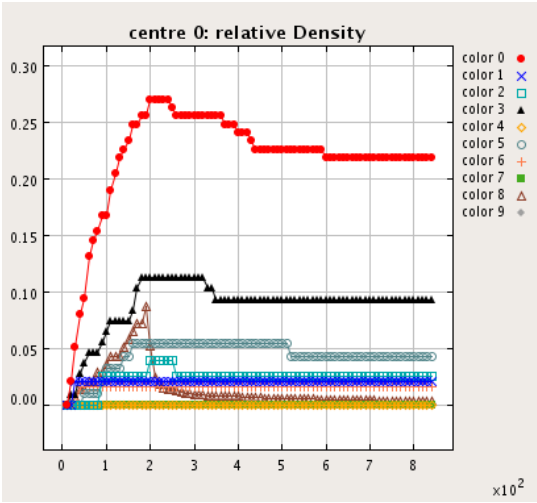
Figure 8.17: Center adaptation experiment: configuration at iteration 843



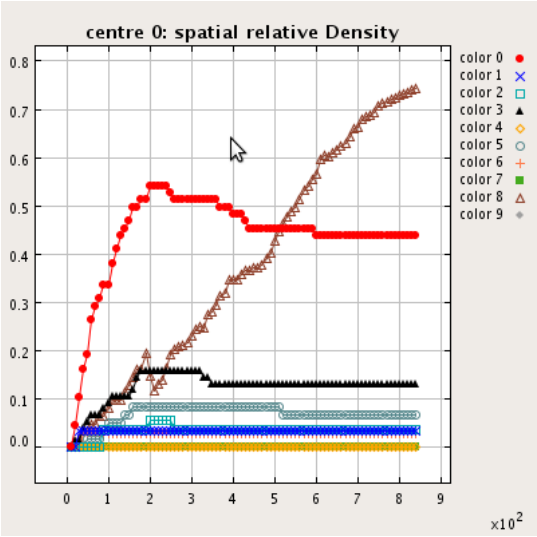
(a) material dominant color density



(b) material color density

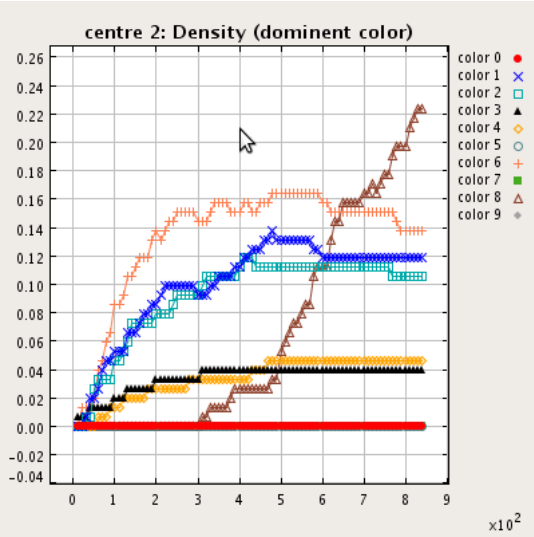


(c) pheromone efficiency

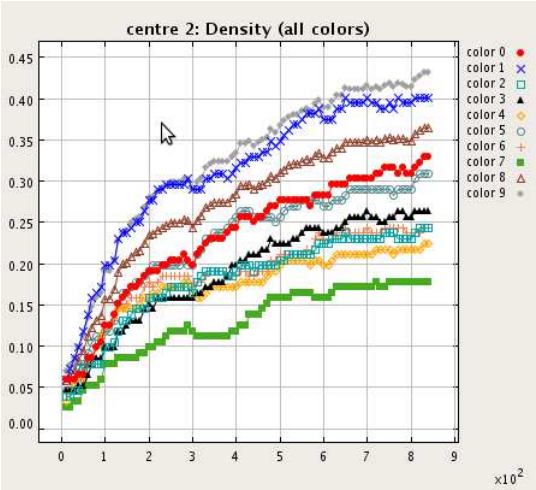


(d) relative pheromone efficiency

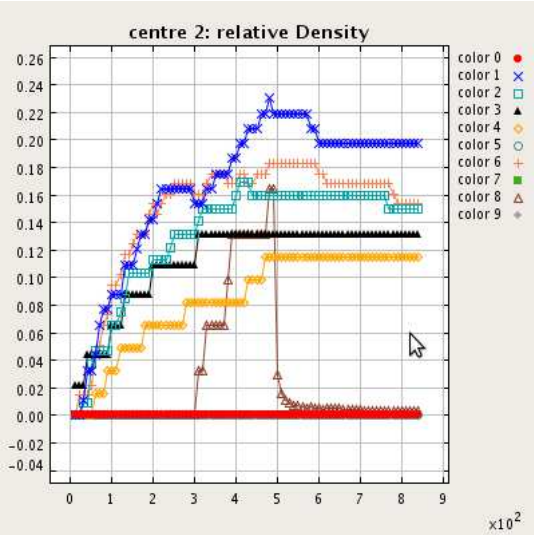
Figure 8.18: Center adaptation experiment analysis: center 0 material distribution until iteration 843



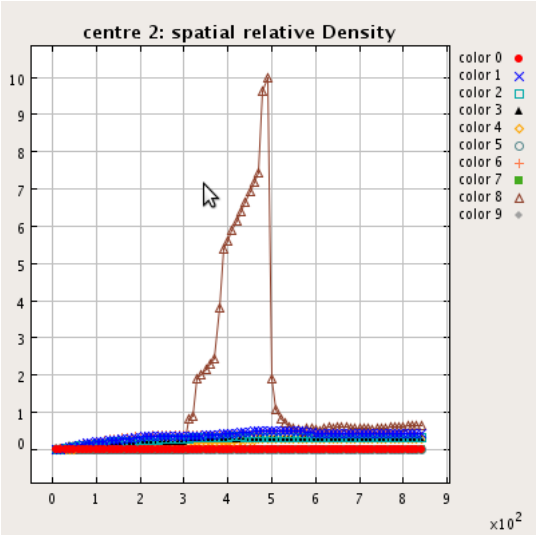
(a) material dominant color density



(b) material color density



(c) pheromone efficiency



(d) relative pheromone efficiency

Figure 8.19: Center adaptation experiment analysis: center 2 material distribution until iteration 843

8.4 Mixing Swarm Intelligence Algorithms with GIS on Rouen Agglomeration Configuration

8.4.1 GIS-Repast integration

The integration of GIS data have been made using Repast and OpenMap GIS software. The main steps can be summarized as follow [90]:

Creating agents from shape file: we have to define agent class by subclassing *DefaultOpenMapAgent* class or by implementing *OpenMapAgent* class.

Using the data classes: after the agent class has been created, we need to have a list of them (one agent for each feature in the Shapefile), using the following instructions:

First, we get the Data class for the GIS system that we are using:

```
OpenMapData gisData = OpenMapData.getInstance();
```

Then we create an ArrayList, and we add the Agents to it:

```
ArrayList agentList = new ArrayList();
agentList.addAll(gisData.createAgents(Agent.class, datasource));
```

Here, *Agent.class* refers to the *GisAgent* class specified.

Now we have a list of agents. If we specified *get* and *set* functions for a specific attribute named Landuse, for example, each agent in the list would have had the Landuse value set by the Landuse field in the dbf file associated with the Shapefile.

