UNIVERSITA' DEGLI STUDI DI TORINO

Dipartimento di Scienze Economico-Sociali e Matematico-Statistiche

Corso di Laurea in Economics

An Agent-Based Simulation Model of a Healthcare System: the Laboratory Network in the Area of Turin

Relatore:
Prof. Pietro Terna

Correlatore:
Prof. Sergio Margarita

Candidato:
Enrico Carlo Girotti

Anno accademico 2013-2014

CONTENTS

INTRODUCTION

Health and care issues enter directly into the everyday life of each individual. Dealing with healthcare systems means dealing with real and concrete aspects of everyday life that include a variety of different actors. In particular, healthcare systems have their main goal in pursuing health and care for the citizens in order to improve their quality of life. So, the personal interest in modeling healthcare systems, that has led to the realization of this work, comes from the concrete attributes characterizing them. The first attempt in modeling healthcare situations by means of agent-based simulations derives from a project developed with other colleagues in order to take the exam concerning simulation modeling for economics at the University of Turin. In this previous work, we have modeled the patient flow affected by oncological pathologies in Piedmont paying attention to real data about the oncological network of the region. This work has emphasizes the attention towards healthcare issues and their evaluation using ABM methodologies. In particular, the capability of interacting with concrete aspects of our everyday life, analyzing contemporaneous challenges that usually receive attention in current debates (as the healthcare field). Agent-based modeling simulations require collection and analysis of real classes of data, meaning that they do not only consist of computer programs based on random computations, but they are the result of a research activity leading to a closer connection with the reality under investigation.

Healthcare systems are gaining an increasing attention by policy makers and governments all over the world. Reorganization and efficiency are becoming two pillars for care delivery organizations (CDOs) which have to face with several problems such as increasing costs, poor or inconsistent quality and inaccessibility to timely care. In developed countries, healthcare expenditures are rising twice as fast as overall economic growth, with governments reducing coverage for certain services, redirecting spending among other programs. The current status of healthcare systems in developed countries is challenged by several forces: globalization, consumerisms, changing demographics and lifestyles, diseases that are more expensive to treat (chronic diseases), the proliferation of medical technologies and treatments as well as financial constraints and norms. Indeed, a healthcare system is characterized by a multitude of agents and variables that end up in many different behaviors that produce results. Technically speaking, a healthcare system is complex. Complex system theory presents useful methodologies according to which it is possible to investigate the healthcare field, trying to implement new models for promoting health and delivering care. Hence, this work aims at presenting a simulation model, based on the agent-based methodology, which serves as an experimental tool to investigate emergent networks in the healthcare system of the district of Turin. Particular emphasis is given in the identification of two typologies of emergent networks: specialist visits and blood taking centers. Although the model is based on some strong assumptions, it may constitute a starting point from which other studies may enter, implementing it with more reliable data and features. Since a healthcare system is classified as social and complex, decision making strategies are usually biased in that they cannot evaluate the multitude of agents involved. By means of an experimental platform like the one we have outlined in this work, it is possible to evaluate policy decisions through a variety of scenario modifications.

The work presented in the following pages is articulated into four sections identifying two separate parts. The first part is related to the exposition of a literature review concerning the main topics of our model and is given by the first three sections, one for each key argument.

Section 1 introduces the complex systems theory as a fundamental instrument to analyze complexity. The entire argumentation establishes a direct path that starts with the characterization

of complexity, passes through the adoption of simulation methodologies to deal with complex systems and ends with the use of those methodologies in the healthcare field. So, there are three main topics under analysis: complexity, simulation and healthcare. The contents of the section may be resumed as follows:

Paragraph 1.1 explains the difference between complicated and complex systems, focusing on the role of complexity and complex adaptive systems. Complex adaptive systems (including healthcare systems) are characterized by emergent properties that derived from myriads of interactions among several elements composing these systems. Moreover, they are adaptive in that they learn from the experience.

Paragraph 1.2 reports some historical notes about complex adaptive systems.

Paragraph 1.3 deals with two examples of application fields for the complex adaptive systems theory, economics and political science, highlighting some preliminary researches.

Paragraph 1.4 classifies complex systems into three categories.

Paragraph 1.5 deals with the complicated issue of measuring complexity, identifying possible strategies.

Paragraph 1.6 points out that, even if complexity may be seen as an abstract concept, the analysis of complex systems by means of models is a concrete activity.

Paragraph 1.7 presents the main drivers of researches in complex systems theory, stressing the multi-disciplinary approach characterizing it.

Paragraph 1.8 introduces healthcare complexity, highlighting the varieties of agents and individual behaviors that produce uncertain outcomes. Uncertainty is the main characteristic of complex systems and healthcare does not make an exception. Moreover, the paragraph highlights some challenges that governments in developed countries have to face with in order to improve health and delivery care.

Paragraph 1.9 explains the adoption of computer simulation techniques in healthcare application studies, providing a general introduction on the topic.

Paragraph 1.10 identifies four major fields of application of healthcare simulations, trying to present the purpose of the simulation adoption in healthcare.

Paragraph 1.11 classifies those areas, characterizing healthcare systems, in which simulation may constitute a powerful analysis tool.

Paragraph 1.12 points out the challenges that healthcare simulation applications usually face with (theoretical, user acceptance and application challenges), providing some possible solutions, for example by means of multi-paradigm approaches and reliable data collections.

Finally, *paragraph 1.13* classifies the typologies of simulation models that usually take place in healthcare studies.

Section 2 focuses the attention on a particular simulation tool: agent-based modeling (ABM). This section contains the literature background features characterizing agent-based simulation techniques paying particular attention on healthcare ABM applications:

Paragraph 2.1 deals with the modeling issue and its purposes, highlighting those features that have to be taken into account when a model is developed and analyzed.

Paragraph 2.2 is a general introduction on agent-based modeling and the role it has in science applications, covering a variety of disciplines.

Paragraph 2.3 defines agent-based models as computational methods: building models as computer programs in order to analyze agents interactions.

Paragraph 2.4 highlights the importance of experimental issues that ABMs provides to social scientists in that agent-based simulation tries to represent complex social systems with their emergent properties which cannot be isolated in the real world.

Paragraph 2.5 provides a characterization of model typologies with a quick historical background.

Paragraph 2.6 introduces the main component of an agent-based model: the agent. An agent interacts with other agents within the environment and react to altered conditions by means of modeled behavioral rules. Furthermore, the paragraph defines the main features of agents.

Paragraph 2.7 goes in details by examining those agents that usually characterize healthcare models: patients and care providers.

Paragraphs 2.8-2.9 refer to the environment in ABMs, making reference to healthcare simulation scenario features: physical objects and informational objects.

Paragraph 2.10 deals with scenario analysis which regards the experimental results verification. Changing various variables and settings (interface specification) in the model, the user is able to verify outcomes (results specification) after the alterations, comparing them with previous settings. Two typologies of scenario analysis are defined: demand and event/crisis scenarios.

Paragraph 2.11 recalls further characteristics that make ABMs different with respect to other methodologies: ontological correspondence, heterogeneous agents, environment representations, agent interactions, bounded rationality and learning.

Paragraph 2.12 introduces two additional methodologies related to ABMs: microsimulations and system dynamics.

Paragraph 2.13 presents a general digression on ABMs in healthcare, anticipating the argumentation contained in paragraph 2.14 which highlights the role of ABMs in modeling health and care delivery processes and units. The paragraph insists on a typical modeling case, presented in a variety of ways in the literature: the emergency department.

Paragraph 2.15 shows an example based on the work of Kanagarajah et al. (2006), considering the model of an emergency department unit.

The ABM approach in the emergency department case is defined in *paragraph 2.16*.

Finally, *paragraph 2.17* contains some notes about the agent-based simulation program adopted for the realization of our model: NetLogo.

Section 3 presents the additional theoretical material connected with the evaluation of agent-based models. In particular, since agents interact with each other generating behaviors characterizing the system in which they operate, the study of such interconnections is undertaken by network analysis (social network analysis in social science phenomena). Network analysis theory provides a variety of tools that are extremely useful in defining emergent networks of agent-based models: measures, structures and typologies of networks. Hence, the argumentation presented in this section stresses the importance of a cross-fertilization that must recur between agent-based modeling and network analysis. The contents are the following:

- *Paragraph 3.1* introduces social network analysis (SNA), giving some notes about its historical background and presenting a first classification of social networks.
- *Paragraph 3.2* starts with theoretical features of SNA, providing formal definitions based on the work presented in Cioffi-Revilla (2014).
- By means of the correspondent graphs, *paragraph 3.3* classifies four typologies of social network taking into account the nature of social relations and the state of a specific nature.
- *Paragraph 3.4* deals with paths and levels of analysis in social networks, from micro to macro levels of analysis ("bottom up" process).
- *Paragraph 3.5* characterizes the different typologies of architectural structures that occur in social networks. Those structural patterns provide useful advantages in terms of network evaluation by means of several measures quantifying social networks.
- Such measures are exposed in *paragraph 3.6* and are divided according to their level of analysis (micro or macro).

- *Paragraph 3.7* highlights the importance of the joint support that must occur between network analysis and agent-based modeling in order to better characterize models.
- *Paragraph 3.8* distinguishes among explicit and implicit structures that occur in agent-based models: the formers are clearly implemented modeling hypotheses while the others are structures inferred from the model.
- *Paragraph 3.9* deals with the definition of network structures in agent-based models: lattices, grids, regular graphs, random graphs, small world networks and scale-free networks.
- *Paragraph 3.10* describes the agent population distribution issue in agent-based models and the characterization of links between agents. Moreover, it is stressed the need of indicators and network layouts in ABMs in order to better manage chaotic emergent networks.
- Finally, *paragraph 3.11* introduces network analysis concepts in healthcare applications defining six typologies of relations that usually take place in this field and four classes of agent "flows".

The last part of this work (*section 4*) is devoted to the exposition of our model. The argumentation takes into account each aspect of the model developing process, starting from the environment of the simulated system, passing through the agent sets definitions as well as the procedural rules that model agent behaviors. Finally, the section ends with a set of experiments that show how the model can be used as a potential tool to discover and analyze the healthcare system of the district of Turin. In particular:

- *Paragraph 4.1* refers to the modeled environment. Our model addresses the healthcare system of the district of Turin, and, as a consequence, the paragraph reports the procedures connected with the world settings of the simulation: the characterization of the district territory, its division into four main areas and the geo-localization of the hospitals by means of coordinates.
- *Paragraph 4.2* deals with the first agent set of our model: the hospitals of the district of Turin. Such agents are correctly represented by means of precise geographical coordinates. Moreover, they provide some health and care services, divided into three main category of "treatments": medical exams (paying particular attention on the role of blood tests), specialist treatments or visits (pathologies or visits implemented by precise medical division inside each hospital), treatments characterized by high level of emergency (pathologies that requires to be immediately treated and which often involve emergency departments). Buttons and interface controls give the user the possibility of managing some hospital features.
- *Paragraph 4.3* presents two typologies of doctors: specialists and ERs. These agents are affiliated to a precise hospital and identify a precise health and care service provided by the hospital itself. Specialists deals with specialist visits or treatments while ERs refer to the emergency department of the hospital. We have assigned some variables and network measures to these agents in order to characterize the emergent networks. Again, the user can change some features related to these doctors, for example, selecting the probability that a hospital contains an emergency department.
- Following the same description pattern, *paragraph 4.4* presents the private clinics of our model, the so-called "professionals". These agents are private structures providing various types of medical services, selectable by the user. They represent the private provision of health and care services in the model. If the "public supply" is characterized by null costs and positive waiting lists, the private structures present positive costs and no queues (this is an assumption we have introduced in the model). As for the "public" structures, the user may choose the probability according to which private structures provide blood taking tests

and blood analysis laboratories. Furthermore, the user may select the total amount of "professionals" for each area of the district.

- *Paragraph 4.5* portraits the family doctor agent set. The family doctor is the rational decision maker of our model and decide in which structure his patients have to be treated, assuming his perfect informational knowledge.
- *Paragraph 4.6* deals with the patient population of the model. Patient proportions are directly characterized following real population data of the district of Turin. However, the main patient feature deals with the identification of "recipes" that identify health demand events in the course of the patient life. We have modeled the entire health lifetime of each individual. The paragraph presents some literature notes about the meaning of the "recipes" in ABMs. The user, by means of several sliders, may manage the patients related probabilities of incurring in illnesses for each age category (patients ages are grouped into five classes of ages).
- *Paragraph 4.7* shows the overall simulation environment representation with all the agents included.
- *Paragraph 4.8* highlights the behavioral rules followed by patients and family doctors. We have modeled a decision formula implemented by family doctors which is based on a patient preferences evaluation. Moreover, the characterization of patients preferences is described.
- *Paragraph 4.9* shows the link identification procedures according to the various agents connected by these links. The typologies of links are divided according to the agents involved: checkup visits to family doctors, specialist visits, blood tests, emergency department admissions.
- *Paragraph 4.10* reports further procedures that serve as controls and simplifications for the user that works with the model.
- *Paragraph 4.11* emphasizes the procedures connected with network identification and measures.
- Finally, *paragraph 4.12* presents a set of experiments regarding the blood tests laboratory network in the district of Turin. By changing different set of parameters, the aim of the paragraph is to present the experimental potential that the model may provide in healthcare applications.

SECTION 1

COMPLEXITY, SIMULATION AND HEALTHCARE

Understanding and exploring useful concepts for management and policy decisions in the healthcare field

Nowadays, healthcare systems all over the world are becoming one of the central questions that governments and policy makers have to deal with. An interesting technical report made by IBM (2008) refers to the main challenges that healthcare systems will face with in 2015, analyzing possible solutions and providing new methodologies and approaches to the various problems characterizing the field. These few lines may show clearly the attempt of the IBM technical report (2008):

> Healthcare providers can work collaboratively to achieve new milestones in defining, measuring and delivering value, activating responsible citizens and developing new models for promoting health and delivering care, even within growing resource constraints and other challenges. This is important more than ever before as the paths of healthcare systems in many countries are increasingly unsustainable. Moreover, we envision this will lead to a variety of strategic decisions affecting service delivery models and underlying competencies. These decisions could impact the organization's leadership, culture, business models, organizational structures, skills, processes and technologies.

The lines presented above focus the attention on the modeling activity which is in turn at the basis of this work, providing the central idea that has driven us towards the realization of our model. This section aims to explain the main difference between simple, complex and complicated systems, focusing on the role of complexity in healthcare systems and providing some cases that can be useful to develop an analysis on problems, strategies and methods concerning healthcare. Moreover, we want to stress the link that goes from complexity to healthcare and then to simulation methods. The evidence that comes from this observation is that healthcare is a complex system and has to be studied using specific tools that provide a correct specification for complex problems. Here comes the use of simulation techniques to investigate complexity and, as a consequence, they constitute a potential tool in the healthcare system in order to develop strategies, policy decisions and process improvements. Firstly, a deep part is dedicated to the examination of what complexity is in general terms. The overall concept of complexity is deeply analyzed also with respect to other important applications, making reference to the work of Dodder and Dare (2000) Secondly, referring to Sholom Glouberman and Brenda Zimmerman (2002) that presents a case regarding the Canadian healthcare system, we analyze the connection between complexity and healthcare. Furthermore, it is discussed the use of simulation as a instrument able to overcome complex problems with particular attention on the healthcare field. This is done by examining each potential that simulation methods can provide to healthcare.

1.1 COMPLEXITY AND COMPLEX ADAPTIVE SYSTEMS

Understanding the difference between simple, complex and complicated systems is crucial when we deal with management decisions or policy decisions. It is useful to remark immediately it:

- In **simple problems** the main object that characterizes them is the recipe. A simple problem can be described in the same way as cooking: an activity which requires to follow a series of precise steps in order to reach a precise result. The recipe is the essential feature that assures easy replication and standardization of results every time.
- In **complicated problems**, formulae or recipes are critical and necessary to solve them but are often not sufficient. So, these problems contain subsets of simple problems but can be not easily transposed into them. Quoting the example adopted by Glouberman and Zimmerman (2002), a complicated problem is like " sending a rocket on the moon" where not only recipes and formulae are needed, but high levels of expertise in a variety of fields are required. If the aim is reached and the rocket is sent, then another rocket in another mission can be sent with an higher degree of success because rockets are similar to each other.
- **Complex problems** are different in the sense that there is no assurance of success in future replications of the strategies adopted before. In particular we have to consider **complex adaptive systems** (hereafter CAS)**:** complex means that they are diverse and made up of multiple interconnected elements and adaptive in that they have the capacity to change and learn from experience. There are various examples of these systems such as the stock market, ant colonies, human brain, political parties and so on. The following table refers to the Glouberman and Zimmerman work (2002).

Table 1
Simple, Complicated and Complex Problems

Following a Recipe	Sending a Rocket to the Moon	Raising a Child
The recipe is essential	Formulae are critical and necessary	Formulae have a limited application
Recipes are tested to assure easy replication	Sending one rocket increases assurance that the next will be OK	Raising one child provides experience but no assurance of success with the next
No particular expertise is required. But cooking expertise increases success rate	High levels of expertise in a variety of fields are necessary for success	Expertise can contribute but is neither necessary nor sufficient to assure success
Recipes produce standardized products	Rockets are similar in critical ways	Every child is unique and must be understood as an individual
The best recipes give good results every time	There is a high degree of certainty of outcome	Uncertainty of outcome remains
Optimistic approach to problem possible	Optimistic approach to problem possible	Optimistic approach to problem possible

Complexity science and complex systems modeling are terms which have grubbed the public attention since the rise to prominence of the Santa Fe Institute in the 1990s. Like chaos theory, complexity science has grown in popularity because of its applicability to prominent topics like social networks. A clear definition of what a system is must be presented: a system is an object which consist of a number of inter-related and interconnected component parts, and whose overall behavior and properties cannot be deterministically predicted merely by aggregating or averaging all the individual constituent parts (Brailsford et al. 2011). As a consequence one can be interested in studying the "emergent" behavior or properties exhibited by the system as a whole and not by any individual component part. Complexity science can address various fields: neuroscience, biology, medicine, engineering, networks and social sciences. In particular, human and social systems are clearly highly complex and, nevertheless, they exhibit emergent behavior.

One important emphasis with CAS is on crossing of traditional disciplinary boundaries. However, there are a series of commonly repeated characteristics noted in the literature that clearly define CAS (Dodder and Dare, 2000):

- CAS are balanced between order and anarchy, at the edge of chaos. Waldrop (1992) reports: "…frozen systems can always do better by loosening up a bit, and turbulent systems can always do better by getting themselves a little more organized. So if a system isn't on the edge of chaos already, you'd expect learning and evolution to push it in that direction…to make the edge of chaos stable, the natural place for complex, adaptive systems to be."
- CAS are made up of networks of many agents gathering information, learning and acting in parallel in an environment produced by the interactions of these agents.
- These systems co-evolve with their environment.
- Order is emergent, not pre-determined. One can talk about "perpetual novelty" in that CAS are always unfolding and in transition over time.
- It is possible to identify CAS in many levels of organization: agents at one level are the building blocks for agents at the next level. For example cells, which make up organisms, which in turn make up an ecosystem.
- Finally, CAS are unpredictable. Uncertainty is the main feature of CAS.

1.2 BACKGROUND OF CAS

CAS are usually linked with the Santa Fe Institute, which efforts to conceptualize a common theoretical framework for complexity were built upon past works in different field of application. However, long before the Santa Fe Institute, Belgian laureate Ilya Prigogine was exploring questions about sources of order and structure in the world. Waldrop (1992) refers to Prigogine's studies about self-organizing structures in nature. The outcome of such studies was that systems are able to spontaneously organize themselves into a series of complex structures. This work represent some of the early thinking on self-organization of systems. Anyway, the essence of the CAS studies comes from the Santa Fe Institute which remains a powerful force in developing and promoting this body of thinking.

In addition to the Santa Fe Institute, the New England Complex Systems Institute (NECSI) is another organization that presents a strong intellectual commitment in studying complexity and CAS.

1.3 APPLICATIONS IN ECONOMICS AND POLITICAL SCIENCE

Dealing with policy decisions and managerial problems that can occur in healthcare systems is the focus of this work. Despite this fact, one has to take into account that the healthcare field can be linked closely with economics and political science. Firstly, one may treat health as a "public good", with all the problems associated with its correct provisions which refer to public economics for example. So, healthcare is strongly associated with social sciences.
Economists have played an important role in bringing together many of the ideas that would come to be defined as Complexity (Dodder and Dare, 2000). The central question to be investigated refers to economic systems as evolving complex ones, characterized by six "difficult" features identified by the economist Brian Arthur:

- Dispersed interactions
- No global controller
- Cross-cutting hierarchical organization
- Continual adaptation
- Perpetual novelty
- Out-of-equilibrium dynamics

The complexity perspective and economic modeling develop further researches involving concepts such as positive feedback, lock-in and the impact of historical "accident" when path dependence is an important factor in the subsequent development of economic systems. Exploring complexity in economic terms means also recognizing that there is a difference between the individual economic agents and the aggregate economic system that emerges from their interactions. In addition to this, the interactions of these heterogeneous agents lead them to self-organize into network-based structures that may never settle into equilibrium (Dodder and Dare, 2000). This approach is mainly due to the work of the Santa Fe Institute and represents a profound break with many of the assumptions of the standard neoclassical paradigm by moving away from an equilibrium-based view of the economy, which tended to assume away the six features described above. The new paradigm that takes place consider the economy as an adaptive nonlinear network, which needs new tools fro theoretical and empirical modeling. A fundamental issue in this new approach is the multidisciplinary interaction between economics and other sciences such as nonlinear dynamics, statistical mechanics and neural nets (concepts of network analysis will be discussed in details later since they are one of the fundamentals of this work).
Other social sciences, particularly political science, are influenced by the change in paradigm of economic systems. The idea of complexity undermines the traditional paradigm of rational actors, focusing on the evolution of behavior and strategies that are often characterized by limited local information, with some difficulties that do not allow for foresight and optimization of strategies. Dodder and Dare (2000) report that much of complexity-related work in the political and social sciences has employed the tools of agent-based models and modeling of "artificial societies" to probe underlying behaviors and motivations and derive results as to their emergent properties (agent-based modeling will be deeply analyzed later in which it is the main tool adopted to simulate the healthcare environment presented in this work). The political scientist, Robert Axelrod, is one of the earlier users of computer simulation tools for social science investigations. He applied agent-

based models to game theory, trying to model the complex and unanticipated behavior that can emerge from simple iterated games such as the Prisoner's Dilemma.

Joshua Epstein and Robert Axtell (1996) characterize complex systems as open and highly interconnected:

> The broad aim of this research is to begin the development of a more unified social science, one that embeds evolutionary processes in a computational environment…Artificial society-type models may change the way we think about explanation in the social sciences.

The two authors explore the so-called "bottom-up or generative social science". Given this way of thinking, simulation techniques can provide a sort of "social science laboratory" (Dodder and Dare, 2000) that allows to move beyond the problems that arise from models based on assumptions of homogeneity and aggregation.

1.4 IDENTIFYING COMPLEX SYSTEMS

So far, the Santa Fe approach has been presented and based upon CAS. In such systems complex and patterned output emerge form simple, fundamental principles, but require many actors and multiple interactions over time to produce the emergent complexity. However, one can identify a huge variety of factors that make a system complex. Dodder and Dare (2000) point out a characterization of a complex system, grouping three different categories:

i. *Static complexity*: it deals with structural aspects of the complexity inside systems. Such concept includes notions of hierarchy, connectivity, detail, intricacy, variety, and levels/strength of interactions. Here, concepts from network analysis can describe static complexity as a pattern of links and nodes. It is also, to a certain extent, context dependent, since the structural complexity would appear much differently on the micro versus macro-level scale, and would change as one re-establishes the scope and boundaries of the system.
ii. *Dynamic complexity*: it deals with ideas of complexity based on behaviors, processes of cause and effect, feedback mechanisms, fluctuations and stability, cycles and time scales. Complex Adaptive Systems are strongly associated with the notion of changes in behavior over time. This is the reason why the literature refers to that phenomenon as "evolving complexity". Moreover, this evolutionary aspect based on such dynamics can result from two elements at the same time: the adaptation of the systems and the adaptation of the individual agents in the system. It is important to stress the fact that a system may evolve without any adaptation by the individual agents.
iii. *Informational complexity*: this is a somewhat abstract notion linked with the issue of measurement of complexity. It can be defined as complexity involved in describing or evaluating a complex system. Surely, this concept "contains", in a sense, static complexity (the intricacy of a network), as well as the dynamic complexity (the complexity of the processes involved in the creation of a system). It is possible to talk about "evaluative complexity" (Dodder and Dare, 2000) which could be a form of information complexity needed to describe and evaluate the function, performance and "success" of a system.

1.5 MEASURING COMPLEXITY

This paragraph concerns the difficult question of measuring complexity and tries to give an answer to the question "how complex is a system?". The issue of measurement is a critical component to advancing the understanding of and ability to work with complex systems as Dodder and Dare (2000) point out. First of all, it defines a common criterion to compare a variety of complex systems in a more accurate way, ranging from the human immune system to the international financial system to a transportation network. Secondly, it can be used to evaluate, to predict, to modify, to control, to design a complex system. Third, measuring complexity would enable one to follow the evolution of complexity in a system over time, in order to establish if the complexity degree follows an increasing or decreasing path.
Different methods in establishing measures for complexity can be found in various field such as Thermodynamics, Information Theory, Statistical Mechanics, Control Theory, Applied Mathematics, and Operations Research. Nevertheless, the approaches developed to measure complexity show two common features (Dodder and Dare, 2000): *knowledge* and *ignorance* of the system. With respect to the ignorance factor, it is associated with the level of entropy of a system and provides a measure of our ignorance about a system. With respect to the knowledge of a system, a crucial element that has to be taken into account for measuring complexity, it can be identified with the information processed or exchanged by the system under study.
Among different techniques, Shannon's information theory uses the quantity of information (knowledge) as an indicator of complexity. Another deeply used measure is the Algorithmic Information Content (AIC), which refers to the minimum amount of information needed to describe the system, as measured by the shortest computer program that can generate that system.

Measuring complexity with a combination of the two measure described above, knowledge and ignorance, reflects the concept of a complex system as inhabiting somewhere in the realm between a deterministic and rule-bound state of order and a random and anarchic state of chaos. However, the two measures are useful to analyze and illuminate some tiny features that characterize complexity. As an example, since AIC approximates the magnitude of complexity as the amount of information, it cannot differentiate complexity and intricacy from pure randomness (Dodder and Dare, 2000). Because of the high degree in creating purely random state, AIC misjudges randomness as complexity. Despite this fact, a random system should actually be considered "simple" because random states are easily built up. Simple systems are also those which are completely deterministic or easily specified.

If one tries to imagine an ideal measure of complexity, he should think about a measure able to combine information required to describe regularities of a system as well as the magnitude of the irregularities. The correct question to be addressed is: what is the combination of deterministic and chaotic behavior that give rise to the complexity of the system?

1.6 THE CONCRETE SIDE OF COMPLEXITY

One can asses that complexity is only an abstract concept. However, the science associated with complexity characterizes also engineering systems in every field of application. First of all, we have to stress the fact that, due to an infinite number of possible initial conditions and "accidental" perturbations along the way that can generate non-linear and often nearly chaotic effects, accurate prediction and control of the outcome and performance of complex systems would be a hard task. Anyway, it may be possible that the real value of modeling complex systems comes less from any predictive properties and more from the ability to provide insights regarding the dynamic and structural characteristics of the systems (Dodder and Dare, 2000). An important evidence of complexity science is characterized by the fact that tools and models allow observations of the system both at the end point and at points where systems undergoes transitions. This work, for example, will present an agent-based model in which the user can observe the initial starting situation, the process of undergoing transition and the end of the simulation. Therefore, complexity may provide insights because it is possible to control critical stages in the process of emergence. Such stages may also be called "lever points" of a system and offer a great utility both to policy and engineering applications.

1.7 FURTHER CONSIDERATIONS ON COMPLEXITY

In order to conclude with the complexity argument, it is possible to come up with a short characterization of some categories that usually drive research activities in this science making references to the Dodder and Dare work (2000):

- *Recognizing Patterns of Complexity*: the main purpose of this activity is to investigate the extent with which one may make comparisons across systems. Moreover, this issue concerns a series of important goals: improving the analytical method for recognizing and describing patterns in complex systems (both in structure and dynamic behavior terms), trying to understand the reason why some networks or systems persist (despite the continual changeover in the components of the system), studying to what extend it is possible to separate a common set of features or properties that are not context dependent.
- *Measuring Complexity*: as described above, the problem of measuring complex systems is also a problem of comparison across different systems. The development of a correct measure of complexity not sensitive to the context is also a major issue in the research activities in this field.
- *Modeling Complexity*: this issue is primary connected with computer-based modeling and its further developments in the future. Secondly, in studying complexity and phenomena such as emergence, an important question is how one can create a model without undertaking the two extremes of reduction (dissecting and studying the parts in isolation) or abstraction (describing the emergent patterns and macro-structures without much of the detail). Surely, a model cannot represent in details the reality, but it has to represent the critical aspects that the research wants to focus on.

It is pointed out many times in this lines the fact that Complexity Theory has embraced a broad range of disciplinary boundaries, especially between the natural and the social sciences, resulting in

an exchange of concepts and methodologies. Indeed, this sense of commonality in the patterns and emergent behavior in complex adaptive systems makes the bridging across disciplines come true. As a consequence, the presence of such common features has generated theories that have led to "universal laws of complexity", although the diversity and constantly evolving nature of complex systems may place a limit to the amount of possible generalizations and laws that can be derived. One must reach for "lessons" that might, with insight and understanding, be learned in one system and applied to another. Complexity does not imply the unification of different sciences, but it implies interactions (Dodder and Dare, 2000) just like a language, a terminology and sets of methods for describing and analyzing complex systems.

To sum up, Complexity Theory and Complex Adaptive Systems provide the science community with understandings of physical and social systems that are an alternative mode of thinking with respect to more linear and simplistic approaches. Computer-based modeling above all represents much of these advancements, in particular the use of agent-based simulations which will be deeply analyzed in this work and which have expanded the set of tools used to explore complex system behaviors. Although modeling complexity can allow researchers to represent the behavior and understand the structure of a system, there are natural limitations that affect the predictive power of these models. As a result, this fact may create some resistances in using such models in more applied settings.

1.8 HEALTHCARE COMPLEXITY

As the main topic under analysis in this work, we focus the attention on the healthcare system which can be treated as a complex one. Although expertise can contribute to the process of decision making or management in valuable ways, they provide neither necessary nor sufficient conditions to assure success. Every patient, for example, in the healthcare system is unique and must be understood as an individual. As a result there is always some uncertainty of the outcome. However, the complexity of the process and the lack of certainty do not have to induce to the fact that dealing with the healthcare system is impossible.
Treating healthcare systems as complicated ones is a failure as Glouberman and Zimmerman have shown with their work on the Medicare system in Canada (2002). On the other hand many dilemmas can be solved if they are treated like complex systems. Making references to this Canadian case it is possible to find some analogies with the Italian healthcare system and with its problems of reorganization, policy and decision making strategies. Dealing with health care is often a matter of ideological lines with polarized solutions such as the British National Health Service which changed its orientation from right to left, from "managed competition" to "collaboration" the day after the political transition. The same can be noted for the United States with the Obamacare plan. Most of these planning strategies are based on rational approaches that do not consider the complexity of the systems under analysis, with significant unintended consequences. Anyway, quoting Glouberman and Zimmerman (2002), the problem can be resumed as follows:

> Although most of the experts and advisors have recognized that the health field and its problems are not simple, they do not exhibit an adequate understanding of the theoretical frames of complex systems and how to intervene in such systems.

Going back to the definition of complexity, we have seen that complex problems may encompass both complicated and simple problems, but they cannot be transformed into either since they present special requirements, unique local conditions, interdependency with some kind of non-linearity, and the adaptation capacity to changing conditions over time. So **uncertainty** is the main characteristic of complex systems. Although it seems reasonable and seductive to bring back complexity to complicated problems, applying models, theories and language for such problems to a complex adaptive system such as the health care one produces misspecifications and ill-equipped investigations.

The technical report written by Glouberman and Zimmerman (2002) insists on the process of reorganization of the Canadian health care system and can be useful to compare it with the Italian one. Usually, talking about provisions of health or reorganization plans leads to the analysis of two polarized provision schemes.
On the one hand, we can consider the English speaking health provision scheme, which is essentially based on the fact that heath is a commodity that can be sold and bought. This is relevant in the United States while in UK the supremacy of the private health system comes from the fact that public health generates waiting lists and opportunity costs, inducing patients to look for a private solution.
On the other hand, there are health provision schemes based on the public supply such as the Canadian Medicare and the Italian system. Here, the main characteristic is that health is essentially a free service and can be defined as an infrastructure for the country. Especially the Canadian Medicare system was considered deeply embedded in the values and culture of Canadians.
As Complex systems, interventions in each of these health provision schemes differ according to social and cultural baggage of each particular country. Nowadays, almost every country must face health care inflation and the sustainability of the then existing systems, with an epidemic of retrenchment and massive restructuring strategies. In this scenario, complexity plays a crucial role and useful instruments to interpret it are needed (simulation models in our case). Several common diseases affect both the Canadian and the Italian health care systems: overcrowded emergency rooms, intolerable waiting lists, crises in cancer care, overworked professionals and hospitals, underpaid and undervalued services provided by nursing and so on.
In a period of recession economic sustainability is the question under analysis, which led governments to swing continuously from opposite strategies.

Glouberman and Zimmerman point out that outcomes of health policy interventions are not the only reason to think that health policy has been based on a weak understanding of the nature of health systems and organizations. A much better indication of this failure is the glaring fact that policymakers in different countries have taken diametrically opposite approaches to solve similar problems.
The table in the next page resumes the differences between complicated systems and complex ones.

Table 4
Theory Cluster

Complicated Systems	Complex Systems
Linear	Non-linear (inputs and outputs not directly correlated)
Noise, tension and fluctuations suppressed	Opportunity seen in tension, noise and fluctuations
Solution as external to system	Solution as part of system
Adaptation is to a static environment	Interaction with the rest of a dynamic environment

Table 5
Causality Cluster

Complicated Systems	Complex Systems
Simple causality	Mutual causality
Designed and intended outcomes	Adaptive and emergent outcomes
Deterministic	Probabilistic
Certainty	Uncertainty
Assumed predictability	Recognized elements of non-predictability
Focus on boxes	Focus on arrows
Structures determine relationships	Structures and relationships are interactive

Table 6
Evidence Cluster

Complicated Systems	Complex Systems
Reductionism/analysis	Holism/synthesis
Averages dominate: outliers irrelevant	Outliers seen as possible key determinants
Classical economics ignores historical evidence because systems always tend towards equilibrium	History contains meaning of change and systems evolve in part based on where they have been
Measures of efficiency, fit and best practice	Functioning of actual relationships and feedback loops (+ve and –ve)

Table 7
Planning Cluster

Complicated Systems	Complex Systems
Convergent thinking	Divergent thinking
Reductive characteristics	Emergent characteristics
Decision procedure as an event	Decision as emergent
Environmental scan	Developing insights into own practice
Big issue needs big change	Butterfly effect – size of change does not determine size of change

As we have already noticed, in the healthcare field, there is often little proof of the direction of causality, uncertainties are ignored and the resulting pictures tend to distort or ignore the picture of health as complex, probabilistic, with many factors interacting not only with the individual but also with each other. So, here comes the need for particular tools that provide some sort of help in understanding complex adaptive systems. Interventions in such systems require careful consideration and planning, but of a different kind than in mechanistic systems: it's more important to understand local conditions and to be aware of the uncertainty and feedback that accompanies any intervention.

To summarize, complex systems can be evaluated and studied applying correct tools that do not transpose their problems into complicated ones. One of these tools can be find in simulation modeling which represent the main source of this work. The next paragraph focuses on the use of simulation in healthcare and its potentials of application.

1.9 SIMULATION MODELING IN COMPLEX HEALTHCARE SYSTEMS

World health organization's estimates in 2008 present a meaningful fact: global healthcare expenditure stepped into the over 5-trillion-dollar economic sector with most of the industrialized countries spending well over 10% of their GDP on healthcare with several discussions put forward by healthcare managers and decision makers. We can define the debate with a simple question: what health?
Healthcare delivery and services are undergoing dramatic changes due to a series of common factors: decreasing state supports, obligatory cost control, growing market competition, and transition to electronic health records (Barjis, 2011).
In order to face with these new challenges, a change in the approach is needed although there are, and will be, resistances due to the risks and uncertainties that characterized the complex healthcare system. As a potential tool that can be useful in dealing with such kind of problems, simulation setting can offer a virtual environment which, as its name reveals, simulates the reality allowing exploration of possible changes, experiencing situations that otherwise will not be possible.

Looking at the complexity topic discussed so far, it is possible to pose such type of problems in terms of simulation modeling. Such complexity is growing exponentially in the healthcare field as Barjis points out, with various services like laboratories being outsourced, multiplication of specialties, and extreme mobility of patients resulting from competition in the free market. Modern hospitals like, for example, the Molinette in Turin, are complex systems of distributed subsystems with intricate healthcare processes, human interactions, and inter-organizational workflows. Looking at the model described later on these pages this complexity will be examined in detail for the metropolitan area of Turin. As matter of exemplification, citizens easily can plan a different healthcare service based on less waiting time prominent quality, or many other factors that lead them beyond their local, regional or even national borders. This work presents a local analysis of the healthcare system concerning the metropolitan area around Turin and consider exactly such types of variables that can induce a patient to undertake one decision instead of another.
This makes healthcare processes more interconnected and complex with the increasing importance of the concept of network that will be discussed on these pages too. Nevertheless, the complexity of healthcare systems makes simulation a potential tool for healthcare analysts.

Furthermore, healthcare simulation ca be extended beyond the traditional role of comparing scenarios or visualizing workflows. Simulation modeling can be incorporated in some processes of monitoring, improving performances and increasing efficiency. In other words, a simulation can be useful not only as an experimental platform, but can be anchored in the running information systems of health organizations such as hospitals, laboratories, diagnostic procedures and so on. This is done to study the behavior of a system in a longitudinal manner for advising adaptations and changes as the system operates and data are collected dynamically (Barjis, 2011).
Integrating simulation models in routine fabric of healthcare delivery can provide a true benefit, treating them as a tool for conducting not only a one-time set of experiments when major changes are planned but running them in parallel to other applications as a routine part of the everyday work environment. As matter of fact, healthcare efficiency becomes an ongoing objective and with the rapidly changing variables of the healthcare system (finance, policies, markets, technologies and so on) it is becoming more of a moving target that needs to be periodically redefined.

1.10 HEALTHCARE SIMULATION PURPOSE

It is possible to classify the broad potential of simulation in healthcare with few directions around different disciplines or sub-disciplines. Generally, one can identify four major fields of application of healthcare simulations (Barjis, 2011):

- *Clinical Simulation*: simulation is mainly used to study, analyze and replicate the behavior of certain diseases including biological processes in human body. So, this type of simulation addresses directly to doctors, surgeons and the personnel directly involved in medical operations. For that reason it is often referred to as medical simulation.
- *Operational Simulation*: simulation is mainly used to study for capturing, analyzing and studying healthcare operations, service delivery, scheduling, healthcare business processes and patient flows.
- *Managerial Simulation*: simulation is mainly used as a tool for managerial purposes, decision making, policy implementation and strategic planning.
- *Educational Simulation*: simulation is used for training and educational purposes, where virtual environments and virtual and physical objects are extensively used to augment and enrich simulation experiment.

In this work the analysis is centered around managerial and operational directions of simulation in that the two are closely interrelated and address economics science. These two are the core components for healthcare process management (Barjis, 2011). For each direction exposed above, simulation can be used for several activities: analysis, design, learning, training, research and communication purposes.

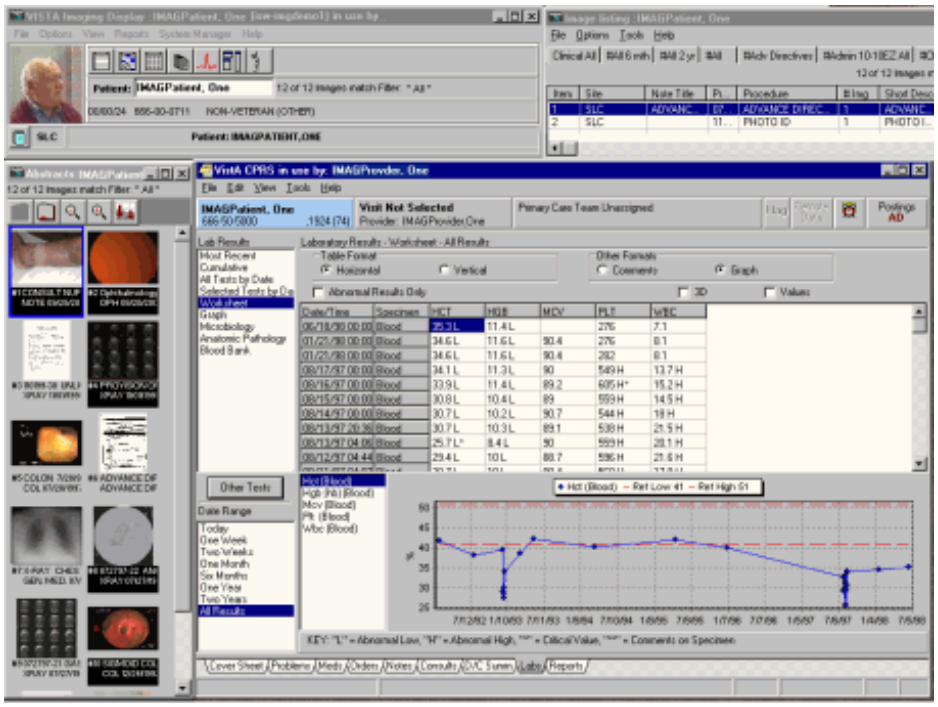
Another classification of healthcare simulation models can be found in Brailsford (2007). Here, the author classifies models in three groups:

- Models of the human body (the so called “disease models”) that include biological processes in healthy individuals.
- Models that examine a precise healthcare unit level such as the clinic level, the department level or the hospital level.
- Models for strategic purposes

1.11 HEALTHCARE SIMULATION: A POWERFUL TOOL

There are few aspects for which healthcare simulation can be used as an effective tool or method, trying to convey some ideas or insights that could improve efficiency in healthcare systems at various levels.

- *IT Alignment*: nowadays the development of national electronic health record (HER) systems is increased and improved, creating unprecedented opportunity for healthcare systems around the transition to electronic health practice (eHealth). An electronic health record (EHR) or electronic medical record (EMR), is a systematic collection of electronic health information about an individual patient or population. This collection is in digital format and is theoretically capable of being shared across different healthcare settings by means, in some cases, of network-connected, enterprise-wide information systems and other information networks or exchanges. The figure below refers to a sample view of an health record based on images:



EHRs may include different types of data for example demographics, medical history, medication, laboratory tests results, personal statistics like age and weight and so on. The system is designed to represent data that accurately captures the state of the patient at all times without the need to track down the patient's previous medical record volume and to assist in ensuring accurate, appropriate and legible data.

However, the path for harvesting the benefits of eHealth lies through the development of innovative healthcare processes and through the improvement of existing practices to cope with the changes resulting from the adoption of the new technology. Nevertheless, simulation application in redesigning existing healthcare business processes and IT alignment is a critical scientific potential to explore (Barjis, 2011).

- *Decision support*: Healthcare decision makers need reliable tools to achieve various goals: support them in decision making for adapting policies to help cutting costs or reducing waiting time, provide visualization which allows them to verify innovative ideas before their implementation. Simulation models should facilitate an evidence-based and informed decision making environment. Especially with transparency into their structure and underlying variables, which can be easily understood and trusted by decision makers, simulations are helpful in decision support, communication and discussion of ideas, policy decisions and analysis of scenarios.
- *Training & Quality*: Improving training sessions of clinicians means improving the quality of services, reducing errors and promoting the adoption of best practices. Surely, not only clinicians but also administrators and managers of the healthcare staff can benefit from simulation with a significant impact on costs of training and on the time consuming of such an activity. In fact, it sometimes happens that some commitments and dedications are not embraced because of time constraints due to training sessions. Simulation can enhance and improve clinicians' expertise, increasing the possibility to work out with new procedures and processes, and can prevent errors that are caused by the lack of training and hands-on experience.
- *Complexity*: the utility of simulation models in healthcare in order to overcome and analyze complex problems has already been depicted above. The healthcare system is characterized by complex macroscopic collections of relatively similar and partially connected micro-structures, formed in order to adapt to the changing environment. Each healthcare system at every kind of level can produce dynamic networks of interactions and individuals or collective behaviors mutate and self-organize corresponding to the change-initiating micro-event or collection of events. Therefore, simulation can be used to model such a complexity trying to reproduce the system of interactions among agents (we will present agent-based models and networks later in this work).
- *Process improvement*: one of the most pursued goals in the healthcare field is the reduction of patient waiting time. The waiting time for the service date or the waiting time while receiving services are important indicators of efficiency. Higher waiting times affect patient perception of the quality of a service or a structure and can induce him to choose other healthcare deliveries (for example going private instead of going in public structures), require more spaces (waiting areas) and cause many no-shows and cancellations. Waiting time and quality are closely associated and will be deeply discussed in the presentation of the model centered around the healthcare system in the metropolitan area of Turin.

1.12 HEALTHCARE SIMULATION CHALLENGES

The debate on the use of simulation models in healthcare is always opened by new arguments and potential challenges that these methodologies of analysis can offer in each field of application. Insisting on the healthcare sphere we can quote Barjis (2011) on the presentation of some possible challenges that healthcare simulation can face with.

Theoretical Challenges:

Starting from the fact that healthcare systems are complex as described above, it seems obvious that they are made by a variety of different disciplines in every field. Such multi-disciplinary characteristic is become one of the major breakthrough that healthcare simulation faces with. Barjis (2011) presents the so called "**Multi-Paradigm Approach**" as solution tools and theoretical frameworks capable of dealing with various disciplines, allowing multi-level abstraction for the targeted domain and multi-perspective view of the domain problem. Healthcare simulation has to look at multi-methods (for formal and informal representation), multi-paradigms (discrete event simulation, continuous paradigm and agent based simulation models that we will analyze deeply across each section of this work) and multi-disciplines (organization, information, technology, policy and so on). Although some researchers emphasize the multiplicity of theories and paradigms, the current simulation usage is almost single-method, single-paradigm and single-discipline minded. As an example, Fontana and Terna (2014) refers to the benefits of the cross-fertilization of network analysis and agent-based modeling. Nowadays, the attempt at applying these two methods jointly are rare, although the combination of them can offer a huge contribute in the studies regarding complexity-based policies.

As an example of cooperation and integration across different disciplines we can make references to a project in UK called the Care Life Cycle project (CLC 2010), a five year program at the University of Southampton. The project is concerned with both complexity science and traditional methods to issues of supply and demand for health and social care in a changing and ageing society (Brailsford et al. 2011). The team involved in such work cover a wide range of disciplines: agent-based modeling (complexity science), demography, gerontology, operations research and social statistic. Like in many other countries, Italy above all, UK's population is ageing. Of course, older people are the major users of health and social care services and, as a consequence, population ageing is affecting the supply of health and social care professionals as the health workforce grows, diversifies and ages too. This set of phenomena characterizes a major challenge that is critical to the UK's prosperity and quality of life.

Surely, population ageing is a complex set of issues influencing both the supply of and the demand for health and social care. First of all, demand is not simply a function of age but also of need (Brailsford et al. 2011), which is also influenced by a variety of different factors such as changes in the profile of disability and disease, new technologies, changes in levels of income and wealth. On the other hand, the supply of formal workforces is determined by both demographic trends and economic factors, including above all the level of wages relative to other sectors, the policy environment on education, training places and workplace retention.

The aim of this British project is to bridge the gap between different disciplines and to develop a suite of models which provide insight at several levels into the interactions between the various parts of complex systems like the health and social care ones (Brailsford et al. 2011). The project is an example of integration among different disciplines and gives some evidence to the fact that

simulation methods can be useful to examine complex problems. Quoting the paper written by Brailsford et al. (2011):

> We are committed to dealing with models on multiple scales and levels of resolution because we believe that this is the way science works: the identification of intermediate-level explanatory structures is what makes a real complex system intelligible to policy-makers and to other scientists. We see the project as providing an environment in which fledging models can be compared, contrasted, and integrated. Tensions between models are informative but, ultimately, unsuccessful or inconsistent models will be discarded; effective ones will be retained, further developed, and used to cross-validate the inputs or outputs of other models pitched at different levels of detail. One primary contribution to complexity science tools and techniques will therefore be in the area of model integration. Here we can make progress on the urgent question of how models using complexity science techniques (e.g., agent-based modeling, cellular automata, etc.) can best be related to and integrated with each other, and with results from empirical work, traditional statistical models, and more established modeling techniques such as game theory, discrete-event simulation and system dynamics.

User acceptance challenge:

However, achieving integrated models is only a part of the problem. The main open challenge is to develop and encourage much more detailed methods of carrying this science forward to inform policy. Yet, taking the CLC example as a reference point, the CLC team is committed to work ing with policy-makers and care planners/providers in order to build models that are suitable for the real world. Nevertheless, in order to make this attempt true, engagement will occur throughout these projects with both local and national health and social care organizations (Brailsford et al. 2011).
Although it seems to be verified the fact that healthcare industry is more prepared and ready to embrace simulation with all its potentials in order to improve operational and management processes, simulation is still a highly technical and sophisticated tool for common user comprehension (Barjis, 2011). This is another element that leads to user resistances which represent a major barrier to a successful simulation implementation in healthcare. It has to be noted that simulation, especially detailed one, requires tremendous effort and time requiring theoretical breakthrough. Anyway, while simulation tools can be improved through innovative approaches such as different libraries, reuse of models, rich graphical interactive development environments, the lack of acceptance by users is still an uncovered field in details by researchers.

Application Challenges

Following the work of Barjis (2011), we can enumerate four major challenges that simulation has to face with in healthcare implementation.

1. *Data Collection*:

Input data are extremely important to achieve a good simulation model. Yet, in healthcare field we assist to a lack of sufficient input data for simulation models which then deliver approximate results. Data collection, hence, is a major challenge because historic data may not be available in a useful format or data collection should require too time to spend on. It is also hardly sustainable to talk with healthcare professionals because of their busy schedules. The input data have to be real and complete (not approximate), based on ongoing operation of the system (Barjis, 2011). As an example, if some hospitals may have agile or dynamic staffing, a useful role that a real time data based simulation can undertake is the prediction of nursing and staffing on daily basis, allocation of nurses between hospital and homecare operations, and many other possible applications which might be developed using a simulation model based on accurate and real data.