It is also possible to interrogate data, which means to look into a shapefile and see what fields it contains. The interrogate function returns an array of type *FieldNameAndType*.

```
FieldNameAndType[] nameTypes =
            gisData.interrogate(MyProgram.datasource);
for (int i=0; i<nameTypes.length; i++) {
    System.out.println("interrogate " + i +
            " field name: " + nameTypes[i].getFieldName() +
            "type : " + nameTypes[i].getFieldType());
}
```

Displaying agents with open map and using open map display: The following steps should be followed in order to display the agents with OpenMap:

- The Shapefile data must be in decimal degree coordinates. OpenMap does not handle pre-projected data.
- Create the agents and add them to a list (as shown in the section on Data)

- Create a new instance of OpenMap Display:
  OpenMapDisplay omDisplay = new OpenMapDisplay();
- Add the agents to a layer:
  omDisplay.addlayer(gisAgents, "AgentLayer");
- Update Agents: after changes have been made to the agents, you can update the layer containg them:
  omDisplay.updateLayer(gisAgents, "AgentLayer");

8.4.2 Model of Cultural Dynamics within Rouen Urban Area GIS

On the left part of figure 8.20, we represent a map of Rouen agglomeration composed of two shapefiles. The first one describes the location of municipality centers and their associated area. The second one describes the location of cultural equipments (red points).

On the right part of figure 8.20, we show a first result of the simulation mixing these shapefiles with the swarm intelligence process. Three cultural centers have been represented with big yellow ellipses and the process described in this figure shows the beginning of the attraction phenomena.

As we explain previously, this simulation is the first step of an important regional project where a technical engineering work will be developed later to cover the whole cultural center system of Rouen agglomeration. Our model and its ability to be extended both on attraction phenomena and on the adaptive processes, allow to make in an accurate way, this engineering tool which is not the aim of the research work developed in this Ph.D. thesis.

8.5 Perspectives and future works

In the previous section, we propose an adaptive process in order to model the feed-back of the centers on their attraction mechanism according to their user characteristics. This adaptive process can also be extended to the user behavior by a another calculation mechanism. This mechanism is based on the calculation of the satisfaction degree of each individual attached to a specific center. If this degree passes a given threshold, the individual can change the chosen center to another one with a better satisfaction degree. This mechanism could be inspired by the segregation model of Schelling described at the end of chapter 3.

In the Ph.D. work, we focus on the implementation of the centers adaptivity as feed-back of the centers as systems on their constituents. The implementation of the user adaptivity is only described here as a perspective of this work.

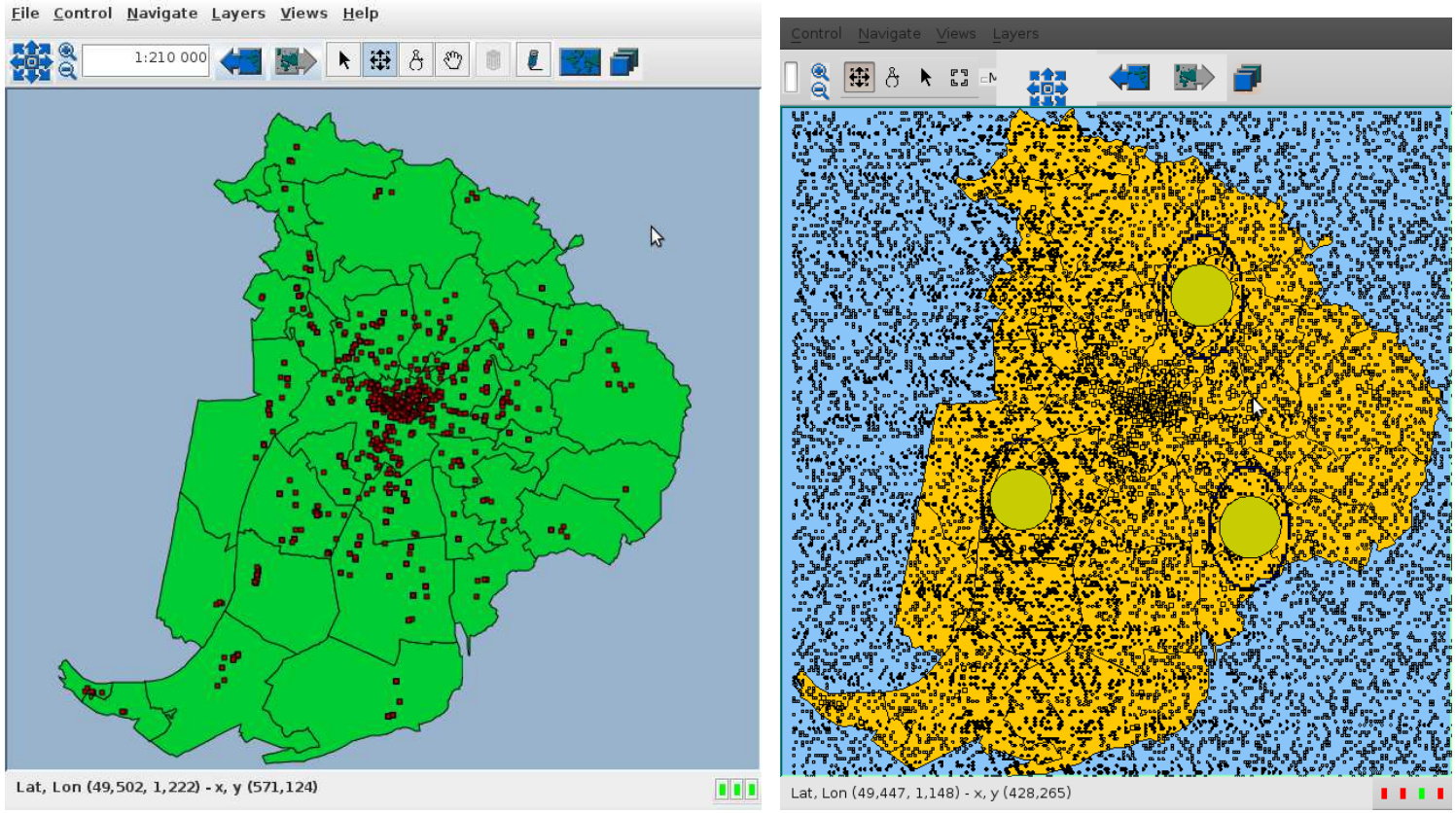


Figure 8.20: Urban cultural equipments over Rouen agglomeration shapefile (left figure) and the dynamics simulation of users interaction based on swarm intelligence within Repast-OpenMap mixing

Part IV

Conclusion and References

Chapter 9

Conclusion

The problem addressed by this study concerns the dynamics of organizations from services and users interactions. Our contribution is to model such phenomena respecting their complexity. This modeling is based on two main aspects which are the adaptive evolution of these organizations according to their usage and the spatial dimension of the processes which influence the organization formations and evolution. This understanding allows us to find, in evolutive way, the best policies for the services and the best choices for the users. The problem can be, in that way, described as a multi-scale decision making: individual decision of the users and decision about the services. Both of these decisions are function of multi-criteria aspects. These decisions have also spatial dimension. For all these reasons, it is difficult to have a deterministic decision making process without simulating various scenarios within spatial environment evolving accurate spatial data (GIS).

Developing dynamical simulations over GIS leading to adaptive and intelligent decision processes is nowadays a great challenge. Urban development and management needs decision making processes which have been developed since many years on deterministic global evolution laws (differential models, for example). The spatial dimension within its complexity is not generally considered in such global model and are often unable to understand some self-organized systems development. Furthermore, the modern development of the cities make them being perceived as a huge complex network of distributed communicating and intelligent devices as mobile phones, PDA, GPS devices and wireless notebooks. All these new technologies bring to citizens an important pervasive environment, full of various information. But finally these environments make the individual decision, a complex problem based on multi-criteria aspects [69].

In order to develop appropriated models and simulations, we need to respect the complexity of the phenomena inside the conceptual approaches of these models. In our work, in order to take into account the distributed nature of the problem, we have used multi-agent systems. In order to take into account the self-organized phenomena, we have used swarm intelligence methods and algorithms.