If one tries to imagine a kind of ideal data collection, he might think about the integration of simulation models with the organization information system which supports the daily operation. Other applications such as appointment scheduling or operating room reservation create new data which in turn are automatically fed into the simulation models. Such mechanism of inclusion between simulation models and IS applications can prevent possible misspecifications or strong assumptions in the models, which derive most of the times from lack of data support or limited data range. Moreover, such mechanism may put simulations in a continuous improvement process, instead of being used just for a one-time endeavor. For example, scheduling activities, which imply utilization of resources, will have huge impacts on costs of operation and quality of delivered services (Barjis, 2011).

Nowadays, input data are very simplified and, as a consequence, simulation results usually provide insights in terms of general forecasting and planning rather than daily decision making. In order to achieve efficiency in terms of costs and marginal profits, healthcare systems must support data on daily basis.

2. *Healthcare Processes*:

It has been already described the complexity of organizational and workflow streams in healthcare systems. One may think about hospitals such as the Molinette in Turin which has a large number of interacting units such as specialized and acute units, third-party facilities, external labs, inter-hospital transfers. In such a confusion, the complex collaboration and interaction contribute to a complex inter-organizational workflow, building also complex business models. One goal that simulation wants to achieve consists in capturing these complexities of inter-organizational flows in a systematic and manageable manner. A fundamental issue, models have to be an easy means of communication and understanding across different stakeholders, including those who do not own technical knowledge.

3. *Verification and Validation*:

Here comes the "real devil" of simulation according to Barjis (2011). Making any decision or forecast based on model outcomes without a correct verification and validation is extremely dangerous and risky. If, on the one hand, model-verification is a relatively easy task to satisfy correctly using innovative modeling approaches, the validation, on the other hand, seems to be a serious problem. Indeed, the development of a valid simulation model, the design of valid experiments based on the model, and the attempt to maintain a rigorous analysis of the experiment results represent an open challenge for researchers.

4. *Conceptual Modeling*:

Starting from the fact that simulation modeling is based on the understanding of a reality, such a reality is depicted in conceptual models that work as blueprints for the development of the simulation models and for their validations in the sense that the conceptual model is the benchmark used for comparisons between the simulated model and the conceptual one. So far, as Barjis (2011) points out, research on healthcare conceptual modeling has been paid very little attention. Despite of this, conceptual models are the basis for the success of simulation in healthcare.

1.13 CHOOSING THE MODELING APPROACH

Searching the literature concerning simulations in healthcare, one can find a variety of different solutions. The literature suggests six types of simulations that usually occur in the healthcare field (Kanagarajah et al. 2006) and that can be associated with the other classifications reported above:

- *Systems*: This typology of simulations deals with strategies and policy studies, generally within organizations, at the regional or metropolitan area levels to study impact on organizational levels. The model presented in this work is based on such type of simulation.
- *Health Systems*: The focus is centered around strategy and policy studies at regional or national level in order to develop new policies.
- *Clinical*: This type of simulations is associated with models regarding patient issues and, generally, is adopted by medical practitioners.
- *Delivery*: Typically, these tactically focused studies are focused on a single facility or a department within a unit, emphasizing patient flow characteristics.
- *Prevention*: This typology refers to all the simulations which focus preventions of illnesses, diseases or even incidents, with a deep attention on prevention mechanisms and strategies generally involved in some type of clinical research.
- *Epidemiology*: Developed only in the medical field, such studies refer to spreads of illnesses, diseases or even physiological understanding of an illness or disease.

Despite the classifications reported in these pages, a particular attention must be put in formulating assumptions that will present a model as realistic as possible. Surely, as Kanagarajah et al. (2006) point out, if these assumptions do not hold true, then all the models that are generated on their basis may provide unrealistic or distorted answers. Hence, the implications of this situation can be resumed in three cases:

- The developed simulation model is very specific to particular situations
- Going beyond the modeling assumptions leads to unrealistic results
- The time, money and resources invested in are centered around a specific purpose

Exploring simulation models developed in the healthcare field, one may identify a huge utilization of Discrete Event Simulation (DES) and System Dynamics (SD, explained later on these pages). DES uses patient flow models which in turn require huge details and data accuracy. On the other hand, SD models, dealing with aggregates, do not consider patient flows but consider data referring to patient classes.

The simulation strategy developed in our model is characterized by the use of an agent-based approach, which represents an important decision support tool to deal with internal inefficiencies within the operational-level of health care (Kanagarajah et al. 2006). In addition to this, agent-based modeling can support greater understanding of system-wide factors beyond the immediate control of the operational layers.

SECTION 2

MODELING HEALTHCARE SYSTEMS: AGENT-BASED STRATEGY.

The usage of agent-based simulation techniques in healthcare systems

This section aims at explaining the core tool adopted in our work: agent-based modeling. Starting from a characterization of the modeling activity in order to capture the fundamental issues of modeling, the section passes through the identification and classification of agent-based modeling in each aspect, paying particular attention to the healthcare sphere which represents the complex system under analysis in our model. Moreover, a case concerning the development of an Emergency Department simulation using agent-based is presented, in order to give some insights and to provide some ideas on how an agent-based model in healthcare works and is created. The explanation concerning agent-based modeling misses voluntarily the part connected with networks in that it will be the central topic of the section dedicated to the network analysis.

2.1 WHY MODEL?

It could not be possible to start a digression about agent-based simulations, without considering what is a model and what is its main purpose. There are usually several misconceptions about the concept of modeling and, above all, there is the false common thought that the main goal of a model is always prediction. On the contrary, one can identify two main purposes of modeling: explanation and prediction.
Macal and North (2010) say that many people come to learn about agent-based modeling and simulations with the serious intent of building models, but without any previous of knowledge or experience with modeling. Central issues of modeling must be clarified: how to go about modeling, where to begin the process, what models mean. Sometimes people do not have a clear idea of the problem they are trying to solve or the questions they are trying to answer (usually covered in model requirements). These are typical side-effects in ABM and, in order to introduce this modeling technique, some notes about modeling activity must be clarified.
As a sarcastic way of presenting modeling activity, we report a quotation from Joshua M. Epstein (2008):

> The first question that arises frequently, sometimes innocently and sometimes not, is simply, “Why model?”. Imagine a rhetorical (non-innocent) inquisitor, my favorite retort is, “You are a modeler”. Anyone who ventures a projection, or images how a social dynamic, an epidemic, war or migration, would unfold is running some model. But typically, it is an implicit model in which the assumptions are hidden, their internal consistency is untested, their logical consequences are unknown, and their relation to data is unknown. But, when you close your eyes and imagine an epidemic spreading, or any other social dynamic, you are running some model or other. It is just an implicit model that you haven’t written down.

Another recurrent challenge is also model validation as we have already pointed out in this work. Following Epstein's way of thinking the choice is not whether to build models but whether to build explicit ones. In *explicit* models, assumptions are deeply explained and formulated, in order to give the possibility of a better understanding and investigation of what they entail. On such assumptions something happens while altering them produces some changes in the results. Writing explicit models let others replicate with different results. Here comes one of the advantages of modeling: the comparison across different studies and across different disciplines. For example, one may calibrate a model on historical data if they are available and then can test against current data. Moreover, one can extend a model incorporating other domains in a rigorous way.

Another point in favor of explicit models is the feasibility of sensitivity analysis. Indeed, one can slide a huge range of parameters in order to present a variety of possible scenarios as well as to identify the most salient uncertainties, regions of robustness, and important thresholds. One thing must be clear from the beginning: in the policy sphere models do not obviate the need for judgment (J.M. Epstein, 2008). Models can discipline the dialogue about opinions and make unavoidable judgments more considered.

Regarding the prediction issue, in the very moment that a model is posed, prediction is assumed to be the main goal. Surely, a prediction might be a goal, and it might be well feasible, particularly if one admits statistical prediction in which stationary distributions show regularities on interest (J.M. Epstein, 2008).

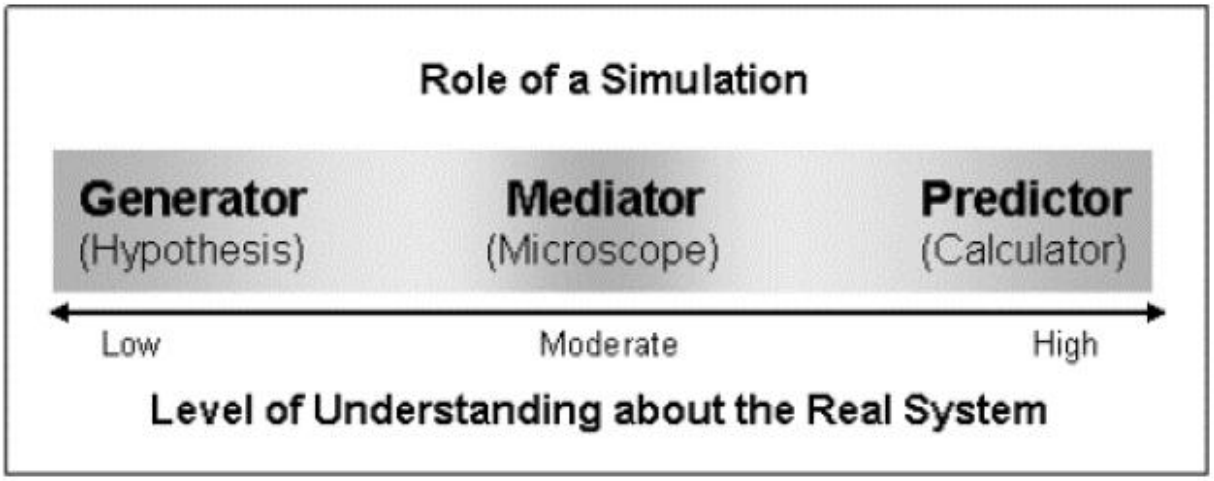
However, prediction is not the only purpose of a model like Epstein points out (2008). It is possible to enumerate a series of modeling goals other than prediction:

1. *Explain*: It is the other fundamental issue of every model. As an example, Electrostatics explains lighting, but one cannot predict when or where the next bolt will strike. Epstein develops an approach called "generative" explanation for the social sciences, according to which macroscopic explananda (large scale regularities such as wealth distributions, spatial settlement patterns, or epidemic dynamics) emerge in populations of heterogeneous software individuals (agents) interacting locally under behavioral rules. This is a clear example of agent-based modeling in social sciences that we deeply analyze in this section.
2. *Guide data collection*: As Epstein points out (2008), a theory can be formulated after the observation of data (a clear example is provided by social sciences in general where the researcher first collects data and then runs regressions on it), but in other sciences, theory often precedes data collection (think about the General relativity theory which predicts the deflection of light by gravity later confirmed by experiments). A model can be useful to identify correct data that have to be collected.
3. *Illuminate core dynamics*: The main feature of a good model is that it is fruitfully wrong. Indeed, a model illuminates abstractions capturing qualitative behaviors of overarching interest. All models are idealizations (J.M. Epstein, 2008) and the main point is whether the model offers a fertile idealization.
4. *Suggest dynamical analogies*: we have already insisted on the fact that a variety of seemingly unrelated process can instead be represented with identical models (the same underlying formalism). As an example one can associate the behavior of a monopolistic firm of a maximum system with an entropy-maximizing thermodynamic system because temperature and entropy show the same relationship as wage and labor or land rent and acres of land. In other words, analogies across different disciplines can be thought as the unifying power of models.
5. *Discover new questions:* models can help to discover new questions and huge advances in each field.

6. *Promote a scientific habit of mind*: Epstein insists on a contribution that modeling activities provide to the scientific community, which can be addressed to as the capability of enforcing a scientific habit of mind (also called "militant ignorance"). With this definition the author wants to stress the fact that science is about uncertainty, contingency, processes of revision and falsifiable in principle. Science is not based on authority but on evidence and modeling enforces such sense of doubting activity.
7. *Bound outcomes to plausible ranges*
8. *Illuminate core uncertainties*
9. *Offer crisis options in near-real time*
10. *Demonstrate tradeoffs / suggest efficiencies*
11. *Challenge the robustness of prevailing theories through perturbations*
12. *Expose prevailing wisdom as incompatible with available data*
13. *Train practitioners*
14. *Discipline the policy dialogue*
15. *Educate the general public*
16. *Reveal the apparently simple (complex) to be complex (simple)*

2.2 AGENT-BASED MODELING: AN OVERVIEW

After having specified what is modeling, it is now possible to begin an argumentation regarding the approach used in this work: agent-based modeling (hereafter ABM). It is a new analytical method in social sciences, but it is quickly becoming very popular because its capability of building individual entities and their interactions in a direct way. The term "agent" is used in different ways in a variety of disciplines such as artificial intelligence, social science, complex science, game theory, but there are several views about what an agent is (Escudero and Pidd, 2011). In general, an agent is defined as an autonomous entity which makes decisions based on a set of rules as we will explain in this section. Broader definitions consider agents as entities that possess skills and resources and that are capable of acting, perceiving and communicating (Escudero and Pidd, 2011), with behaviors driven by a set of tendencies. Nevertheless, there is some kind of agreement in the literature on one definition above all: in complex adaptive systems, agents are the decision making components (Escudero and Pidd, 2011). Thus, an agent is anything that makes choices in a system.
In addition to this, as we will noticed in these pages, an agent must be responsive, proactive and social. As a result, agents are characterized by attributes that make them uniquely identifiable individuals with behaviors, who interact with one another to produce system behaviors.
Operational science has traditionally focused on the process view of the world whereby the process or activity is the central focus of analysis and modeling. The agent-based view of the world is not the traditional approach taken by operational science with its emphasis on process and normative decision making (Macal and North, 2010).
Escudero and Pidd (2011), focusing on agent-based simulations, suggest three different archetypal approaches to simulation modeling, based on the modeler's level of understanding of the system to be simulated. The next figure can be useful in interpreting the variety of roles that a simulation can cover:



The picture shows that when the level of understanding is high, a simulation can be used a s a predictor, and thus, it can work as a machine which produces clear forecasts about the system behaviors under conditions. Instead, when the level of understanding is very low, a simulation model may serve as a generator to support the generation of hypotheses and theories about system behaviors, although not in a precise manner (Escudero and Pidd, 2011). When the level of understanding lays in the middle, a simulation model may serve as a mediator, providing insights into the behaviors of the system without offering a complete representation of these behaviors. Surely, as in many theoretic characterizations, a simulation model can embrace different roles, being used both as a mediator and a predictor, or a mediator and a generator. Escudero and Pidd (2011) define agent-based models as mediators or generators, in that they offer ways to provide insights and to generate hypotheses about system behaviors by representing them as a result of the interaction of individual agents.

With respect to variable-based approaches which use structural equations or system-based approaches which use differential equations, agent-based techniques offer the possibility of modeling individual heterogeneity, making the user able to represent explicitly agents' decision rules, and situating agents in a geographical or another type of space (Gilbert, 2008). Such models provide multiple scales of analysis , the emergence of structures at the macro or societal level from individual action, and various kinds of adaptation and learning. All these possibilities are quite far form being easy if one uses other approaches.

So, agent-based simulation is an abstracted representation of reality involving the elaboration of a model which reproduces the behavior of the system through the recourse of representing the decision making entities of the studied system as agents (Charfeddine and Montreuil, 2008).

It is necessary to provide a clear definition of what agent-based models are: agent-based modeling is a *computational* method that enables a researcher to create, analyze and *experiment* with *models* composed of *agents* that interact within an *environment*.

We treat each characteristic separately in the following digression.

2.3 ABM AS A COMPUTATIONAL METHOD

To begin with, ABM can be associated with the so called computational social science. First of all, such a science involves building models that are computer programs. Let us recall the idea of modeling described above: one creates some kind of simplified representations of "social reality" that express possible ways in which one believes that reality operates. As an example, a regression of econometrics is a model according to which one tries to explain a dependent variable using independent variables and exploring their relationships. Similarly, networks with nodes and edges can be seen as models (in the section dedicated to network analysis we will return on this argument).

Computational models are developed as computer programs in which there are inputs (something like independent variables), and outputs (dependent variables). Gilbert (2008) reports a useful example that can be useful to understand what a computer program is. Starting from the fact that the program itself represents the processes that are thought to exist in the social world, suppose that one wants to theorize the influence of friends in the purchasing choices of consumers. It is possible to start creating a program in which there are individuals (agents) that buy according to their preferences. The interesting evidence that comes from such program is the interconnection between the agents. Indeed, what an agent buys will influence another agent, and conversely what the other buys will influence decisions of his friends and so on. These mutual reinforcements are the fundamental issue of agent-based modeling techniques.

Another advantage that computational methods provide to their users is the precision that is required to formulate them. The user is forced to be precise because a computer program has to be completely and exactly specified in order to run correctly (Gilbert, 2008). Secondly, computer programs are quite easily used to model theories about processes. Computational models may be associated with computer games especially the kind where the player has a virtual world to build (such as The Sims or Age of Empires for example), although contents in the latter case are less centered around social theory but more on graphical potential.

2.4 EXPERIMENTS

While in natural and physical sciences experimentation is the fundamental method that provide the insights, in social sciences doing experiments is impossible or undesirable. Doing experiments means taking an isolated system and applying different treatments to it, observing what happens (Gilbert, 2008). At the end of the experiments, the treated system is compared with the system that has not been treated. The importance of an experiment comes from the fact that one is absolutely sure it is the treatment which causes changes in the system and not something else. Indeed, both the control and the treated systems are isolated from any other potential changes.
Despite of the importance of experiments, in social science is impossible to isolate social systems and treating them separately is dangerous and undesirable from an ethical point of view. Hence, experiments are rarely used by social scientists, but in spite of that, agent-based modeling provides interfaces and simulations that give the user the possibility to treat social systems separately without ethical restrictions or impossibility constraints. In addition to this, experiments can be repeated several times, using a range of parameters or allowing some factors to vary randomly (Gilbert, 2008). Surely, we have to stress the concept of goodness of a model another time, because in social phenomena the modeling activity requires good approximations of a human system. However, it is

hard to establish when a model is good or not and, as a consequence, it is an instrument and people do not have to take it as a panacea.
We can find other reasons underneath the experimentation activity. First of all, cost saving is one of the major reasons of experimenting. It can be extremely costly to analyze phenomena directly. Secondly, an experiment is often the only possible way to obtain results. Analytical techniques of modeling are usually the best strategy because they provide information about how the model will behave given a range of inputs, but often analytical solutions are not possible, giving way to experimental strategies that compare different inputs to see how the model behaves. To conclude we can stress the term "simulation", to identify a model as something that simulate the real world as it might be in a variety of circumstances (Gilbert, 2008).

2.5 MODEL SPECIFICATIONS

We have already introduced what a model is and how it helps users to understand the world. In social sciences modeling activity has a long history that starts before the computers invasion. Precisely, modeling in social sciences begins when statistical methods start to be used in the analysis of large amounts of quantitative data in economics and demography. Again, a model is intended to represent some real, existing phenomena which are addressed to as targets of the model (Gilbert, 2008). One can individuate a bilateral function that a model satisfies: on the one hand it expresses the relationships between the features of the target, and on the other hand it allows to discover things about the target by investigating the model.
As a matter of historical background, one of the earliest models in social science is the Phillips hydraulic model of the economy which is dated in 1950 and is guarded at the Science Museum in London. According to this early model, water flowing through interconnected glass pipes and vessels is used to simulate the circulation of money. Changing the water flow through these glasses simulates the effect of a change in the interest rate.

Anyway, going back to the model characterization, one can identify some differences across models that may be useful in understanding what an agent-based model is. Gilbert (2008) reports three typologies of models:

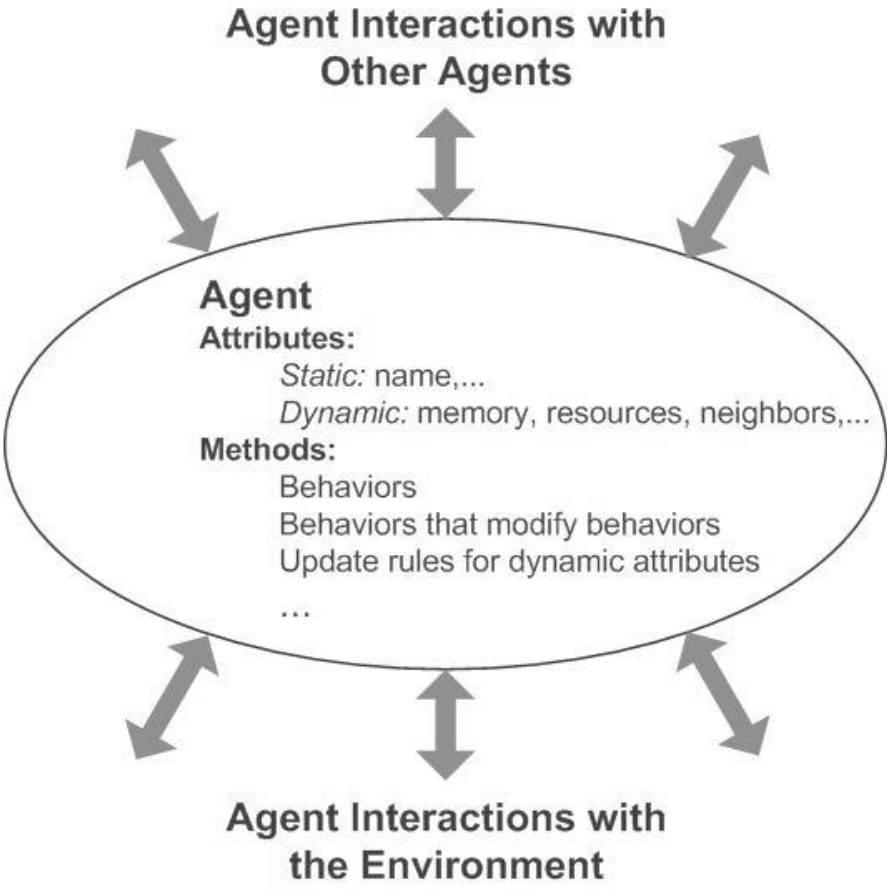
- *Scale Models*: They represent small versions of the target under analysis. Main features of such models are the reduction of size together with the reduction in the level of detail or complexity of the models themselves. Hence, as an example, a scale model for an airplane is, surely, built with the same shape of the target, but it does not contain details such as the electronic control room systems or the engines of the real plane. Also the model of a city or a region can be a scale model in the sense that it does not represent every dimension of the real target but consists of such dimensions that are considered to be critical for the analysis. In deriving conclusions from such models, the user has to take into account the fact that the results have to be rescaled back up to the target dimensions and he has to verify if other not modeled features are affecting the validity of the conclusions.
- *Ideal-type Models*: They are characterized by the exaggeration of some features of the target reality in order to make it simpler to be modeled. As an example, one can assume instantaneous information flows across agents in a stock market model or, as we will seen in our model, one can imagine a healthcare system where hospitals provide only few treatments. The idealization strategy has the important function of removing complicated factors that may show negligible effects on the model itself. If that is true then the model can produce some conclusions about the target.

- *Analogical models:* These models present an analysis of the target based on analogies between some better understood phenomena and the target. Here the attempt is to carry over well-established results from the analogy and apply them to the target. Of course, the analogy has to be adequate and accurate.

Surely, this characterization is not strictly close and compulsory in that a model can be composed by features corresponding to more than one typology described above.
Moreover, there is another category of models that needs to be discussed apart because is something different. It is the category of the so-called *mathematical* or *equation-based* models and it is also used in social science quite often. Such modeling technique is relevant in quantitative sociology as well as in neoclassical macroeconomics models. First of all, the main feature of such models is the relationships between a variety of variables and, unlike the three typologies above, they do not imply any kind of analogy or resemblance between the model and the target (Gilbert, 2008). These models are usually valuated trough the goodness of estimations and the degree to which some data fit the equation. What has to be pointed out is that such equations are not the core interest of such models. The famous Cobb-Douglas production function in economics represents itself a mathematical model that links inputs with output with a form derived from statistical evidence rather than theorizing the behavior of firms. Indeed one has to point out that, although mathematical models are deeply used in any science (social sciences too) in that they clarify relationships across variables, they do not work well in explaining why one variable is related to another (Gilbert, 2008) and in understanding processes and mechanisms.

2.6 THE FUNDAMENTAL ACTOR IN ABM: THE AGENT

Agents represent the crucial subject in the modeling strategy described in these pages. ABM, in fact, consist of agents that interact in an environment. An agent has behaviors, which often are described by simple rules, and interacts with other agents, learning from experience and changing behaviors in order to better suit the environment (Macal and North, 2010). The following picture describes the relationships that occur in an agent-based simulation:



They can be, as Gilbert (2008) reports, both characterized by different computer programs and, more commonly, distinct part of a program, identifying social actors (for example firms, patients, doctors, structures, nations and so on). The user programs them and analyzes them reacting to the computational environment in which they are located. Such an environment is a model representing the "real world" under investigation. By modeling agents individually, the full effects of the diversity that exists among agents with respect to their attributes and behaviors can be observed as they give rise to the dynamic behavior of the system as a whole (Macal and North, 2010).

The fundamental issue characterizing agents is the capability of interacting: agents interact with each other passing information and acting as a result of a learning activity from other agents. So, interconnection is the main content that agents provide to the user and is the trademark of ABM techniques.

Agent-based modeling offers the agent perspective as its central concept, allowing one to come at the modeling problem from the standpoint of the individuals who comprise the system and consider their individual decision-making behaviors and rules. Agent-based modeling allows us to work with models of real, or supposed, agent behaviors, rather than idealized versions and to see what the logical implications are of agent interactions on a large scale (Macal and North, 2010).

Fewer assumptions have to be formulated in terms of aggregating agent behaviors or working with only "representative" agents.
An agent can be defined as an entity, theoretical, virtual or physical, capable of acting on itself and on the environment in which it evolves, and of communicating with other agents. Charfeddine and Montreuil (2008) propose the following properties of an agent:

i. *Autonomy*: an agents operates without human being or other direct interventions and neither the actions it realizes nor its internal state are submitted to any control.
ii. *Reactivity*: an agent perceives its environment and reacts in an appropriate way.
iii. *Pro-activity*: an agent must be able to develop behaviors directed by internal goals
iv. *Sociability*: agents interact with each other using communication languages and common sociability rules.

2.7 AGENTS IN HEALTHCARE ABM

In the healthcare system, as we have pointed out several times, the complexity, the degree of uncertainty of some processes, the involvement of multiple distributed service providers and decision makers as well as the dynamics of a healthcare delivery system give to ABMs large scale of applications and utilizations. Indeed, Charfeddine and Montreuil (2008) say that, due to their principal characteristics such as autonomy, reactivity, pro-activity and sociability, agents seem adapted to consider these problems and help develop efficient tools and decision systems in the healthcare domain. In addition to this, agent-based simulation techniques and multi-agent simulated environments combine these benefits to those of the simulation modeling approach providing researchers, policy makers and managers in healthcare with a powerful tool to pose "what-if" questions as well as testing different scenarios about the implications of their decisions on the care delivery performance.
Charfeddine and Montreuil (2008) identify two types of agents in the healthcare sphere:

- *Operational agents*: they correspond to the patients and the care providers.
- *Managerial agents*: they refer to humans and software managing the modeled healthcare system.

The modeler has first to identify the set of agents in the modeled case. After that, he has to characterize them according to their role and their peculiarities. At the end the modeler has to document the intent and behavior of each agent.
Concerning the operational agents set, we can analyze its two main elements: patients and care providers.

Patients represent the main users of the healthcare system (the so-called "demand side" in economic-science terms) and the core element of the care processes (Charfeddine and Montreuil 2008). If one analyzes contexts in which patients have to pay for health care services, they can also be considered as the clients of the system. With respect to the modeling objectives, patients can be classified according to one or multiple criteria (Charfeddine and Montreuil, 2008):

- *Demographic characteristics*: include variables such as age, gender, profession and so on. These characteristics usually adopted by modelers are those identified as risk factors regarding the considered diseases or patient group. We will show this in our model exposition.

- *Patient type*: this classification may be useful to separate, for example, regular and new patients.
- *Priority within the system*: here the classification addresses to some levels of urgency such as normal, urgent, extreme urgent or whatever similar. The criticality levels are determined by the urgency of medical intervention which depends on clinical factors such as the severity of the pathology, the risk that the pathology induces other, the presence of multiple pathologies and so on.
- *Clinical needs*: this classification may be specified according to Charfeddine and Montreuil (2008) as follow:

    a) Type of service needed (in case of multi-service networks or facilities).
    b) Type of treatment (inpatient or outpatient, chirurgical intervention or/and medication therapy and so on).
    c) Type of examination which can be general or specialized.
    d) Type of pathology (different illnesses or categories of disease such as cancer, diabetes, heart disease, etc).
    e) Need for ancillary and paramedic services: laboratory tests, external professionals, radiologists and so on.
    f) Type of visit: simple visit, follow up, cyclic follow up, specialist visit or family doctor consultation.

- *Patient trajectory characteristics*: as we will see in the example proposed in this section, patients can be classified according to their type of arrival (simple arrival, transfer arrival, ambulance arrival) or the type of departure (back to home, hospitalization, transfer and so on).
- *Patient arrival rules*: these can be due to scheduling (appointments, walk-in), delayed arrivals, no shows, clinical sessions of the arrival time (midday, afternoon, evening), presence of accompanying persons and so on.

This classification can provide a useful benchmark when we will deal with the presentation of our own model concerning the healthcare system in the metropolitan area of Turin.

Concerning **care providers,** the classification in agent terms usually refers to their skills and competencies. Such agents are involved in providing care to patients in the healthcare system and, when they are created, the modeler has to assign them one or more roles within the system according to their function in the organization. Generally, these roles implies responsibilities that the agents are committed to do, although sometimes they work as differentiation elements. Charfeddine and Montreuil (2008) report main categories of care provider agents:

- *Medical professionals*: this category involves physicians, surgeons, anesthetist and so on. In most models, for each patient it may be identified a main medical actor who is responsible for his treatment and who can require the intervention of other medical actors for consultation.
- *Medical assistants*: residents, nurse practitioners, etc.
- *Nursery personnel*
- *Ancillary service providers*: this category includes different specializations such as radiologists, pharmacists, dieticians, physiotherapists, etc.
- *Technicians*: laboratory personnel, special medical machine operators and so on.
- *Admission and discharge personnel*

- *Clinical support personnel*: archive, security, cleaning, transportation, supplying, etc.

With respect to managerial type of agents, we can trace out the main differences between the two main subjects in this category as Charfeddine and Montreuil (2008) refer to:

- *Human managers*: they represent human resources within the healthcare system regarding managerial functions and responsibilities. In this category one may identify healthcare executives and professionals working in various fields concerning economics and finance as well as business administration (accounting, human resources, management, operations, supply and logistic, maintenance, etc).
- *Virtual managers*: this category represents healthcare management software systems, modules and agents that are integrated in the healthcare system, responsible for taking specific sets of decisions and providing support to human managers. Some example may be useful to clarify this category. So, a virtual managing agent may model a patient queue priority management software or another may be responsible for scheduling treatment units, insuring the follow-up and the global coherence of the various planning tasks like appointment management, shared resource schedules and so on. Moreover, another may model a system responsible for collecting, centralizing and circulating information in the overall system.

2.8 THE ENVIRONMENT

Great importance is also due to the environment in which agents interact. It may deeply affect agents and their interactions or may be entirely neutral. Charfeddine and Montreuil (2008) define the simulation environment as follows:

> The simulated environment component describes the modeled milieu organizationally and behaviorally through its systemic processes and networks, as well as the scenarios of demand, events and crises the system will have to live through.

Usually, the recurrent environment represent geographical spaces such as regions, metropolis, departments, nations and so on. Models that show such environments are called *spatially explicit* and the model developed in this work is a good example in that it presents an environment based on a geographical representation of the metropolitan area of Turin. In other models, on the contrary, the environment might represent something different from geography. However, spatial models are quite common and agents usually are based on precise coordinates that represent their location. Another possibility is to model links across agents without presenting a proper spatial representation, but insisting on the analysis of a network which shows agent relationships. Our work melts the two features as we will see later on: spatial representation and link representation. The importance of network analysis is particularly significant in ABMs and it need a section to be better analyzed.

2.9 THE ENVIRONMENT IN HEALTHCARE ABM

In developing a healthcare environment, modelers often adopt some objects that work as *physical* and *informational* entities. They are resources used by agents to accomplish their activities (Charfeddine and Montreuil, 2008), and are characterized by attributes such as functionalities, available quantity, used quantity, cost, etc.

Physical objects

With respect to the physical objects, Charfeddine and Montreuil (2008) identify two elements: supplies and sites.
Supplies model all tools, instruments, materials and equipments used in the healthcare system. It is possible to classify them as follows:

- *Medical equipment*:
    - Some need to be installed
    - Others are mobile

- *Communication and administrative equipment*
- *Transportation equipment*: Ambulances, stretchers, wheelchairs and so on.
- *General-use equipments*
- *Beds*

- *Medicines*
- *Material and clinical supplies*

Sites model physical locations and spaces (such as buildings) that characterize the healthcare delivery system. Generally, they are assigned to specific organizational units. Relevant characteristics are dimensions, quality certifications, resources (agents and objects) that determine their capacity limit. They can also be decomposed in a hierarchical structure or mapped. Charfeddine and Montreuil (2008) report the most commonly used sites:

- A country, state, province or region;
- A healthcare institution, hospital, clinic or centre;
- A department unit or service;
- A care room, box, office or ward;
- A care station or bed area.

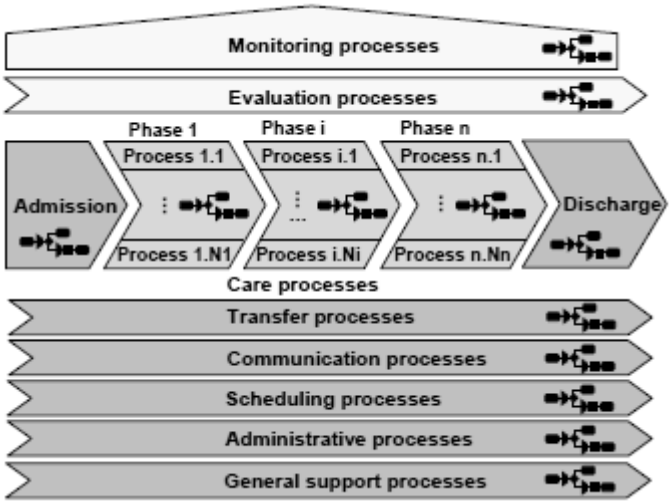
In dealing with particular model types regarding home-care services for example, other sites can be considered such as home, mobile units, social services providers, governmental administrative entities and so on.

Informational objects

Charfeddine and Montreuil (2008) report two types of informational objects that typically occur in healthcare agent-based simulations:

- *Forms*: they deals with specific data that need to be filled in the program. They consist of any paper or electronic document such as progress notes, order and track tests, prescriptions, track medications and so on. In case of software application usages, computer screens used to enter data are also considered as forms.
- *Databases*: this type of informational object represents every source of stored data. The source might be on paper (for example in protocols) or reference manuals. In some cases it might be in electronic format, as with electronic patient charts, scan images and patient records. Databases usually work as consultation tools, with search functionalities. Moreover, they can be used for adding new data, for deleting or modifying existing data. Finally, these databases have to be secured, insuring that only authorized agents can have access to them.

We have already stressed the importance of networks and processes in the general definition of a simulation environment. The formers will be described in details in the section dedicated to network analysis. Here, we focus on the *processes* that characterize a healthcare system.
Charfeddine and Montreuil (2008) report that processes model sets of interrelated activities collectively intending to produce a desired result. The relations between activities define their logical precedence and dependence relationships. Generally speaking, the basic process, involving a single activity, is often referred to as an operation. Moreover, activities are executed by agents directly or remotely for example using telemedicine techniques. In some cases they may necessitate the presence of the patient while in some other cases they do not. As an example, examining a patient requires the patient to be present while analyzing test results does not require the patient to be present. Charfeddine and Montreuil (2008) provide also a clear characterization of healthcare processes in ABM simulations that can be described with the following figure:



The classification of healthcare processes can be resumed as follows:

i. *Care Processes*: such typology includes those processes which are sometimes standardized in protocols such as clinical practice guidelines. With respect to care processes, in general they are preceded by a patient admission process and followed by a discharge process and in some cases they can be divided into sequential phases.
ii. *Transfer Processes*: they occur within a healthcare network or between services.
iii. *Communication Processes*: this typology deals with processes which structure the exchange of information across agents.
iv. *Scheduling Processes*: they are adopted for admission, resource allocation and other similar functions.
v. *Administrative Processes*: they deal with the managerial processes including operation rules and policy decision processes.
vi. *General Support Processes*: this typology consists of supplying or training activities that address to the medical personnel.
vii. *Evaluation Processes*: they involve data collections, dashboards and so on.
viii. *Monitoring Processes*: they include control, decision making, etc.

Charfeddine and Montreuil (2008) insist on the fact that processes define normal, proposed or probable way of functioning of a healthcare system and so, they serve as guidelines. Nevertheless, agents in ABMs are intelligent and pro-active and, thus, they sometimes do not follow the rules of the game or these processes. This is an important feature of agent-based simulations where modelers can decide to design agents with closure conformity to the processes or they can allow them to have more or less deviated behavior. For example, one can imagine, as we will see in our model explanation, that patient agents undergo a common process that identifies the family doctor as the main decision maker who chooses where to send his patients in search of treatments. However, the modeler can introduce an element of reality in that in healthcare the fundamental principle of freedom in choices must be respected and so, he may introduce some patients that choose on their own. In addition to this, the simulation environment can also include some events or crises (the so-called “scenario components”), that may affect the normal progression of one or more processes.

2.10 SCENARIO ANALYSIS

Typically, a scenario contains all the externally specified nature and distribution of demand event and crisis occurrences to be experienced in specific simulations like the ones concerning healthcare systems. The scenario analysis can be associated with the experimental activity described above which in turn represents the real utilization of a simulation model as a tool to discover phenomena and to deal with them. Charfeddine and Montreuil (2008) individuate two sides of scenario analysis: demand and event/crisis.

Demand defines the simulation load that the system will undergo (Charfeddine and Montreuil, (2008). As an example, it is very common in healthcare agent-based simulations to express demand as probability distribution of the quantity of each type of patients arriving, including their time and geographical dispersion (our work is characterized heavily on probability distributions). Moreover, demand may be expressed more deeply, by means of stochastic modeling of health degradation of each individual in a population of potential patients, the implications of this degradation generating the demand in terms of patient arrivals. Finally, beyond the arrivals, demand can also define the stochastic load generated in the system by each new arrival. Generally, a population of an agent-based simulation is segmented using percentages and weights. As an example of typical demand statistic parameters in healthcare, the tables showing Charfeddine and Montreuil (2008) parameters can be useful:

General population

- Total population : 648 730 persons
- Demographic characteristics

Residence location	*Sex*	*Age*	*Smoking habits*	*Education level*	*Exposure to pollutants*
Vieille-Capitale : 45,1 %	Women: 52%	<45 : 59,5%	Current Smoker : 28 %	Primary : 17%	Yes : 150%
Portneuf : 7,1%	Men: 48%	45-64 : 26,7%	Never smoker 31%	Secondary : 58%	No : 85%
Québec-Nord : 43,0%		65-74 : 7,8%	Ex-smoker 31%	University : 25%	
Charlevoix : 4,8%		>=75 : 6,0%			

Vulnerable population

- Considered risk factors : Age, Smoking habits, Exposure to pollutants
- 15 to 25 % of smokers develop a COPD disease
- 5 to 10 % of ex-smokers develop a COPD disease
- Persons aged 75 and more have additionally 75% of probability to develop COPD disease
- Persons of age group 65-74 have additionally 40% of probability to develop COPD disease
- Persons exposed to pollutants have additionally 60% of probability to develop COPD disease

In can be noticed how the population is divided, because data in healthcare are usually collected around classes of ages, gender and regions.

Affected population

- 80 to 90% of COPD patients aged 75 and more are in moderate and severe COPD disease levels
- 70 to 80% of patients under 75 years are in the At risk and mild COPD disease levels
- Population having a family physician : 70%
- COPD disease manifestation

Main symptoms	*Number of respiratory symptoms*
Morning cough: 26%	0 : 47%
Chronic cough: 12%	1 : 21%
Phlegm cough: 26%	2 : 14%
Wheeze: 22%	3 : 8%
Dyspnoea attacks: 12%	4 : 5%
Dyspnoea grade 2: 12%	5 : 3%
	6 : 2%

- Deterioration of health status

	At risk → Mild COPD	Mild COPD → Moderate COPD	Moderate COPD → Severe COPD	Severe COPD → Death
Patients not already diagnosed as having COPD	60%	60%	80%	70%
Patients diagnosed with COPD who are under treatment or follow-up	20%	20%	30%	10%

Inputs	%	Outputs	%
Emergency referrals	82,4%	Discharged patients (back to home)	36,5%
Premptive pulmonology specialised clinic referrals	14,6%	CSSS referrals	4,8%
Pulmonology ambulatory clinic referrals	2,0%	Family physicians referrals	31,0%
		Premptive pulmonology specialised clinic referrals	18%
		Dead patients	8,7%

The utilization of cumulative probability distributions makes the population easy to be represented in the simulation program.

Events and crises, on the other hand, model the perturbations that may occur in the simulated environment and that can influence components of the system (Charfeddine and Montreuil, 2008). Healthcare environments are particularly prone to major events and crises affecting drastically its dynamic load. As examples of common events in healthcare simulations, one can imagine absence of some physicians, broken devices, lost of documents and so on. Crisis, instead, are major events that are normally less frequent but have important disaster consequences. Very common in healthcare simulations, we can find epidemics, general breakdowns of the information system or strikes. Modeling explicitly external events and crisis enable modelers to test the performance of the simulated system in terms of reactivity to such circumstances (Charfeddine and Montreuil, 2008).

In each simulation model, the experiential component is a fundamental objective that a modeler must analyze deeply. It allows to answer crucial questions such as Charfeddine and Montreuil, 2008):

- What do we want to be able to do with our simulation model?
- What do we want to see and analyze during the simulation execution? (this question addresses the *interface* of the simulation).
- What are the finalities that we want to obtain from it? (this question addresses the potential *results* of a simulation).

As it can be seen, each modeler has to answer to these questions through the development of an interface and result specifications.

Result specification

Charfeddine and Montreuil (2008) propose an interesting characterization of simulation results in terms of *dynamics* and *performance*.

Dynamics refer to observations related to any continuous change, transition or progress of the agents, objects, process activities, and of environment states. A modeler needs to define the healthcare system components which he wants to observe and whose state evolution along the simulation horizon he wants to analyze. These specifications serve as guidelines towards the selection of views of simulation results according to the modeling objectives. As an example, one may interested in studying the dynamic travel patterns of a medical agent during the simulation in order to understand and then to optimize them. In healthcare systems, dynamic analysis provides important insights about a series of different topics as Charfeddine and Montreuil (2008) point out:

- *Flows and trajectories*: a typical case is given by flows of patients, resources and information across the healthcare system under investigation;
- *Interactions between agents*: we have already highlight the importance of interactions among agents and in healthcare systems is a crucial element to deal with. It is useful to identify if there are some cooperation or conflicts phenomena.
- *Punctual or short time phenomena*: these are common dynamic analyzes when the modeler needs to focus the attention on congestion phenomena during some periods of a clinic session or reactions immediately after an urgent case arrival, cases of “bed gridlock” or “bed blocking” in some departments and so on.

In considering **performance** Charfeddine and Montreuil (2008) define it as statistics and metrics generated by, and reported after the simulation execution, providing insights on the quality, efficacy and efficiency of the healthcare system given the modeled scenarios and systems. Moreover, Charfeddine and Montreuil (2008) identify eight main types of performance indicators that are often used in the healthcare context:

i. *Outcome Indicators*: related to the impact on the health of the treated patients;
ii. *Time Indicators*: generally related to patient waiting times, total patient time spent in the system, working time of some doctor agents and so on;

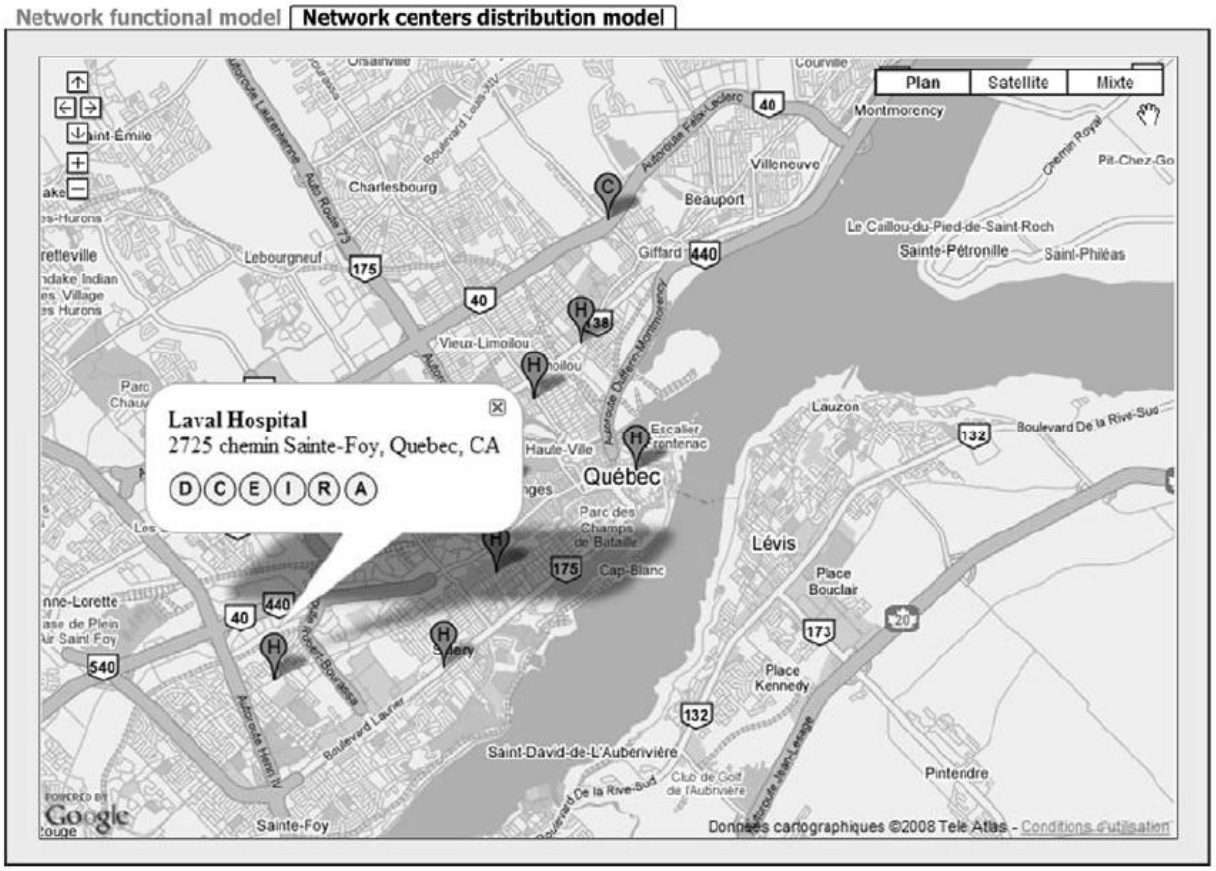
iii. *Utilization Rates*: related to care provider utilization, equipment utilization, site utilization, bed occupation and so on;
iv. *Congestion Indicators*: for example, they may measure number of patients in waiting areas, number of patients within the system and so on;
v. *Quality Indicators*: usually related to patient satisfaction degrees, served patient rates and so on;
vi. *Cost Indicators*: care provider costs, equipment costs, unit costs, costs associated with each medical treatment and so on;
vii. *Stock Indicators*: they measure the amount of different critical materials such as medicines, supplies, beds, etc;
viii. *Complementary Indicators*: these indicators may serve the modeler for specific purposes or needs.

In addition to this characterization, indicators may be associated with the modeling project objectives. As an example, in modeling an healthcare system at a regional level in order to improve and analyze services and structure capacities, the emphasis may be centered around accessibility indicators, continuity indicators, service quality indicators, management indicators and so on.

Interface specification

Charfeddine and Montreuil (2008) divide interface specifications into two separate sets: Animation and Sate mining.

The **Animation** component refers to the visual representation of the modeled healthcare system under investigation, including the agents, the objects and their environment, dynamically depicting their characteristics, including their properties, abilities, movements and behaviors (Charfeddine and Montreuil, 2008). It is obvious that correct specifications must clearly define the animated interfaces that the final user wants to see and analyze. In configuring the animated interfaces, the modeler must respect the importance order of its different elements and have to present them in simple, vivid, interactive and user friendly manners (Charfeddine and Montreuil, 2008). As an example, if one wants to present an extended health network, he should use a geographic map (or at least adopt geographical coordinates) while, on the contrary, if one attempts in visualizing a hospital building, an architectural plan may be more suitable. The following picture represents an example of a healthcare network which come from the work of Charfeddine and Montreuil (2008) and is based on Google Map API directly integrated in the modeling platform:



With respect to state mining Charfeddine and Montreuil (2008) identify it as something that defines how deep the user wants to be able to dig into the dynamic state of the various agents, objects, processes, networks, etc., and how he wants to be able to perform this mining. In other words, the central idea around state mining is that through drill-down techniques, it is possible to go from a general view integrating high level elements to more detailed views present in more depth a subset of these elements. In order to consider the simulation modeling objectives, modelers have to make a compromise between three elements quoting Charfeddine and Montreuil (2008):

- The level of detail that final users want to reach in their analysis;
- The navigation complexity between the interfaces, affecting the interface usability;
- The system development cost

2.11 CHARACTERIZING ABMS

Now that we have exposed some main features of agent-based modeling, we report a list of additional characteristics useful in identifying ABM referring to the work of Gilbert (2008).

Ontological correspondence

The correspondence between computational agents and real-world actors is extremely relevant making easier the development of models and the interpretations of their outcomes. This is a peculiar feature of agent-based modeling. It is possible for a model, to present a single agent standing for the whole class, for example “patients” in general, or even to present a separate agent for each class of agents, for examples patients in our work which are much more characterized individually.

Heterogeneous Agents

Economics and social sciences in general make strong assumptions about the homogeneity of agents. One can notice, indeed, that agents are usually presented as rational, identical, with same preferences. As Gilbert points out (2008), actors may differ in their preferences, but it is unusual to have agents that follow different rules of behavior, and when this is allowed, there may be only a small number of sets of such actors, each with its own behavior. This is so because analytical solutions are very difficult or even impossible to be implemented with not homogeneous actors. With a computational method one can overcome such obstacles in the sense that an agent can be created with precise preferences which drive it in a precise way defining rules of action. As an example, always in healthcare terms, one may imagine a patient that decides the hospital in which he wants to be cured according to his own preferences about the distance of the hospital, or the quality, or even the cost and so on.