The proposed method is based on successive steps. In the first step, we develop elemen-

tary models based on bio-inspired processes leading to self-organized swarm behavioral systems. In the second step, we develop these elementary swarm systems inside complex heuristics mixing multi-criteria aspects in a complex spatial environment. The third step consists in applying these general model to specific applications. The final step leads to link abstract components to practical features of the case study developed in each application.

The innovative work proposed here aims at developing these complex heuristics. This approach shows that we can model complex phenomena by linking simple elementary models and we can model adaptive systems with the interaction of these elementary models.

We develop in this work a case study based on the complex dynamics of urban cultural facilities development. The model is based on an extension of nest building algorithms to multi-criteria aspects integrating the various elements of the users characteristics and preferences (gender, age, social origin, etc.). The innovative model is based on two major steps. The first step consists in modeling the attraction phenomena of the users for the cultural facilities with a pheromone based model. The second step consists in modeling the adaptive behavior of the cultural facilities in order to adapt them to the users. In that way, we model the complex loop between the users and the services. The simulation approach allows us to understand this complexity in order to control or make decision on urban cultural planning.

The perspectives of this work are various. We can first remark that the developed model is applied in this document only to the urban cultural facilities development. The generality of our model allows us to apply it to many applications where users and services interact dynamically in spatial multi-criteria complex environments (telecommunication infrastructures, wireless sensor networks, etc). Non homogeneous components systems can be managed by our method.

The ant nest building swarm algorithms are typically based on numerous parameters (number of ants, pheromone amplitude, various thresholds, etc.) which need to be tuned according to the problem configuration (space size, number of centers, etc.). We do not focus in this study on how to adjust these parameters. This problem can be solved by some optimization methods like particle swarm optimization or also the use of intelligent controllers.

On this study, we focuss on the swarm algorithm development and the mixing of this intelligent methods with GIS. Further studies could focuss on a more advanced interaction between the agents and the shapefile in order to modify or update the spatial GIS data.

The usage of multi-agent models within spatial self-organized systems is nowaday in increasing research development. We believe that swarm intelligence methods can have

a promising future in this context, both for the development of theoretical models and also for the applications of new research fields.

Chapter 10

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Adaptive Modelling for Spatial Emergence within Complex Systems

ABSTRACT: The aim of this work concerns the implementation of swarm intelligence models in order to study the spatial emergence of organizations within self-organized systems, under multi-criteria constraints. The scientific context of the modeling formalism is developped in this document. A methodology is presented and leads to the development of a complex heuristic linking bio-inspirated elementary models, based on ant algorithms. An application is developped and concerns the service/user modeling - specifically for cultural services - in urban dynamics. Models of adaptive mechanisms of services during their usage are also proposed.

KEYWORDS: Complex Systems, Self-Organization, Swarm Intelligence, Ant Algorithms, Multi-scale Decision Making, Urban Dynamics.

Modélisation adaptative pour l'émergence spatiale dans les systèmes complexes

RESUME : L'objectif de ce travail consiste à mettre en place des modèles d'intelligence en essaim pour l'étude de l'émergence spatiale d'organisations dans des systèmes complexes auto-organisés, sous des contraintes multi-critères. Le contexte scientique de la formalisation dans le cadre de la modélisation des systèmes complexes est développé dans ce document. Une méthodologie est présentée et conduit au développement d'une heuristique complexe tissant des liens entre des modèles élémentaires bio-inspirés des algorithmes de type fourmis. Une application est développée et concerne la modélisation de l'usage de services - notamment des services culturels - en dynamique urbaine, ainsi que la modélisation des mécanismes d'adaptation de ces services en fonction de leurs usages.

MOTS-CLEF : Systèmes complexes, auto-organisation, intelligence en essaim, algorithmes fourmis, aide à la décision multi-échelle, dynamique urbaine.