Representation of the environment

In agent-based modeling, the user can create directly the environment in which agents operate. Starting from physical aspects such as geographical boundaries, barriers, buildings and so on, one may also generate the effects of other agents in the surrounding locality or the influence of factors such as crowding and resource depletion (Gilbert, 2008). An important methodologies can be adopted in ABM environment setups: the use of the so-called GIS (geographical information system). In an agent-based model, the user can geolocalize coordinates, making the environment as close as possible to the geography of the correspondent real world.

Agent Interactions

We have already stressed the importance of interconnections between agents in an ABM context. This topic affects also a major part of analysis in the section dedicated to networks. Indeed, network analysis cannot be separated from ABM techniques. Anyway, these interactions can consist of the transfer of data from one agent to another, generally another agent located close by in the simulated environment. However, the user can complicate interactions by separating agents according to their function and their data elaboration. Each type of agent contains some data and the connection with other types of agents produces elaborated results.

Bounded Rationality

The rationality of agents is another common feature across agent-based models. If an agent behaves rationally, then he acts following a precise set of rules that maximizes its utility or welfare. The obvious alternative is to model irrational agents that do not maximize utility or welfare, but can provide insights and may implement a model. However, the rationality assumption is criticized quite often, referring to it as "hyperrationality". This term emphasizes the people engagement in long chains of complex reasoning in order to select optimal courses of action, or even the capability of following chains of logic that extend indefinitely (Gilbert, 2008).
To avid such criticism, the literature usually adopts the term "bounded rationality" developed by Herbert Simon (1957). According to him people should be modeled as boundedly rational, limited in their cognitive abilities and thus in the degree to which they are able to optimize their utility. Agent-based models make it easy to create such type of agents and the main challenge is not to limit rationality but to extend the their intelligence or introduce some sophistications.

Learning

The last common feature in ABM techniques is the capability to simulate learning processes at both the individual and population levels. For example, agents can learn from each other make the whole system under analysis able to improve its conditions. Learning can be modeled in three ways (Gilbert, 2008):

- *Individual Learning*: agents learn from their own experience .
- *Evolutionary Learning*: the population of agents learns because some agents "die" and are replaced by better agents, improving the overall population average condition.
- *Social Learning*: some agents imitate or are taught by other agents, leading to the sharing of experience gathered individually but distributed over the whole population.

2.12 OTHER APPROACHES RELATED TO ABM: MICROSIMULATION AND SYSTEM DYNAMICS

In order to expose a complete argumentation, it can be interesting to introduce some related modeling techniques that differ from ABM but may be useful in some modeling tasks. We want to briefly discuss microsimulation and system dynamics methods which in turn represent other powerful tools adopted by social sciences.

Microsimulation

The main characteristic of this modeling technique consists of large databases describing a sample of individuals, households, organizations and so on using rules to update the sample members as though time was advancing. Referring to the example proposed by Gilbert (2008), the database may be derived from national surveys of households and may include data on different variables such as households' members, age, gender, education levels, income, employment or pension arrangements. Such types of data refer to a particular time period of the related survey publication. The microsimulation technique let the user able to ask what the sample would be like in the future. One may want to investigate future retired workers, or the future redistribution of income. Having some rules about the likely changes in individual circumstances during the course of a year, gives the possibility to apply them to every person in the sample finding the changes occurred from the time the survey was publicized. At the end of the ageing process, then aggregate statistics can be derived for the sample, making some inference about expected changes in the population from which the sample belongs.
The huge difference of microsimulations with respect to ABM is that the formers start not from some hypothetical or randomly created set of agents but from simple and real samples. Thus, the prediction accuracy of future states of the population is much more evident and easy to be implemented with microsimulations rather than with ABM. However, Gilbert (2008) presents two main disadvantages that characterize microsimulations. First of all, the ageing process must be based on very detailed transition matrices which specify the probability that an agent currently in some state will change to some other state in the following period of time. Secondly, the transition probabilities will certainly differ across the population according to various characteristics such as gender, employment, children in the family, old people and so on, making such matrices extremely complex and conditional on several probabilities for each individual circumstance. Collecting data for such a relevant quantity of probabilities is far from being an easy task and, in addition to this, agents are treated individually, isolated in the world, without making possible any kind of interactions between them. So, no interactions and even no geographical representation of spaces are possible in microsimulations.

System Dynamics

What characterizes system dynamics techniques is the expression of the temporal cause-and-effect relationship between variables. Agents are not represented directly as in ABM. As their name suggests, simulation dynamics models are based on interacting variables and able to handle direct casual links. Some examples reported by Gilbert (2008) are growth population leading to increased depletion of resources and feedback loops.

Usually, a system dynamics model is presented via a series of arrows representing the casual links between variables as it can be noticed in the figure on the following page. The example presented in the picture on the following page refers to a model of an ecosystem in which sheep breed in proportion to their population, wolves eat the sheep, but if there are too few sheep, the wolves starve (Gilbert, 2008). Rectangular boxes represent the stocks of sheep and wolves, the tap-like symbols are flows into and out of the stocks, and the diamond shapes are variables that control the rate of flow. The population of sheep increases as sheep are born and the rate at which this happens is determined by the constant sheep-birth rate. The curved arrow from the stock of sheep to the flow control labeled sheep-deaths represents the function rate at which sheep die. The arrow from the predation from the predation-rate variable represents the probability that a wolf will catch a sheep while the arrow from the stock of wolves represents the number of wolves.

Just to pint out some characteristics of system dynamics models, they are based on the evaluation of sets of simultaneous differential equations, each of which calculates the value of a variable at the next time step given the values of other, causal variables at the current time step. Software like NetLogo can help in drawing the diagrams and execute the simulation using these equations.

What differs from ABM is the utilization of aggregate rather than individual agents. In the example above, the user deals with an overall population of sheep and wolves, without creating individual specific agents. Here comes the major disadvantage of system dynamics with respect to ABM : it is a hard task to model heterogeneity among agents. Moreover, another difficulty is due to the representation of agent behaviors that depend on the agent's past experience, memory or learning. However, system dynamics techniques offer some advantages too. They deal with aggregates and, thus, they are useful in analyzing topics where there are large populations of behaviorally similar agents.

With respect to human performance modeling in the healthcare field, the use of system dynamic models is not very common, although they work as meaningful generators of hypotheses (Escudero and Pidd, 2011). Some examples of system dynamic models in healthcare can be found in some investigations on the relationships between healthcare demand, healthcare capacity and waiting times under different scenarios, incorporating behavioral assumptions. Moreover, system dynamics may be useful in understanding different factors contributing to the long delays for unplanned, urgent admission to acute hospitals and to explore dynamics of the system of which the emergency department is one element.

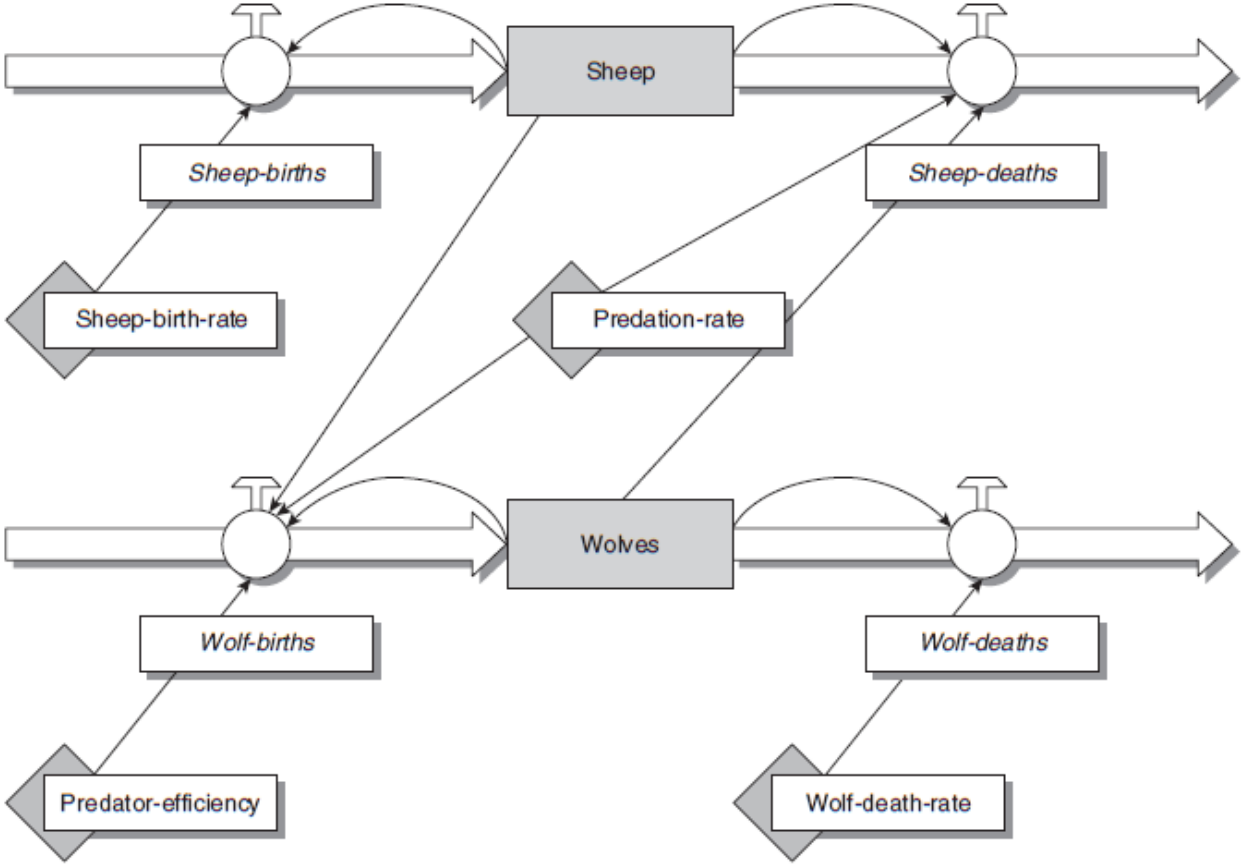


Figure 1.2 A System Dynamics Model of a Simple Ecosystem, With Wolves Eating Sheep According to the Lotka-Volterra Equations

SOURCE: Wilensky, U. (2005). NetLogo Wolf Sheep Predation (System Dynamics) model. http://ccl.northwestern.edu/netlogo/models/WolfSheepPredation (System Dynamics). Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

2.13 MODELING HEALTHCARE COMPLEXITY USING AGENT-BASED SIMULATIONS

After having described important issues concerning complexity, modeling activities and agent-based techniques, we put all these items into the analysis of healthcare systems, as it is the main topic under discussion in this work.

In general, healthcare improvement efforts do not consider properly the interdependencies among individuals, while they seem to be focused more on changing behavior of individuals (Leykum et al. 2012). The application of complex adaptive systems (CAS) approach to studying healthcare delivery changes the focus, moving the analysis from the individuals to their relationships and interdependencies.

Focusing on the behavior of individuals presents some typical strategies such as pushing knowledge to providers through continuing education, clinical reminders to prompt providers to deliver indicated care, decision support tools to help providers deliver guideline-concordant care or even attempts to improve system performance through quality improvements efforts broken down into parts performed by individuals (Leykum et al. 2012).

On the other hand, complex adaptive systems approach to healthcare settings is centered around relationships among individuals in the organization. As we have already reported, complex systems are characterized by interconnections between individuals. Moreover, CAS analysis adds concepts of non-linearity and uncertainty into the healthcare sphere. As an example, in clinical settings, the implications of the CAS framework for how one thinks about improving clinical systems are profound (Leykum et al. 2012). Firstly, the focus is on interrelationships and not individuals. Secondly, strategies to improve the collective ability to act effectively in the face of uncertainty are critical to clinical system performance. Here, agent-based modeling represents a compelling strategy fro studying clinical organizations as complex adaptive systems.

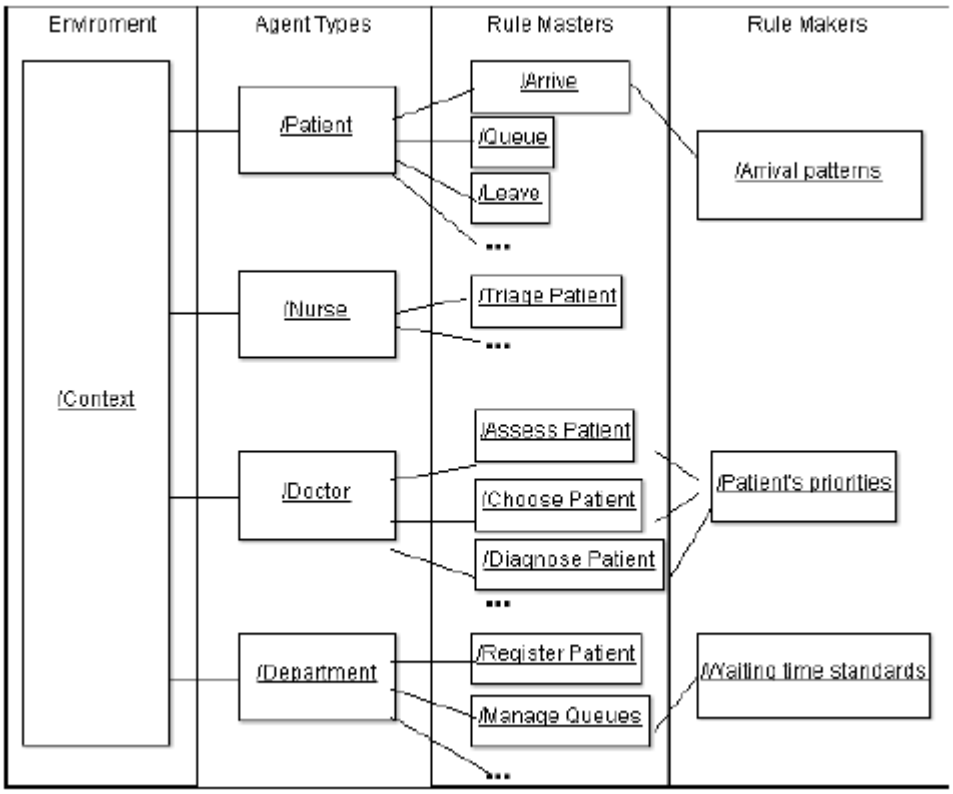
Anyway, the topic described on the following pages regards the use of agent-based modeling in healthcare systems. We will look at some examples in the literature to give a complete characterization of what capabilities ABM can provide in the examination of problems in healthcare.

2.14 IMPROVING HEALTH CARE DELIVERY SYSTEMS: THE EMERGENCY DEPARTMENT CASE

Modeling an Emergency Department occupies a large body of literature. Escudero and Pidd (2011) identify some issues to be faced with in using ABMs to model Eds. One of the main challenges in simulation modeling (and this is true for every simulation model) is to keep a model as simple as possible, trying to include the essential of the system under analysis in order to focus the efforts on the objectives of the simulation. Designing a model that can be accepted by different people with different levels of understanding of a particular system is far from being a simple task. Conceptual modeling is the primary answer to the challenges described above. For conceptual modeling, one refers to the appropriate level of simplification of a system (Escudero and Pidd, 2011).
In developing ABMs it is crucial to begin with the presentation of the two main components of an agent-based model: agents and agent behaviors. Gilbert and Terna (2000) emphasize the importance of a precise way to proceed in developing an ABM. The authors suggest that the modeler should first define the capabilities of the agents, the actions they can perform and the characteristics of the environment that surrounds them. The general schemes provided by Gilbert and Terna (2000) is called ERA, meaning Environment-Rules-Agents scheme. We have already examined these concepts in details in this section, but the ERA scheme identifies the environment as the context through rules, general data and the agents. Agent behavior is then defined by two types of rules:

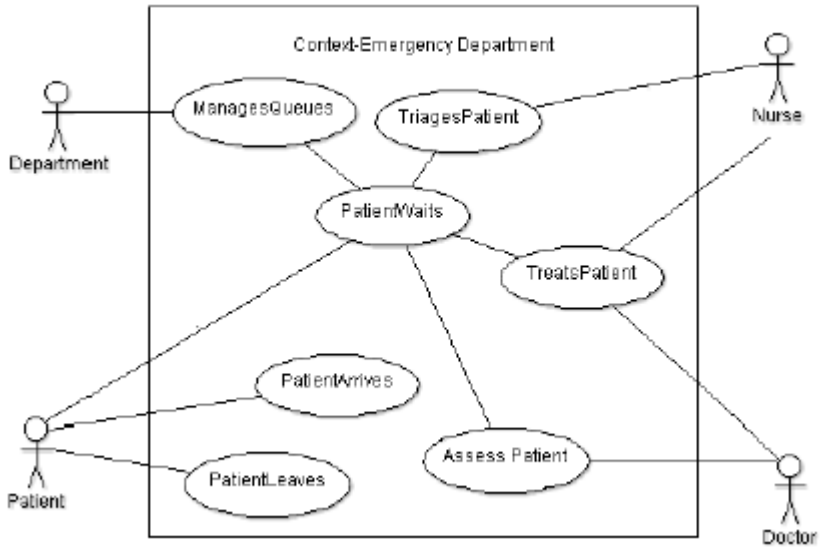
- *Master rules*: represent the cognition of the agent called.
- *Maker rules*: modify the master rules.

The ERA scheme is significant in presenting an ABM based on an Emergency Department in which main agents are patients, nurses, doctors, managers, laboratories and procedures. The ERA system in general can fit perfectly with every ABM simulation concerning healthcare.
In presenting an ED context, Escudero and Pidd (2011) provide an interesting characterization following the ERA scheme by Gilbert and Terna (2000). The ERA scheme in an ED case can be presented as follows:



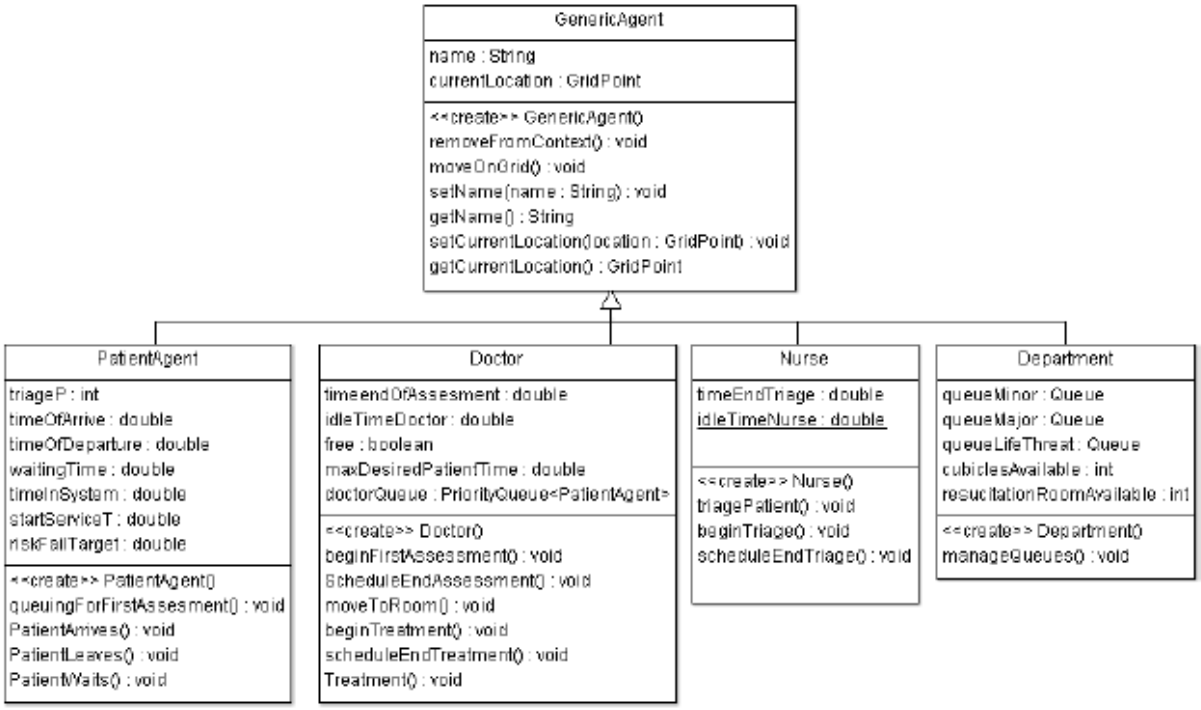
This picture is a good starting point in developing a ED simulation model using agent-based techniques.

The next step to implement after having specified agents and their behaviors is the conceptual representation that can form the basis for model coding (Escudero and Pidd, 2011). Generally, ABMs are implemented in an object-oriented platform, and a case diagram can provide specifications of actions that agents may perform with outside actors. An example of a case diagram in an ED application can be presented as follows (Escudero and Pidd, 2011):



Moreover, a class diagram is useful to specify the available properties and potential behaviors of agents like Escudero and Pidd (2011) point out. The static structure derived shows inheritance sources or super-classes. We can represent the following class diagram for an ED in which the super class agent is called Generic Agent which possesses general characteristics and methods inherited by the subclasses below it:

Escudero and Pidd



In presenting the ED case some notes about the general setting of the model must be analyzed. As Kanagarajah et al. (2006) point out:

> Patient safety, acceptable workloads and economic imperatives are interdependent dynamic forces that often come into conflict in healthcare environments. For example, reducing the total number of available doctors could lead to increased work load for individuals causing fatigue. This could lead to oversight of tasks and eventually affect patient safety. Balancing these competing forces is increasingly a major pre-occupation of government regulators and senior hospital managers.

As it can be noticed in the quotation, one can identify three forces that interact in a healthcare system: patient safety, economics and workload on the system. In order to analyze the balance

between these three forces, it is useful to introduce the “safe operating envelope model” developed by Cook and Rasmussen. The figure below addresses to such model.

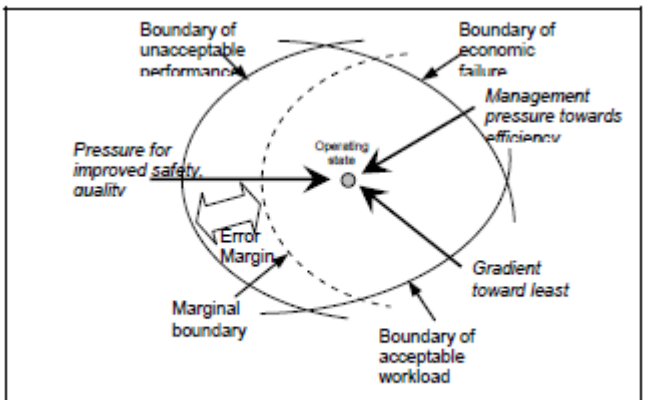


Figure 1: Rasmussen’s modified safety dynamic model

In this model, patient safety is a dynamic property of the dynamic system.

A kind of analysis described above can be better integrated using an agent-based simulation approach. A typical case, very common in the literature, is the simulation of an Emergency Department (ED). Therefore, we can present an example making references to the work of Kanagarajah that will also be useful in discussing the effect of efficiency improvements within this organization. Common problematic issues in EDs are managerial/technical changes and work saturation as bed-gridlock. The “Bed block” in an ED is a situation within hospitals where patients stay in the waiting room for a treatment-bed despite having completed arrival in the ED for treatment. Waiting comes from the fact that there are no more beds being available within the ED. This example can be useful in that it provides the methodologies underneath an ABM approach in a healthcare case, providing an exemplification of what we have developed in our model.

2.15 THE EMERGENCY DEPARTMENT

We have already defined health care delivery systems as Complex Adaptive Systems. As we have seen, such systems address the public directly and present some non-linear dynamics (Kanagarajah et al. 2006). The nature of such systems makes the analysis of their boundaries and their decision processes difficult to deal with. Indeed, the observer of a healthcare system shows adaptive behavior with not so many control mechanisms. Another important feature of healthcare systems is the interconnection between patients, hospitals and medical divisions. The presence of networks with formal or informal nodes represents also that agents adapt by learning. The concept of network will be discussed in the correspondent section, but for completeness, it is useful to stress the concept according to which the interdependent and networked nature of healthcare means that the activities undertaken in one node, as the ED for example, have the potential to affect behavior in other nodes and across the network overall (Kanagarajah et al. 2006). Hence, because of complexity in healthcare, dealing with predictions of effects of certain actions or performance improvements is a hard task.

In considering an Emergency Department, one can identify it with a unit node within a healthcare system. Setting it as a complex adaptive system via dynamic models of healthcare is possible. Like all complex systems it seems to us simplistic both in the time period and as a complete system. From the organizational perspective, the ED operates at physical, organizational and societal levels as one can notice in the figure below (Kanagarajah et al. 2006).

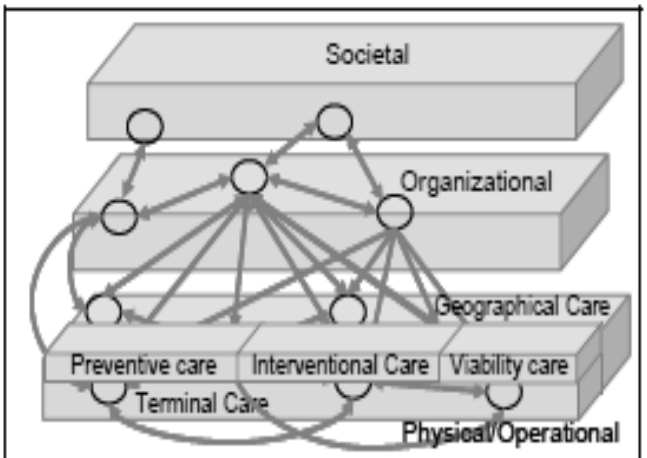


Figure 2: Structure of the health care system

Starting from the bottom of the graph, the first level to be analyzed is the tangible layer of a healthcare system: operational or execution layer. In this level one can find the variety of different care processes including preventive care, interventional care, viability care and terminal care as well as some geographical perspectives which derive from demography and location of the care institutions. In the ED case, this first level implies that a patient usually starts with a diagnostic process which ends with a range of possible treatment modalities before he is discharged back into the community or admitted and transferred to another specialist ward. In general, ED processes deal with interventional care although they may be a channel for preventive and terminal care services too.
The middle level is the organizational one and it refers to the simultaneous care managing activity of many patients as well as supplying line management and appropriate resources allocation. This level is deeply affected by economic and socio-technical aspects.
The highest level is the societal one, where healthcare systems are influenced by epidemiology, cultural, political and demographic characteristics of the population.

As Kanagarajah et al. (2006) point out, the primary goal for an ED is to meet the needs of patients in terms of timing of arrivals and departures, classifying them on their severity (the so called triage). An ED is a typical example of a non-linear complex system, where uncertainty makes overcrowding and bed locking a quiet common risk. Healthcare managers have to ensure that the ED is able to overcome unexpected increases in patient demand that may result from a series of environmental and social factors (epidemics, huge accidents and similar events). As a result, managers have to devote resources in a proper way and appropriate crisis management plans may be functional for that reason. Moreover, managers have to signal to organizational and societal levels possible changes or alternatives in order to develop a variety of response processes.

2.16 MODELING AN EMERGENCY DEPARTMENT WITH AN ABM APPROACH

Referring to Kanagarajah et al. (2006), we can present an example of how agent-based modeling may be used to simulate an Emergency Department. First of all, the modeler has to isolate the problem under analysis in order to simplify the modeling task and to focus the attention on certain phenomena. The example proposed by Kanagarajah et al. (2006) treats the resources available in the ED as the simulation agents. In other words, the agents of the simulation consist of patients, doctors, nurses, technicians, treatment rooms and managers. Surely, one can immediately state that many more agents occur in a real healthcare delivery system, but for the main issue is that the dynamic interactions between agents for the reality and for the model are almost similar. The model can be illustrated as follows:

- The patient arrive at the ED is a simplified stage of an agent. Despite of this, the patient arrival is characterized as a function of what happens within the society and depends on the number of options available for those patients to receive treatments.
- Transfer out to other wards depends on the availability of beds in other areas, formulated as a stochastic function.
- Within the ABM, agents execute behaviors at each time interval.
- The goal of the model is centered around patient outcomes: the focus concerns the minimization of preventable adverse patient events such as delays which in turn increase the risk of secondary complications with an increasing length of hospital stay.
- An important assumption adopted in the model considers that any patient who stays more than four hours in the ED before being diagnosed and treated, counts as a potentially adverse event. The reasons behind this assumption come from the possibility that lack of available treatments or lack of availability of any kind of agents (doctors, nurses, technicians) could occur.

As every agent-based simulation, agents have to follow certain rules. In the simulation work proposed by Kanagarajah et al. (2006), it is possible to identify three rules:

- Patients are classified on the basis of their condition (triage) and are attended to.
- Agents are self directed: doctors and nurses work as required varying the time spent on each patient which in turn depends on demand pressures such as numbers of patients and the emergency degree of patient illness.
- Agents reflect adaptive behavior, based on the stage of other agents: doctors may work faster or work over lunch periods in order to reduce excessive queues in waiting room or the opposite can occur.

In order to give a complete representation of this simulation taken as an ABM example in a healthcare environment, it useful to represent the entire work process underneath the model. First of all, arriving patients are categorized according to different levels of emergency of their own illness by the Triage Nurse. Levels of severity goes from 1 to 3: patients with level 3 are immediately taken to an ED room. Here comes an assonance with our model described later on in details, in that it treats certain pathologies as treatments which have to be imperatively undertaken by an Emergency Department. Going back to the analysis of the ED example, level 3 patients undergo diagnosis and treatments in the ED room and complete the registration process before beign released or admitted into the hospital for further treatments. The other two levels (1 and 2) patients pass through a registration procedure done by a clerk and they are examined another time by a Triage Nurse, before being taken to an ED room. These two typologies of patients complete their registration process in the ED room, before receiving treatments. Analogously with level 3 patients,

level 1 and 2 patients are released or admitted into the hospital for further treatments. Treatment processes are made of another assessment by a nurse and a physician with appropriate tests performed by specialized technicians. With respect to the first two level patients, the registration process that they have to undertake is performed by a clerk characterized by activities such as data collection, payment related information and entering the basic detail of patients into a medical chart.

We have to point out the fact that the example presented so far is built on a Microsaint Sharp® platform, which allows the development of agent-based simulations where multiple entities can be made to stochastically respond to conditions in their local environments Kanagarajah et al. (2006). This software differs from the one used in our model although the overall characteristics and functions are almost the same. Some notes about the software adopted in our work (NetLogo), will be reported in this section.

So the example presented here presents the typical features of ABM modeling: there are agents (patients, doctors, nurses, clerks, technicians, treatment rooms for acute patients and other minor rooms) interacting among them in their local environment through elementary internal rules that work as decision-making, movement, action rules. This simplistic approach allow to study the complex behavior of a system in a conceivable scale and it is common to all the simulation based models.

As many other models, the example proposed here establishes some boundaries that work as standards of comparison in order to measure how the model moves away from the economic failure and work overload or towards the unacceptable performance. In general, modeling activity requires the identification of the extreme situations that can be occurred in every possible scenario. One can identify three types of systems:

- *Stable low-risk systems*: these systems operate well, being far away from the unacceptable performance or situation.
- *Stable high- risk systems*: these systems, instead, operate near the acceptable frontier of acceptability, with the operating point moving in small increments and remaining inside the marginal boundary.
- *Unstable systems*: these systems are also known as chaotic systems and present large rapid shifts in the operating points which quite often move outside the boundaries.

Kanagarajah et al. (2006) establish three boundaries that permits to interpret the results of the model:

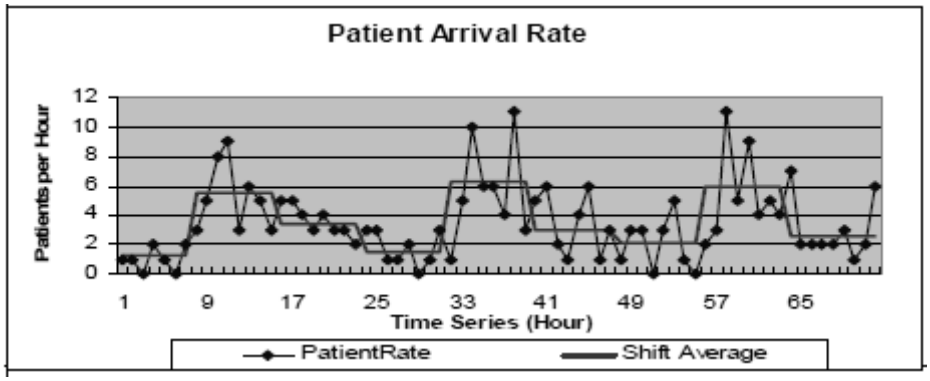
1. *The acceptable performance boundary*: It is defined as the time spent within the ED, measured in minutes. Acceptable performances are estimated under 240 minutes by the UK government. Moreover, the simulation measures the total number of patients within the system, providing an indication of "bed gridlock" or lack of available treatment rooms.
2. *The economic failure boundary*: This limit highlights the over use of funds in which hospitals may incur. The model presents on-call doctors with the purpose of filling in when there is a surge in patient demand. The maximum acceptable number of on-call doctors is 2 for unanticipated situations. More than two on-call doctors per hour is considered failure in economic terms.
3. *The work load boundary*: it deals with the utilization degree of major rooms, minor rooms and nurses. The utilization degree is defined as the effective hours these agents (major

rooms, minor rooms and nurses) spend with the patients over the total scheduled work hours. In addition to this, the model presented in Kanagarajah et al. (2006) considers the time a doctor spends in initial consultation with the patient. With patient queues at normal levels, the nominated time for initial consultation is 10 minutes. Nevertheless, a doctor can be even faster in his work, spending less time with patients in clearing them through the ED. The mean-time of consultation has minimum levels (adaptive behavior of doctor as an individual agent).

Just to give a full representation of an agent-based simulation, it can be useful to provide some pictures regarding agents and measures that the program compute by itself. To begin with, it is a common principle in simulation modeling to represent firstly a sort of base case. Kanagarajah et al. (2006) present the following number of critical agents:

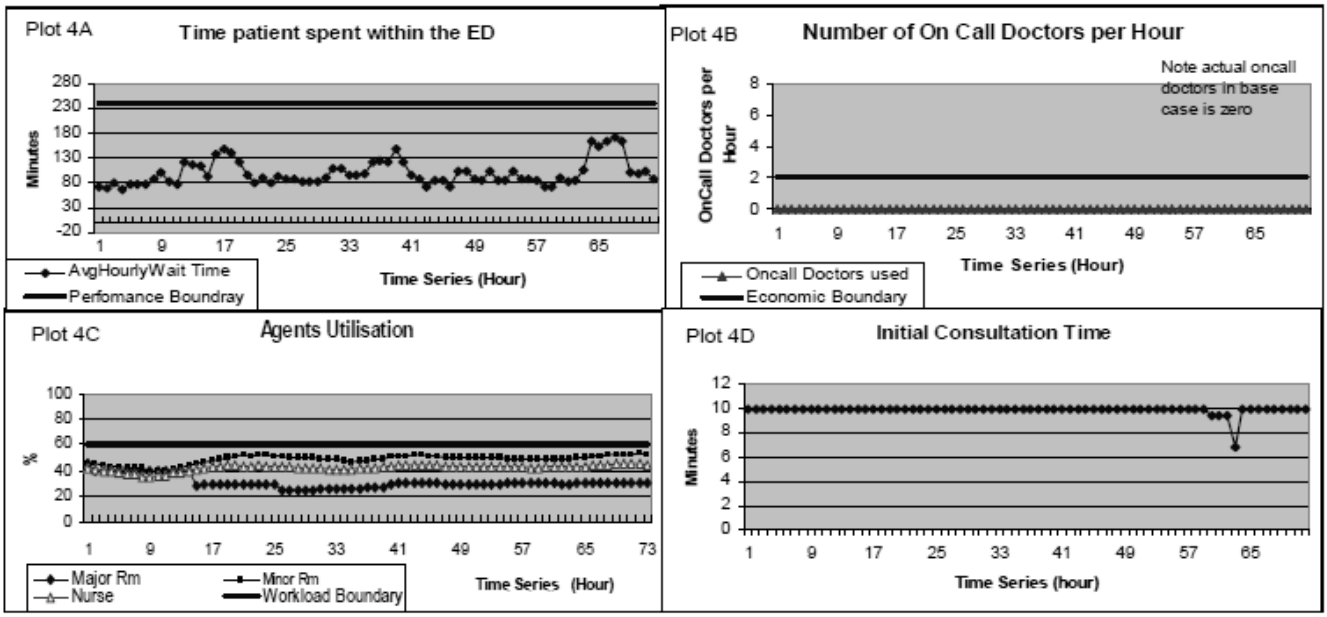
Resources	No of Budgeted Agents (Base Case)
Doctors	3
Nurses	5
Major Treatment Room	2
Minor Treatment Room	8
Registration Clerk	2
Laboratory Clerk	2
Discharge Clerk	2
Triage Nurse	2
Phlebotomist	2
ECG Technician	2
Laboratory Technician	2

It is also important to characterize patterns and probabilities for all sets of phenomena in each simulation. The example considered in these pages takes the patient arrival pattern as randomly generated with the following behavior of the base case arrival and demand pattern:



The graph represents the average number of ED patients arriving in hourly intervals. The pattern is computed automatically by the program and gives to the user the possibility to immediately check the population of agents (NetLogo software provides almost the same tools).

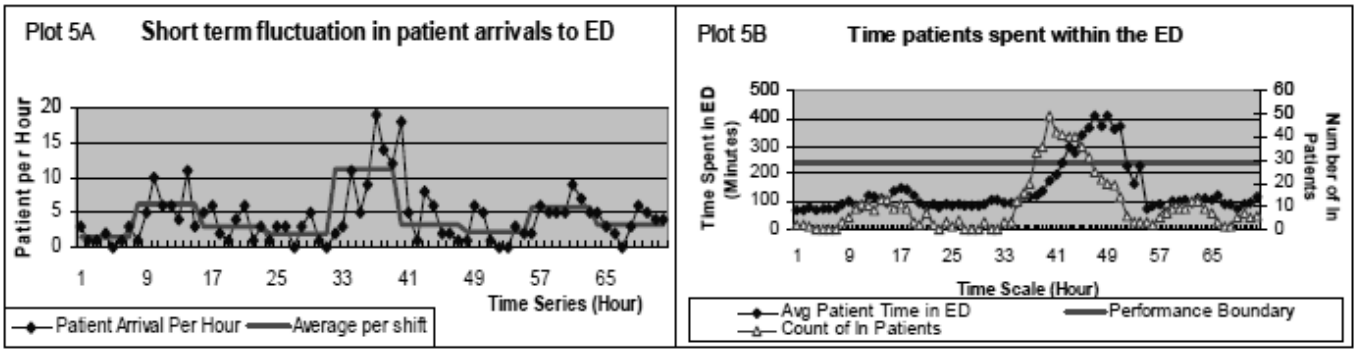
Then, it comes the time for the analysis of first outcomes that emerge from the base case simulation. Kanagarajah et al. (2006), according to their base case, simulate three days of results. The authors assess that the program runs four days of results but the first is excluded for initialization transients. Results and measures of the boundaries are reported below:



The figure above represents measures of the simulation results and the boundary conditions. The base case shows a relatively stable “low risk” system which is operating under a stable condition and would be able to cope with some unanticipated demand increase of resource constraints.

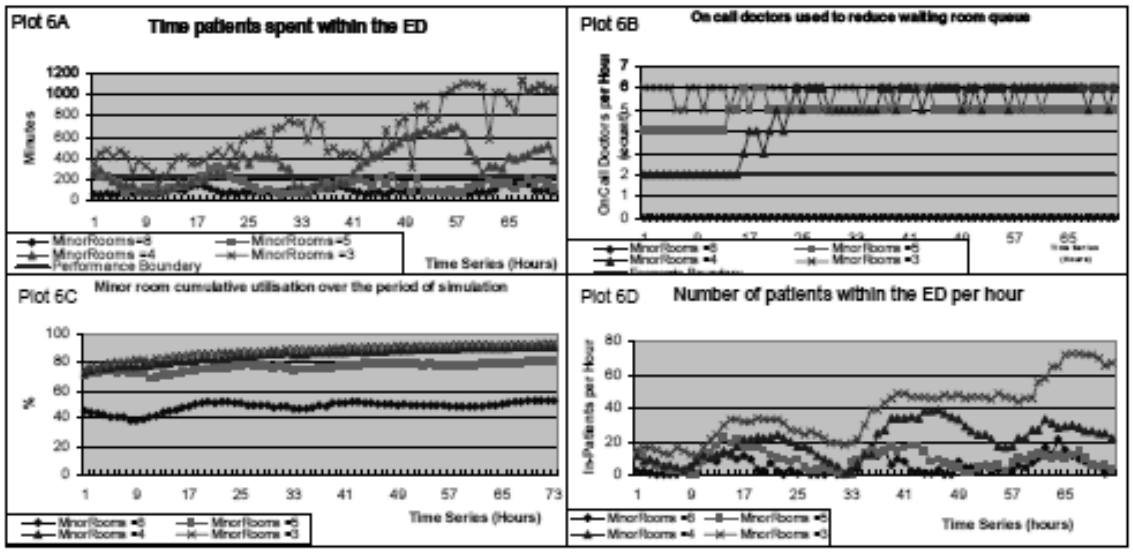
We have already discussed the rules according to which agents of an ABM act and change the behavior. ABM techniques are able to characterize this element that occurs in real life. Agents change their behavior and rules of action as they gain experience through exchanges with other agents, evolving their rules. Kanagarajah et al. (2006) implement a simple rule according to which doctors change their intended consultation time with the patients based on the ED waiting room queue. The figure above reports the initial consultation plot, from which it can be noticed that an increase in waiting room queue due to a short term increase in the number of patients during the hours of 57 to 60.

The next step that each simulation work have to follow is the scenario analysis, considering results and implications of the model itself. In the example proposed of the ED, Kanagarajah et al. (2006) begin with the analysis of the patient arrival rate. This measure depends on various factors such as weather, age of the population, town center activities (which in turn represent traffic accidents), bed occupancy rates in the neighboring hospitals and so on. The picture below gives some useful insights.



First of all, the figure refers to short term fluctuations (increase) in demand pattern relative to the base case. For example, given a bus accident nearby (Kanagarajah et al. 2006), there is a short-term increase in patients between 32-36 hours as the arrival plot shows. If all the other agents remain similar to the base case scenario, this sudden increase in workload pushes the operating region of the safe operating envelope beyond the boundaries of performance and economics. Moreover, the authors constraint all agents to a fixed capacity except for the number of doctors whose capacity can jump up to nine when the waiting queue increased above 9 by calling in additional doctors to assist in clearing the backlog. The capability of increasing the number of doctor agents and doctors who work faster is not enough to absorb the effect of the increase in work load caused by the skyrocketed demand. As a result, from this scenario analysis one can notice that the unacceptable performance boundary is reached with an increase in the total time that patients spend waiting in the ED.

As we have pointed out before, the base case scenario does not violate any boundary condition, because of the excess buffer capacities which made interactions and dependencies between the agents less relevant (Kanagarajah et al. 2006). Another experiment implemented by the authors tests the overall impact of coupling between buffers, reducing the buffer of the minor room capacity. This experiment tries to simulate a “bed block” situation within a hospital where patients still wait in major or minor rooms despite having completed their ED treatment. Such an experiment can be evaluated using the plot on the following page:



Reducing the minor room capacity from 8 to 3 patients, increase the overall utilization of the minor room (Plot 6c). If the number of rooms decreases, the rate of utilization at which patients are cleared increases the waiting queue with a joint increase of the time that patients spend within the ED. So, since the patient queue increases the adaptive behavior of the doctor-agent, it increases total number of doctors by randomly choosing available on-call doctors. The increase in on-call doctors means stabilizing the system until the minor room reduces its capacity to 5 units. Under the limit of 5, an increase in the number of doctors have no impact on the time a patient spends within the ED and is not able to cope with the inflow of patients (Plot 6d). An analogous situation occurs for a work saturation case within the hospital. Such situation leads to “bed block” or “bed crunch”.

The example proposed so far provides some insights about what an ABM simulation is and how it works. In particular it has focused the attention on the non-linearity and on the adaptive behavior of the health care system operating parameters as well as on its interdependencies. Thus, ABM is a potential tool, useful to study the quality of care and health delivers. This modeling technique may provide implications concerning economics, workloads, performances and processes underneath a health care system. Moreover, ABM serve as ways to model unanticipated situations and verify them analyzing potential scenarios. In conclusion, this modeling technique is particularly useful in network analysis in that it may isolate connections across agents.

2.17 SOME NOTES ABOUT NETLOGO

The model presented in this work is developed on a NetlLogo agent-based programming language. NetLogo is a programmable modeling environment for simulating natural and social phenomena, authored by Uri Wilensky in 1999. The spirit of this software comes from the previous Logo programming language and aims at being “low threshold and no ceiling”. It is useful in presenting programming concepts by means of agents in the form of turtles, patches, links and observer. We can briefly present a description for each type of agent:

- *Turtles*: these are agents that move around in the world. Such world is two dimensional and is divided up into a grid of patches.
- *Patches*: these agents are square pieces of “ground” over which turtles can move. Patches have coordinates in horizontal and vertical distances from the origin (0, 0).
- *Links*: these are agents that connect two turtles.
- *The observer*: it has no location on the NetLogo world. One can imaging it as looking out over the world of turtles and patches. However, this agent does not observe passively but gives instructions to other agents.

NetLogo was designed to cover multiple audiences in that it can be used by people who do not present any programming background to model related phenomena.
The most important issue concerning NetLogo environments is their ability to explore emergent phenomena. Modeling complexity is the primary goal of this software where modelers can give instructions to hundreds or thousands of “agents” all operating independently. Hence, the software gives the possibility to explore the connection between the micro-level behavior of individuals and the macro-level patterns that emerge from their interaction. Many scientific publications are based on NetLogo programs in a variety of domains such as economics, biology, physics, chemistry, psychology, system dynamics and healthcare as well.
By means of switches, sliders, choosers, inputs and other interface elements, NetLogo gives the user the possibility of exploring phenomena more closely, monitoring them.

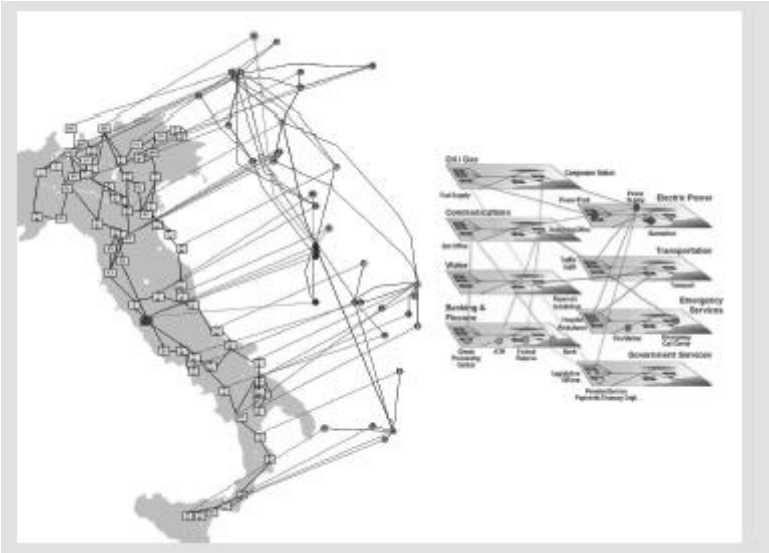
SECTION 3

NETWORK ANALYSIS: WHAT DOES IT BRING TO ABM?

Matching the study of networks with agent-based simulation models

The following section deals with network analysis which has become one of the most visible theoretical frameworks that can be applied to the description, study, understanding, design and repair of complex systems, as well as in strongly coupled multi-level systems (Kenett and Havlin, no year) . Indeed, networks appear everywhere, from man-made systems to human social system, from organic to non-organic organisms, from micro to macro scales, in natural and anthropogenic structures. Hence, understanding networks and their growth, structures, dynamics and functioning (as well as the interrelationships among different networks) helps in developing simulation models, in particular agent-based ones since there are made of agents interactions. Basically, network analysis is essential in order to find precursors of changes, and to make the systems resilient against failures and attacks. In complex systems, the focus of many studies is centered around interrelationships between structures (topology) and dynamics, function and task performance. The applications of such studies undertake several fields of research with huge innovation in science and technology. The phenomena investigated go from cascading failures, blackouts, crashes, bubbles, crises, viral attacks, defense, infrastructures, epidemic spreading and so on. Thus, networks understanding provides huge impact on our field of application which our work focus on: healthcare systems. Healthcare is a complex system characterized by several networks that occur at different levels, with strong feedbacks between the micro states and macro sates of the system. More precisely, each real life system can be better analyzed by means of network analysis. The description of nature may be well represented by network science in which the micro is associated with the nodes of the network and the links between them (Kenett and Havlin, no year), and the macro by the network itself, its topology, dynamics and function. Indeed, the distinction between micro and macro levels is extremely relevant in social and economic systems like healthcare ones. While in physical systems the dynamic is usually bottom-up, in social and economic systems there are interplays on all levels including top-down feedback mechanisms.

After having specified how networks are characterized from a theoretical point of view, the section will insist on the implementation of network analysis in agent-based modeling. In fact, unfortunately, the attempts in understanding function and structures of networks concern individual systems and tend to isolate them. As a result, network analysis tends to be isolated from other science methodologies. However, “networks are not islands” and their study must embrace various fields and systems in that an individual network is often just one component in a much larger complex multi-level network, the so called network of networks (Kenett and Havlin, no year). As an example of multi-level networks, the blackout in Italy occurred in 2003 affected a variety of different networks involving the healthcare system, the railway system, financial markets, communications and so on. This example represents a typical negative feedback case in which networks are interdependent and the failures of the nodes in one network cause failures of dependent nodes in other networks and vice-versa (Kenett and Havlin, no year). The result generated is a sort of “domino effect”, in that the process happens recursively, leading to a cascade of failures in the network of networks system. The following figure present the example in a clear way:



So, future challenges and researches in network analysis applications will undergo more realistic features such as coupling between networks, dynamics of networks, interrelationships between structures, dependencies and spatial properties. These main objects of investigation will provide several tools which in turn will implement models and will make easier to design, predict, and defend many aspects of our social life.
The particular emphasis that is put on the role of network analysis in healthcare system simulations will be useful in understanding the purpose that our agent-based model tries to achieve. Generally, speaking, the healthcare system can also be intended as a social system in that most of the theories regarding networks deal with *social* network analysis.

3.1 SOCIAL NETWORKS: PURPOSES AND HISTORICAL BACKGROUNDS

This paragraph introduces social network analysis (SNA), the main topic of the section. Social networks consisting of actors and social relations are present in almost every social science discipline such as anthropology, economics, sociology, political science and psychology (the so-called "Big Five" social sciences). However, the previous introduction stresses the interdisciplinary areas embraced by network analysis. It had a huge influence on the science across the history in that social networks have been recorded in human history since writing was invented in the ancient Middle East over 5,000 years ago.
Cioffi-Revilla (2014) describes social network analysis (hereafter SNA) as follows:

> Social network analysis consists of a paradigmatic view of the social universe; it is a theoretical perspective, not just a collection of methods. Social network analysis also provides a formal language for developing the science of social networks, including a perspective that enables and facilitates Computational Social Science. Moreover, SNA supports and extends the analysis of complex coupled human-natural-artificial systems by providing useful concepts, notation, and applied principles.

From an historical point of view, contemporary social network science, comprising analysis, modeling and theorizing, is a result of contributions from social, mathematical, physical and computational sciences. Just to point out some milestones in network analysis, an early contribution is due to the famous mathematician Leonard Euler in 1736 who initiated the field of graph theory, the principal mathematical structure employed by social network science. However, the first author who adopted the term "social structure" is Alexis de Tocqueville in his classic "The Old Regime and the French Revolution". With respect to the historical origins of social networks one has to go back in time ca. 100,000 years ago, when humans lived in kin-based networks or families, households and extended family networks. After just 10,000 years ago the very first non-kin networks emerged from social dynamics in the form of simple chiefdoms which in turn evolved into States, forming the first social networks-of-networks-of networks.
Social networks are now quite commonly used in agent-based simulations to explicitly represent the topology of interactions among a population of agents. Amblard and Quattrociocchi (2013) divide modeling of social networks into three categories:

Static networks
Dynamic networks with the dynamics independent of the state of the agents (random processes)
Dynamic networks evolving depending on the state of the agents

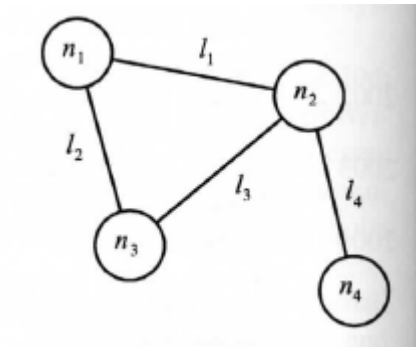
Now we present some theory regarding network analysis and then we center the topic around the joint adoption of ABM and SNA.

3.2 DEFINITIONS AND OBJECTS OF A NETWORK

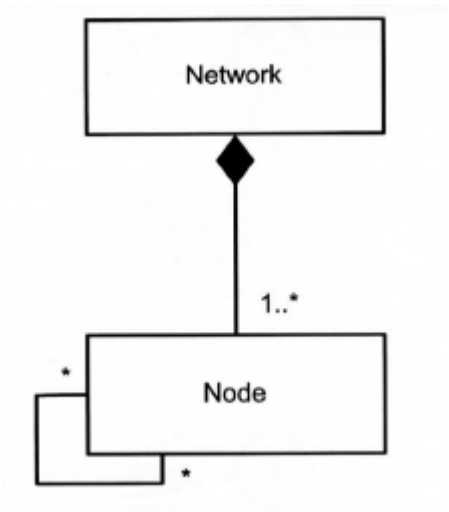
To begin with, Cioffi-Revilla (2014) presents the following constituent parts of a social network:

- *Entities*: actors, values, sentiments, ideas, locations, attributes, etc.
- *Relations*: links, ties, associations, affiliations, interactions, evaluations and so on.
- *Aggregations*: dyads, triads, groups, subgroups.

The mathematical devices adopted in network analysis theory consist of elements coming from graph theory, algebraic methods, matrix algebra and probability theory.
Graph theory provides an appropriate representation of the social network as well as a set of concepts usable in studying formal properties of social networks.
Formally speaking, a network consists of a finite set of entities (nodes and vertices) and a set of relations (called lines, links or edges). A social network made by four nodes and four links can be represented as follows in the picture taken by Cioffi-Revilla (2014):



The number of nodes which compose a network identifies the cardinality of the node sets itself.
Alternatively, UML class diagram may be used in presenting objects composing the network as follows (Cioffi-Revilla, 2014):

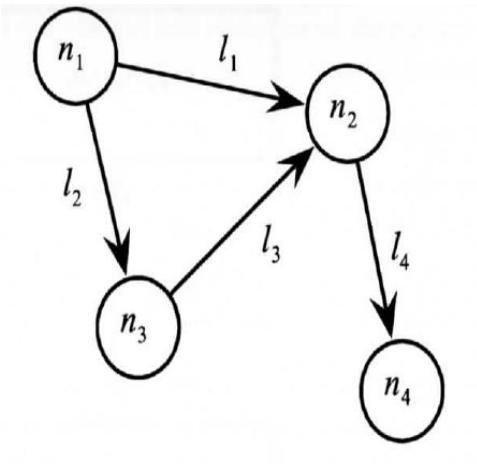


These representations as well as the concepts underneath them, constitute fundamental issues in every model, method or additional concept in network analysis. In particular, defining a social network as a graph, from a computational perspective means viewing a network as a class (Cioffi-Revilla, 2014), a very general type of social object that is composed of nodes of various kinds that can have any number of relations among them. Such idea of a social network as a class having objects is illustrated in the figure above. Cioffi-Revilla (2014) reports that the *self-association* of nodes has *arbitrary multiplicity* in a network. Moreover, the author emphasizes the fact that the type of association between a node and its network is one of *composition* and not only aggregation because a node has no social meaning outside a network. This aspect seems to be obvious but even if it is isolated from other nodes in the network (in the case of an isolate node), a node is meaningful in a social point of view only within the context of some network.

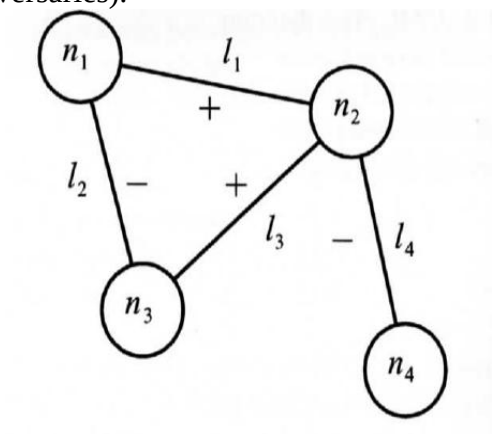
3.3 TYPOLOGICAL NETWORK CLASSIFICATION

Cioffi-Revilla (2014) proposes a classification of social networks based on the nature of social relations and the state of a specific network (all the pictures come from Cioffi-Revilla, 2014):

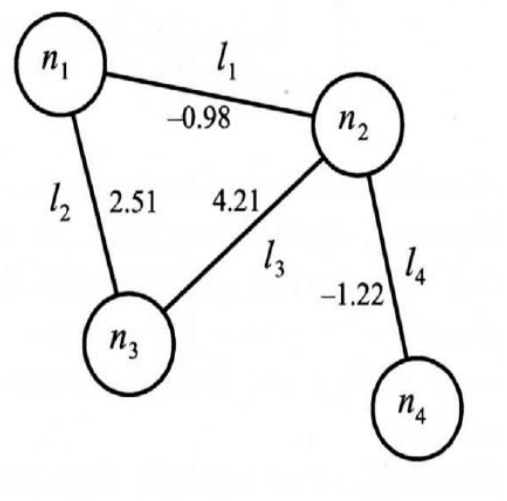
- *Directed networks or digraphs*: this types of network present directional social relations with definite orientations and directions, instead of simple networks where links lack specific directions. In general, this typology involves the vast variety of transaction networks such as those consisting of flows between nodes. Transaction flows typical address people movement such as migrants, tourists, students and patients in the healthcare field. Sometimes transaction flows involve also money or goods or other resources, generally in economic sciences. The corresponding digraph is presented as follows:



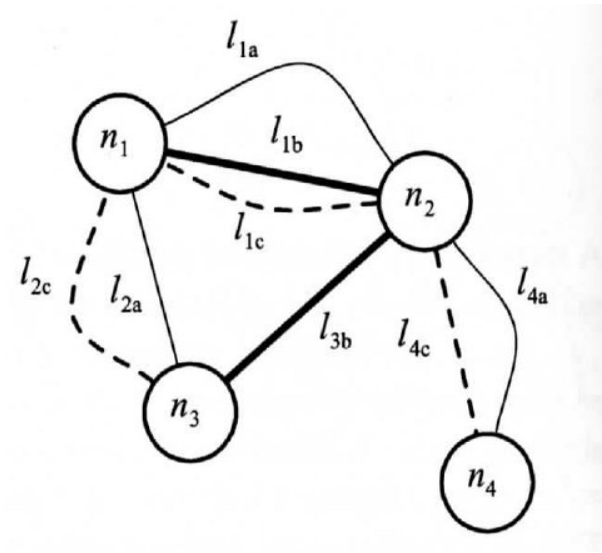
- *Signed networks or valued networks*: this typology of social networks is characterized by links having valence signs (+, -, 0). It is used in psychology (in order to classify ideas as congruent, opposed and unassociated) and in politics too (in order to define allies, neutrals, adversaries).



Weighted networks: in this typology of networks, links have some identifications of weight or intensity. For example, cities are interrelated by distance measures or airports are linked by flying times between them.



- *Multiplex networks*: these social networks present one or more multiple/parallel associations between node pairs. Here, social relations are made by multiple social ties or links between nodes. In healthcare scenarios, the personnel of a hospital is related and associated in a variety of ways, not only through their working association in the hospital. On an empirical level many networks of interest present multiplex relations although most of the SNA study is concerned on single-relation networks.



3.4 PATHS AND LEVELS OF ANALYSIS

SNA theory individuates two types of paths that a network may display (Cioffi-Revilla, 2014):

- *Eulerian path*: It is a path that crosses each link exactly once.
- *Hamiltonian path*: It is a path that visits each node only once.

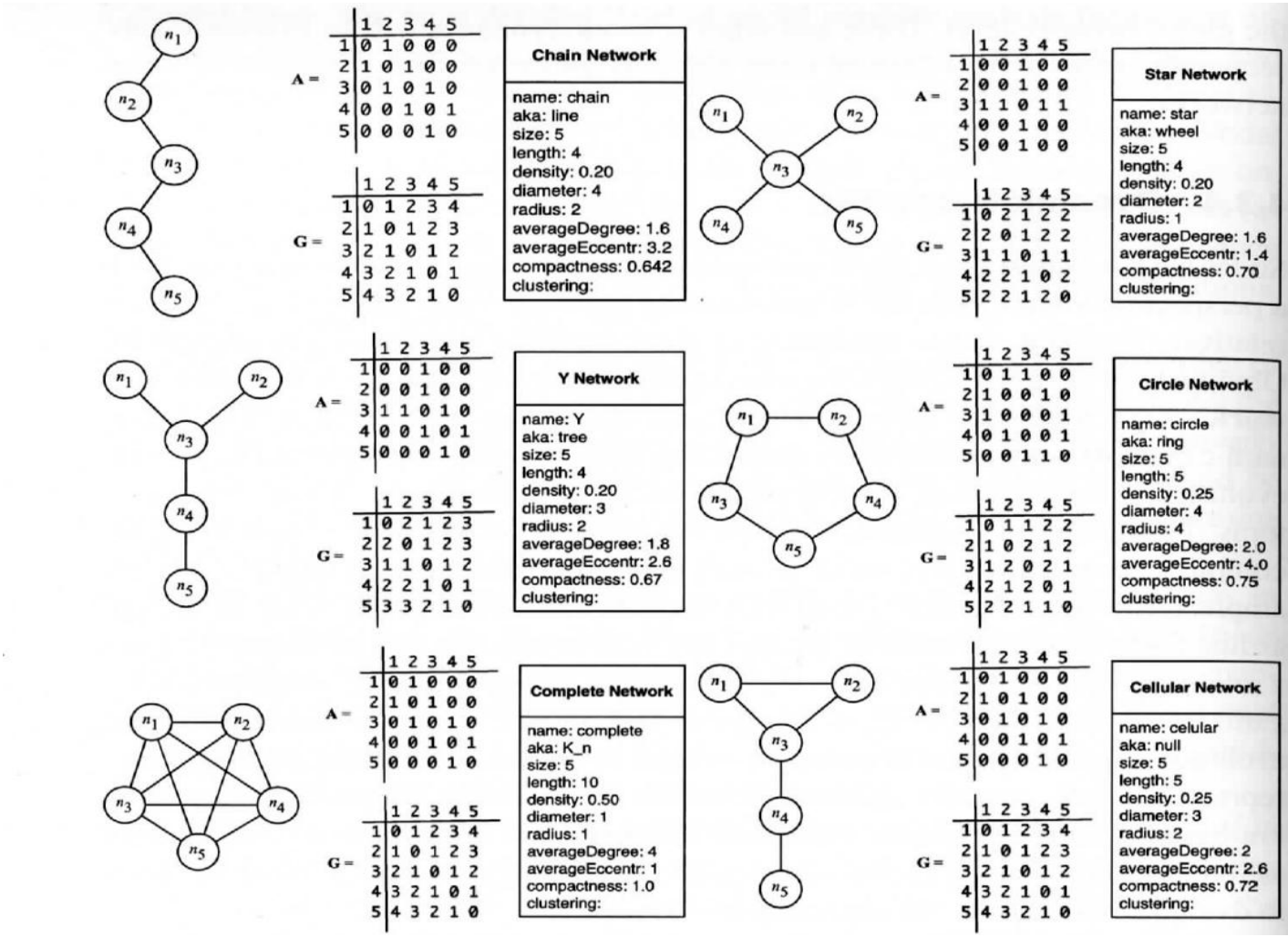
In understanding the architectural structure of a network, Cioffi-Revilla (2014) proposes a characterization of the level of analysis of a network from the micro-level to the macro one (the so called "bottom up" process):

- *Nodal level*: It focuses on attributes of node-entities such as nodal degree, centrality, prominence, status and many other roles. Indeed, the node can be seen as an object with corresponding attributes coming in all kinds of data types such as strings, Boolean, integers and so on. This level of analysis often involves statistical distributions and mathematical models.
- *Dyadic level*: This level puts the attention on relational pairs in binary units from different perspectives. From a qualitative point of view, each type of dyad comprised in a social network may determine the very character of the network itself.
- *Triadic level*: Social triads have meaningful roles in balancing processes and transitive relationships. Such a level of analysis is present on all scales of social networks ranging from cognitive balance in psychological belief systems to international relations and political dynamics in alliance systems.
- *N-adic level*: This level of analysis examines any aggregation of unit nodes and relations, up to the entire size of the network. Typically, this level of analysis is adopted in the field of communication research where audiences may be defined in terms of sub-networks that go from dyads to the complete networks, with combinations in between.
- *Network level*: It is the most aggregate level of a network (the macro level). Here, the level of analysis focuses on aggregate attributes such as size, diameter, connectedness, centralization, density, and others. Moreover, this level aims at analyzing aggregate and emergent properties of various phenomena and, as a consequence, it is adopted in complex system analysis. Hence, in presenting the results of our model, we will adopt a network level of analysis.

Nodal and networks levels of analysis clearly represent the most preferred levels in the literature, although there are several measures that are associated with each level described above. In principle, given sufficient data any social network can be described in great quantitative details.
In addition to this classification, Cioffi-Revilla (2014) provides a further level of analysis: *cross-level analysis*. This level refers to the investigation of properties and dynamics involving multiple network levels. For example, critical changes in properties and dynamics at the level of nodes are consequential for inducing phase transitions at global network levels.
The classification above is referred to static, stable and stationary network compositions. Surely, it may be happen that a network shows time-variant properties and so it can be addressed to as a *dynamic network*. In other words, a dynamic network is simply a network whose state changes as a function of time. Such networks may exhibit a variety of behaviors, from nucleation to growth, from evolution to transformation, disintegration or decay and so on.

3.5 STRUCTURAL FORMS IN SNA

The architectural structure varies across different typologies of network, although some structures may be defined as "elementary structures" as Cioffi-Revilla (2014) points out. These structures are associated with structural patterns that are significant for their properties and recurrence, either in pure form or in combination with others.
This paragraph aims at presenting a network classification based on structural patterns and at providing methods of measurement that are recurrent in SNA, referring to the way of explanation presented in Cioffi-Revilla (2014).
The network classification based on structural properties can be presented in an increasing order of complexity as follows, making use of the picture below (Cioffi-Revilla, 2014):



- *Simple networks*: Are networks without loops or parallel/multiple links. All social networks in the figure are simple.
- *Chain networks*: Also known as line networks, they consist of strings of nodes. Common examples in the literature are given by supply chains and multi-stage processes.
- *Star networks*: Also known as wheel networks, the central node of such networks is radially linked to all the other nodes around it and, as a result, it provides a more centralized structure typically used in hierarchical organizations.

- *Y-networks*: Also known as tree networks, they are made as chains with splits or frayed terminal paths. From a social perspective, organizational charts, games in extensive form and branching processes use this typology of structure.
- *Forest networks*: These networks consist of sets of disconnected trees or set of trees belonging to other networks.
- *Circle networks*: They display as closed chains where nodes are linked in a circle fashion. They seem a circle and may be associated with chain networks.
- *Cyclic networks*: They display as a graph containing one or more cycles with the smallest one being a triad (examples are the complete and the cellular networks in the figure above)
- *Acyclic networks*: This typology refers to all networks that do not contain cycles.
- *Connected networks*: In these networks, every pair of nodes is joined by at least one chain. All the networks in the figure above can be classified as connected networks.
- *Component networks*: They are disconnected sub-graphs.
- *Complete networks*: As it is shown in the figure above, complete networks are those in which each node is connected to all others. They have maximum communication and may or may not indicate lack of hierarchy, depending on the nature of nodes.
- *Bipartite networks*: They are defined as networks with a node set that can be partitioned into two disjoint sets such that every link has one end for each disjoint subset. Price lists, lists of countries and capitals or phone directories are some examples.
- *Cellular networks*: They present one or more nodes with complete graphs attached to them. The last network of the figure has this structure.
- *Non-planar networks*: These structures cannot be represented on a bi-dimensional space. In general, social networks are non-planar.
- *Random networks*: Their structures are characterized by some probabilistic processes underneath the possibility of links forming between nodes. Some examples include networks of relations based on chance, social networks containing dyads intentionally drawn from a lottery and some growth processes.
- *Small-world networks*: Social structures in which most nodes are not adjacent to one another, but can be reached from other nodes by just a small number of links.
- *Scale-free networks*: These structures present nodes with few neighbors and other nodes having more neighbors. However, just a few nodes have a huge number of links.
- *Broad-scale networks*: Similar to scale-free networks, they are not so many connected nodes.
- *Single-scale network*: These structures are characterized by fast decaying tails in the degree distributions.

The World Wide Web is an excellent example of social network in that people are closely associated via URLs. On the other hand, the Internet is a network but it is more likely generated by computers.

In order to better analyze a social network and to provide an explanation about its relational structure, it is useful to introduce the *matrix* form of the relational structure itself. Cioffi-Revilla (2014) reports that when a social network is defined in terms of linked or adjacent neighbors, the network matrix is called *socio-matrix* or adjacency matrix.

We have already pointed out the large use of mathematical tools in SNA. Indeed, also in this case, social network analyses adopt conventional matrix notations from linear algebra and simple tabular notation as follows (Cioffi-Revilla, 2014):

$$\mathbf{A}_{g\times g} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1g} \\ a_{21} & a_{22} & \dots & a_{2g} \\ \vdots & \vdots & \ddots & \vdots \\ a_{g1} & a_{g2} & \dots & a_{gg} \end{pmatrix} = \begin{array}{c|cccc} & n_1 & n_2 & \dots & n_g \\ \hline n_1 & a_{11} & a_{12} & \dots & a_{1g} \\ n_2 & a_{21} & a_{22} & \dots & a_{2g} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ n_g & a_{g1} & a_{g2} & \dots & a_{gg} \end{array}.$$

The matrix above is strictly defined in terms of the node set with elements corresponding to the "*a*ij" terms.
Another typology presented in Cioffi-Revilla (2014) is the *distance matrix*. It is defined in terms of minimal path distances between all connected nodes where the single elements "d_{ij}" denotes the minimal number of links between an i-node and a j-node.

3.6 METHODS OF MEASUREMENT

After having explained structural forms and matrix representations, the theory provides some quantitative measures of social networks. Cioffi-Revilla (2014) presents two main classes of social network measures:

- *Micro-level nodal measures*: defined with attributes of nodes.
- *Macro-level network measures*: made by aggregate attributes that characterize features of the overall network structure.

At the **micro level** of analysis, the attention is focused on nodes and then nodal measures are adopted. Cioffi-Revilla (2014) defines each nodal measure as an attribute of the node object.
The author defines the following nodal measures:

i. *Degree*: Defined both as the number of links incident on a node and as the sum of node elements in the socio-matrix. This is a measure of centrality (sometimes called degree centrality).
ii. *Distance*: Is the distance that occurs between two nodes or, alternatively, is the minimal (geodesic) number of links in any chain connecting two nodes.
iii. *Eccentricity*: Is the maximum geodesic distance between two nodes, or in other words it is the shortest path that links two nodes. This measure reveals how far the node is from the most remote terminal node of the entire network.
iv. *Eigenvector centrality*: It is similar to the degree centrality, but it is weighted by the centrality of each incident/adjacent node. This type of centrality measures the influence of a node.
v. *Betweenness centrality*: It is defined as the number of times that a node is a bridge in the shortest path between two other nodes or, alternatively, it is the number of geodesic paths from all vertices to all other paths that pass through that node. This is an important measure that will be adopted in our simulation model.

With respect to the **macro level** of analysis, Cioffi-Revilla (2014) provides the following measures:

i. *Size*: It is the total number of nodes in a network. Indeed, social networks can vary from large sizes to small ones.
ii. *Length*: It represents the total number of links in a network.
iii. *Density*: It represents the number of actual links relative to total number of possible links in the network under analysis. Hence, network density is linearly proportional to network length and inversely proportional to the square of network size.
iv. *Diameter*: It is the maximum nodal eccentricity or, alternatively, the maximum geodesic distance in the network.
v. *Radius*: It represents the minimum nodal eccentricity or, alternatively, the minimum geodesic distance in the network.
vi. *Average degree*: Concerns the general connectedness of nodes in the network.
vii. *Degree skewness*: Useful for detecting non-equilibrium distributions.
viii. *Average eccentricity*: Measures the general "width" of a network. It has to be interpreted conditionally upon information on its distribution.
ix. *Compactness*: it is represented by an equation providing a coefficient ranging from 0 to 1.

3.7 NETWORK ANALYSIS AND AGENT-BASED MODELING

Since healthcare is a complex phenomenon in which many individuals, groups, organizations interact by exchanging resources and information in a dynamic environment (Marzo et al. 2014), it can be modeled as a dynamic network made by a mix of human subjects, organizations, structures that can exchange information and interact. So agent-based modeling is closely associated with network analysis. Moreover, in the healthcare field the dynamics of the health emerge from behaviors and interactions of heterogeneous individuals and hence interaction is the basic mechanism that mediates social production of health (Marzo et al. 2014).
Agent-based models in healthcare, as we have already explained in the corresponding session, focus on three main applications (Marzo et al. 2014):

- Administrative process support within a single healthcare organization (for example hospitals, local health authorities and so on).
- Clinical process support that encompasses the physical boundaries of a single healthcare organization (for example hospitals, laboratories and so on).
- Integrated care process support with patient-centered approaches.

Marzo et al. (2014) asses that at each of these perspectives, a core rule is played by the concept of network:

> Either in considering exchange within an organization, between organizations and in an environment constituted by several subjects related to a single patient, it is crucial to understand structural and dynamic aspects of the links that let all the subjects together be a system.

As we have already pointed out in the agent-based modeling section, a modeler has to face the design of the agents and their behaviors as well as the design of the topology in which the agents interact. In other words, the environment of a simulation can be presented on two dimensions: a

spatial structure where agents are distributed following a geographical representation, and a social structure, linking agents as nodes in a network (Amblard and Quattrociocchi, 2013).
Hence, agent-based modeling and network analysis are two disciplines that have to be considered jointly when dealing with social models or complex systems in general. Fontana and Terna (2014) stress this concept:

> We argue that the combination of the two methods can increase enormously the potential of complexity-based policies…..The very definition of complex system involves structure and patterns emerging from decentralized autonomous interaction. The exploration of this micro-macro mapping is well conducted through ABMs, but what if the emerging structure is a network? To put it differently, social, economic and technological networks in the real world are generated through the mechanism that we have just described above, so we can generate easily and sensibly networks through ABMs.

Moreover Fontana and Terna (2014) provide a series of limits of network analysis that may be contrasted by means of ABM implementations:

- *Dynamism*: Network analysis is much more focused on static networks rather than dynamics or evolutionary issues.
- *Behavior of nodes*: Network analysis tries hardly to follow two goals sometimes irreconcilable. On the one hand it needs to generate networks through appropriate rules, and on the other hand it needs to embed in such rules a similar version of meaningful social and economic behaviors. So, traditional network analysis often provides rules driving the formation of links that are too far from realistic foundations.
- *Methods*: In previous paragraphs we have passed through a series of mathematical concepts. Fontana and Terna (2014) asses that the behavior of the nodes is condensed in few formal propositions making the analysis of possible set of nodes extremely complicated in terms of number of configurations. This, surely, causes serious problems in mastering models, considering the dimension of real world networks.

With respect to the first element of weakness, the authors stress the fact that with ABM the problem with static network is easy to solve in that ABM involves dynamic directly. Moreover, with respect to the second issue, ABM provides models with a huge variety of behaviors and attributes that might bridge the gap between agent-nodes and the real world. In ABM the number of possible combinations is enormous but it can be overcome by establishing relationships between micro behaviors and emerging networks. Finally, with respect to the third problem, the authors asses that ABM involves specified individual behaviors and dynamics of social interactions in order to analyze the evolution of a network. As a result, the measurement process can embrace simulated networks in different ways as well as investigating whether the network characteristics chosen to measure correspond effectively to the causal mechanism proposed.

3.8 INTERACTION TOPOLOGIES: EXPLICIT AND IMPLICIT STRUCTURES

After having introduce the implementation of network analysis into ABM, we focus the attention on the two types of interaction topologies that can be determined explicitly or implicitly (Amblard and Quattrociocchi, 2013).
To begin with, we have to point out three major issues to solve when dealing with social and spatial structures (Amblard and Quattrociocchi, 2013):

- *Implementation*: It aims at explaining how to represent the structure in a model. For example it implies a continuous or a discrete representation of space or which data structure to choose for the social network.
- *Initialization*: It deals with the initialization of the chosen structure. For example, which initial shape of the network should be chosen and how should the population of agents be distributed on this network.
- *Observation*: It deals with the characterization of a given structure and its evolution over time, taking into account the state of the agents related to their place in the structure. Hence, this point makes the presence of indicators and monitors during the simulation an important factor in order to follow changes in either spatial or social structures.

Then, the difference between explicit and implicit structures can be formulated following Amblard and Quattrociocchi (2013).

- *Explicit interaction topologies* are specified as modeling hypotheses and thus clearly defined within the model. In other words, explicit structures are clearly implemented modeling hypotheses, which can therefore be identified in the model. As an example of network structures in ABM we can analyze the segregation model in NetLogo which is composed by a set of agents of two different colors, positioned on a empty square of a chessboard (the environment). If the proportion of neighbors of the same color falls below the value of agents tolerance variable, the agents moves to a randomly chosen empty square otherwise it stays where it is. One can asses that the spatial structure of the segregation model presented in NetLogo is explicit in that it is designed as a grid, it is discrete, regular and static, meaning that the distribution of agents on this structure evolves without involving the evolution of the structure itself. As an example of explicit social structure, one may refer to social network determined, at least in some parts, from geographical locations of structures, buildings and other agents. The model developed in our simulation is based in part on precise geographical coordinates and so it shows an explicit social structure in some parts.
- *Implicit interaction topologies,* on the other hand, are inferred from other processes and thus not a define part of the model. These structures are not directly defined in the model and are rather determined as a result of other processes and/or hypotheses in the model. Following the segregation model described above, its social structure is, on the other hand, implicit, in that during the simulation the agents take into account the type of their neighbors on the grid, but the corresponding social structure is not defined as such and is inferred from the spatial distribution of the agents.

The difference underlined above, is crucial when dealing with the three issues at the beginning of the paragraph. First of all, implementation and initialization issues can only be asked when dealing with explicit structures. Nevertheless, with implicit social structures in spatial models, the identification at a given time of the whole set of interactions among agents can give useful insights

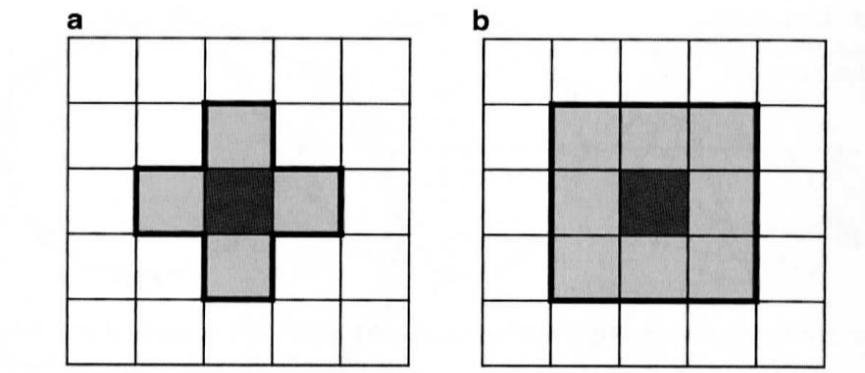
for understanding the underlying dynamics of the model. Indeed, identifying separate components in the implicit social network inferred from a spatial model is more informative than solely identifying spatial clusters as it confirms that there is effectively no connection among the different groups (Amblard and Quattrociocchi, 2013).

3.9 ABM AND SOCIAL NETWORKS: DATA STRUCTURES AND NETWORK CONFIGURATION

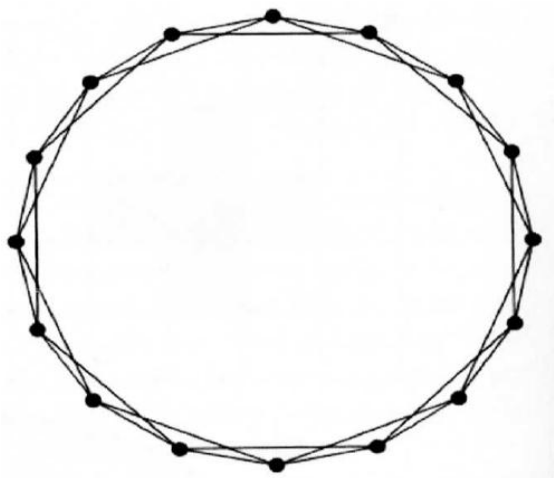
Surely, this issue is important concerning the execution efficiency of any model in that Amblard and Quattrociocchi (2013) asses that biases are linked to some data structures when using particular classes of networks such as scale-free networks.
Amblard and Quattrociocchi (2013) present two options when modeling the data structure: one may embed social links within the agent as pointers to other agents or alternatively one may externalize the whole set of links as a global collection.
The first strategy is more practical when taking into account all neighbors states to determine the new state of the agent rather than picking one agent at random in the neighborhood.
Amblard and Quattrociocchi (2013) emphasize that the difference between the two solutions is mainly related to the used scheduling. One may choose to first schedule the agents, picking an agent at random from the population and then selecting one or more of its social links, or alternatively, one may choose to pick a random link from the global collection executing the corresponding interaction.
It has to be pointed out that in scale-free networks both the solutions may produce biases. We have already defined scale-free networks in which the distribution of the number of links per agent (node) follows a so-called power law: i.e. few agents (hubs) have a huge amount of links while the majority of agents have only a few. In that case, if one chooses to schedule agents first, links involving the hubs will be less frequently scheduled than the links involving agents with few social relations (Amblard and Quattrociocchi, 2013). On the other hand, scheduling the collection of links first, the influence of the hubs in the global dynamics will be strengthened, as they are involved in more links.

Design social structures in simulation models implies choosing a variety of structures to implement that we have already found in Cioffi-Revilla (2014). Typically, in simulation modeling we can distinguish four categories of social structures (Amblard and Quattrociocchi, 2013):

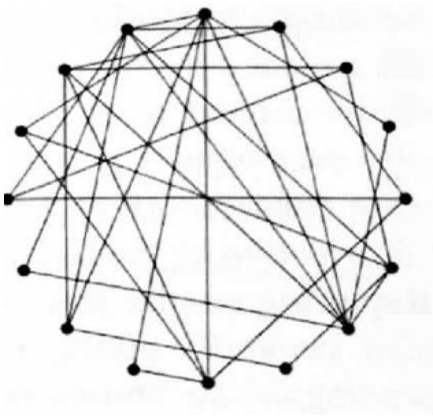
Lattices, grids and regular graphs: In regular grids, the cells of the automata represent agents and their social neighborhood is defined from the regular grid itself with a von Neumann neighborhood (it links a cell to its four adjacent cells) or a Moore neighborhood (it adds four more neighbors: NE, SE, SW, NW) as it can be noticed in the picture below. The main advantage of using grids can be found in the visualization of diffusion processes or clustering processes.



In regular structures it is difficult to change the connectivity of the structure itself (and so the number of links per agent). Moreover, dimension is another critical aspect in that only two-dimensional structures (grids) provide benefits in terms of visualization. The figure below represents a regular one-dimensional structure with connectivity equal to 4.

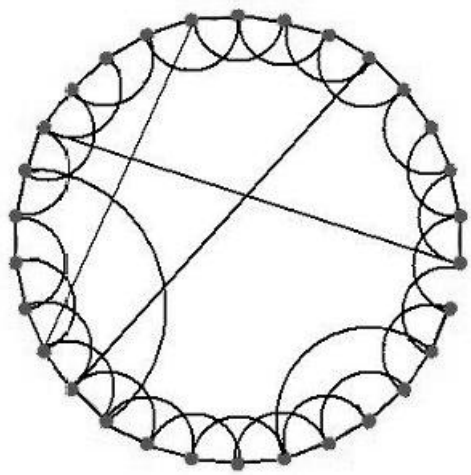


Random graphs: An important property of random graphs is that they show a phase transition when the average degree of a vertex is 1. Below this transition a number of small components come out, while above the threshold the model exhibits a giant component with some isolated nodes (Amblard and Quattrociocchi, 2013). The random graphs that are used most often in agent-based modeling simulations usually are above the threshold, in the giant-component phase with some isolated nodes. Moreover, the degree distribution plays a crucial role in random graphs in that the properties of the behavior of a network are affected in many ways by its degree distribution. Indeed, it is possible to define random graphs with any desired degree distribution. Amblard and Quattrociocchi (2013), asses that in the context of agent-based social simulation, a great advantage of random graphs over regular graphs is that one may easily change and precisely tune the average connectivity of the graph. In addition to this, using random graphs one may experience "social networks" in that he can develop models having different macroscopic behaviors depending on the chosen interaction structure. On the one hand, regular graphs show more clustering or local redundancy than random graphs. On the other hand, random graphs lead to a shorter diameter and average path length among the pairs of individuals (Amblard and Quattrociocchi, 2013). The figure below represent a random graph:



Small world networks: this typology of networks, already defined before in this section, exhibits two main properties:

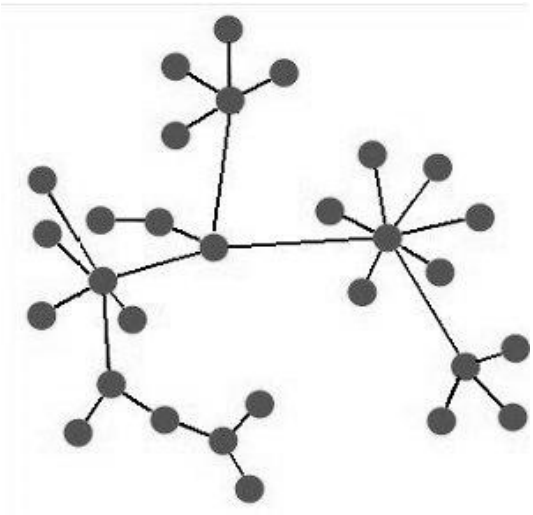
- Small-world effect: many vertices are linked by means of short paths in the network.
- High clustering: it as phenomenon according to which the more neighbors two individuals have in common, the more likely they are to be connected themselves.



As it can be noticed in the figure above (Hamill and Gilbert, 2009), in small world networks, most nodes are linked only to their immediate neighbors.

Scale-Free Networks: the empirical evidence on several data analysis concerning real networks such as the World Wide Web, the Internet, and metabolic networks show that the degree distribution approximates a power law (Amblard and Quattrociocchi, 2013). The power-law degree distribution is the main feature of scale-free networks. Moreover, in considering properties of such network the literature uses graphs that grow dynamically. Indeed, the literature (Barabàsi and Albert, 1999) suggests a mechanism with two components: a network which is growing with vertices added continuously to it and new edges gained by vertices in proportion to the number they already have. Such process is also known in the literature as *preferential attachment*.
Amblard and Quattrociocchi (2013) refer that the use of models like preferential attachment in agent-based social simulations context follows two purposes. On the one hand, these models are used as initial configurations fro the simulation, in that the scale-free network construction can be used in building the initial state of the simulation itself. On the contrary, these models based on preferential attachment may be useful in analyzing social network dynamics.

The figure below (Hamill and Gilbert, 2009) represents a scale-free network based on preferential attachment where few nodes have many links:



3.10 DISTRIBUTING AGENTS ON THE NETWORK AND INDICATORS

In developing a simulation model, one has to consider some questions that deal with its efficiency. In particular the characterization of links between agents which represent interactions is a fundamental issue concerning the interaction space and its emerging properties (Amblard and Quattrociocchi, 2013). For example, crucial issues that must be considered by the modeler address the initial state of the population and the population density (distribution).

With respect to the latter issue, Amblard and Quattrociocchi (2013) reveal that one can always generate ad-hoc situations either using real data or building them artificially, although most of the times one prefers to use a random distribution as a generic way of distributing agents among a network (out model is based on a random distribution). Random distributions imply that agents are distributed uniformly over the network assuming that each agent's state is independent from its location in the network (Amblard and Quattrociocchi, 2013).

When a modeler adopts some hypotheses concerning the relation between the existence of a link between two agents and their actual state, a stochastic algorithm may provide some flexibility in the analysis of such relation. Otherwise, in some cases modelers are only able to describe the global state they want to obtain, operating iterative permutations among the agents. They compute the results for each permutation(Amblard and Quattrociocchi, 2013). Nevertheless, the most prudent approach may consist of taking into account agents characteristics when deciding on the presence of a link between two agents, which is the procedure that we have adopted in developing our simulation model.

Most of the times, when the model is running and each agent is interacting and changing its state over time, the correspondent evolving network may be a chaos. So, the modeler has to introduce some meaningful network layouts, introducing some indicators enabling to better understand what happens in the model. Amblard and Quattrociocchi (2013) classify two categories of indicators:

- Indicators linking the states of nodes with their position in the network.
- Indicators helping to characterize the structure of the network only.

In general, properties associated with graphs influence the dynamics of a network. A typical case is given by clustering coefficients which deal with influence processes or diameters which deal with diffusion processes. If the network under analysis shows a regular structure with all nodes being equal, the structure can be determined on the connectivity and the dimension of the corresponding graph. The clustering coefficient as well may is defined locally for each given node, comparing the rate of existing links among its neighbors and the number of possible links (local redundancy).
Amblard and Quattrociocchi (2013) report a series of common indicators in network analysis that may provide clear representation of networks in simulation models:

- Average similarity measure over the network: it calculates the mean distance among all connected agents of the population. In other words, the modeler is looking at a particular dimension of the agents state vector, trying to see if the agents have a tendency to regroup or cluster according to their state.
- Average path length index: the small-world effect in the corresponding typology of networks is measured by averaging the distance among any pair of vertices in the graph.
- Clustering coefficient: consisting in averaging a local clustering coefficient over all vertices of the network. It is defined as the number of existing links among the neighbors of the vertex divided by the number of possible links among these neighbors. However, this indicator is heavily biased in favor of vertices with a low degree (close to zero) due to the small number of possible links they have.
- Centrality: the focus is centered around relative positions of nodes in a network. The degree centrality, already introduced in this section, measures the number of edges that connect a node to other nodes in a network. There are several centrality measures in the literature that may provide useful insights in network analysis coming from simulation models. The betweenness centrality, already defined in these pages, is an useful measure of the importance of some nodes in a network and it will be presented in our model.

3.11 NETWORK ANALYSIS IN HEALTHCARE SIMULATIONS

Coming back to the environment characterization of healthcare simulation frameworks presented in the ABM section (Charfeddine and Montreuil, 2008), we have to complete the discussion adding the network analysis part.
Networks define the organization of the healthcare delivery system and are composed of nodes and inter-node links. Charfeddine and Montreuil (2008) compare nodes to Health Service Centers (HSCs), meaning either organizational entities such as emergency centers, hospitals and so on, or an agent such as a care provider. Each HSC is characterized by some responsibilities that it has in the network. Relations generally have a structural connotation while flows usually have the function of capturing dynamics. Charfeddine and Montreuil (2008), distinguish six typologies of relation which are common in healthcare network models:

- *Physical embedding relation*: when a HSC is physically located in another.
- *Membership relation*: when a HSC is organizationally or administratively dependant of another.
- *Referring relation*: it permits to model service "corridors" between the network of HSCs and to specify who can refer a patient to whom.
- *Contracting relation*: it specifies when a HSC deliver services in the network as a subcontractor for another HSC . Hence, this typology may be useful in modeling some supporting services that are often subcontracted to exterior providers.
- *Supplying relation*: it is used when a supplier HSC provides goods or services to another (the client).
- *Collaborative relation*: it occurs when two HSCs have to collaboratively and closely coordinate their work to make some tasks or decisions. A classic example is a surgical team during interventions.

Concerning flows, Charfeddine and Montreuil (2008) identify four main types:

- *Patient flows*
- *Physical flows*: including mobile assets, supplies, materials, etc.
- *Informational flows*: including all type of data, information, documents related to patients such as medical records, supplies, materials and so on.
- *Decisional flows*: including control, planning and monitoring decisions exchanged within the network.
- *Financial flows*

Moreover, the authors Charfeddine and Montreuil (2008) stress the fact that networks can have an identity of their own in the field, for example a regional first-line network. In particular networks can become HSCs in higher level networks in that all organizational units can be recursively conceived as networks, each with their internal interlinked HSCs. The authors highlights that a HSC in a network model may refer to an abstract entity. As an example, one can model all private medical clinics or all family physicians in a region as a single HSC or only few family doctors instead of the true number in a region, like in our simulation model. On the other hand a HSC in a network model may refer to a real (physical) instance such as a particular clinic or physician. In the previous case (abstraction) agents are usually identified by a generic label while in the latter case agents are identified by their own precise names.

In addition, Charfeddine and Montreuil (2008) establish eight different types of HSCs according to their mission. The following table refers to this classification:

Type	Responsibility orientation	Processes performed	Examples
Speciality	A medical speciality	All that are part of the speciality	Cardiology, ophthalmology, radiology
Disease	A disease	All required to diagnosis and treat the disease	COPD, diabetes, cancer
Group	A distinct group of diseases or specialties	All required by the diseases or specialties in the group	Cardiovascular diseases
Patient	A type of patient with similar needs	All required by these patients	Elderly people, children, patients at home
Function	An elementary process (function)	Single	Diagnosis, evaluation
Process	A process composed of several elementary functions	Single	Emergencies, intensive care units
Program	A set of activities or procedures to be followed and which are periodically scheduled	All composing the program	Educational centers, Rehabilitation programs
Composite	A combination of other HSC types	All processes required by HSC types	General purpose hospitals

SECTION 4

THE MODEL

The agent-based simulation model of the healthcare system in the area of Turin

This section is entirely devoted to the explanation of our model concerning the healthcare system in the area of Turin. Following the characterization of agent-based simulation modeling reported on the literature review, these pages present each building block of our project starting from the environment and passing through each agent created in the model.
As we have already pointed out, NetLogo is the platform that we have used in order to simulate the healthcare system in the area of Turin. The following explanation will be supported by several pictures coming from the NetLogo interface as well as some parts of the program code that will introduce the procedures run by the program.

4.1 THE ENVIRONMENT

The first step that each modeler has to undertake when developing an agent-based simulation regards the creation of the framework or, better speaking, the environment in which agents interact. In our case, the model framework has to be based on a geographical representation of the district of Turin, the main city of Piedmont region, North-West Italy. For completeness, the district of Turin is one of the eight districts (the other districts are Cuneo, Asti, Alessandria, Vercelli, Novara, Verbania and Biella) that compose the whole region which is represented as follows:

The district of Turin is the biggest district of the region in that only the city of Turin accounts for 902,137 inhabitants. On the healthcare level, the district of Turin is the biggest one with eighteen hospitals that cover a surface of 6,827 km^2 with 316 municipalities.
From a geo-morphological point of view, the district of Turin is characterized by some valleys in the Alps which present less population density, while, conversely, in the metropolitan area of Turin the population density reaches the value of 336.59 inhabitants for each km^2. The following picture refers to the geo-physical representation of the territory under discussion:

The whole territory of the district is then divided into three precincts that surround the city of Turin which may be considered separated from the municipalities around it. Hence, the district is characterized by four components:

- *Turin*: the center of the district with a huge population density.
- *The first belt*: municipalities close to the Turin area.
- *The second belt*: municipalities denoting the sub-urban area.
- *The third belt*: consisting of rural areas in the countryside as well as municipalities in mountain zones.

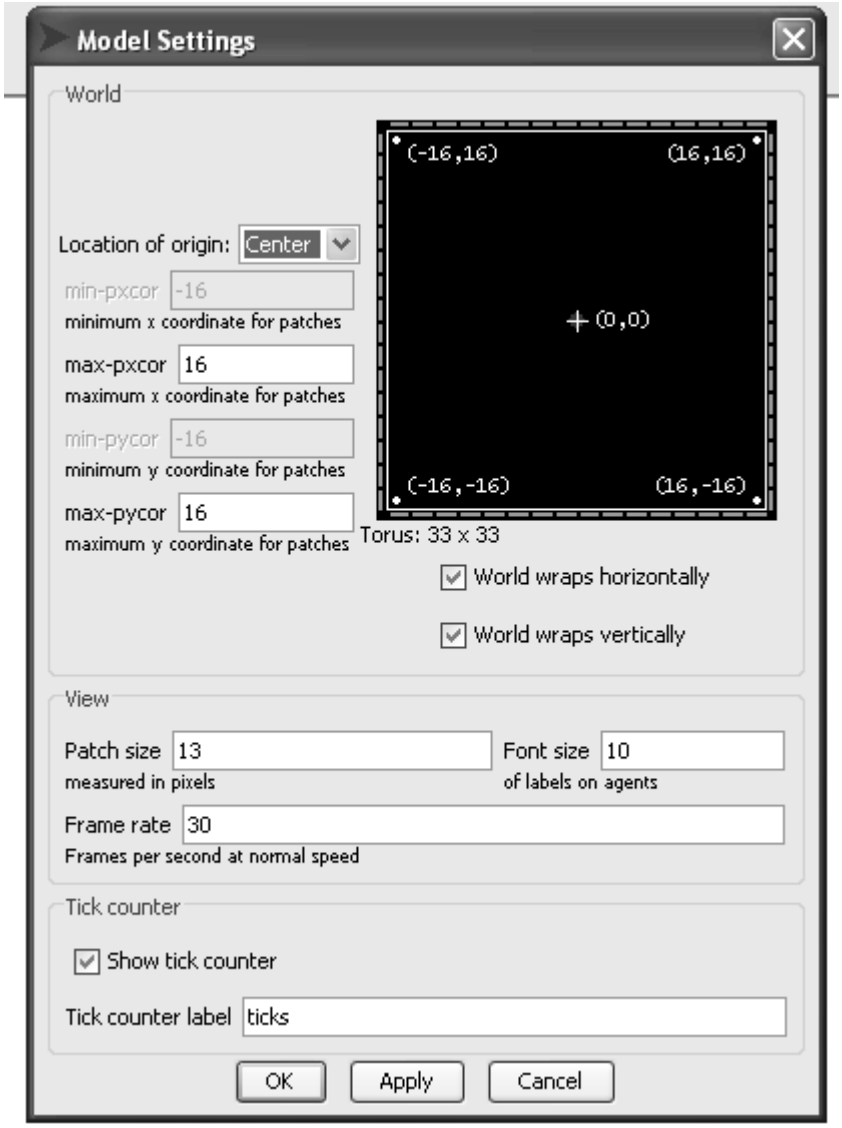
The following table (DemOs, Osservatorio demografico territorial del Piemonte) provides the municipalities shaping the first belt (column on the left) and the ones shaping the second belt (column on the right):

Prima Cintura		Seconda Cintura	
Codice Istat	Comune	Codice Istat	Comune
1008	Alpignano	1002	Airasca
1018	Baldissero Torinese	1013	Avigliana
1024	Beinasco	1034	Brandizzo
1028	Borgaro Torinese	1038	Bruino
1048	Cambiano	1045	Buttigliera Alta
1063	Caselle Torinese	1051	Candiolo
1078	Chieri	1058	Carignano
1090	Collegno	1059	Carmagnola
1099	Druento	1062	Caselette
1120	Grugliasco	1068	Castiglione Torinese
1130	Leini	1082	Chivasso
1156	Moncalieri	1086	Ciriè
1164	Nichelino	1112	Gassino Torinese
1171	Orbassano	1127	La Loggia
1183	Pecetto Torinese	1168	None
1189	Pianezza	1193	Piobesi Torinese
1192	Pino Torinese	1194	Piossasco
1214	Rivalta di Torino	1197	Poirino
1219	Rivoli	1215	Riva Presso Chieri
1249	San Mauro Torinese	1220	Robassomero
1265	Settimo Torinese	1228	Rosta
1280	Trofarello	1240	San Francesco Al Campo
1292	Venaria	1248	San Maurizio Canavese
		1257	Santena
		1302	Villarbasse
		1308	Villastellone
		1309	Vinovo
		1314	Volpiano
		1315	Volvera

The remaining part of the municipalities belongs to the third belt. The boundaries of the city of Turin and the first belt are presented as follows:

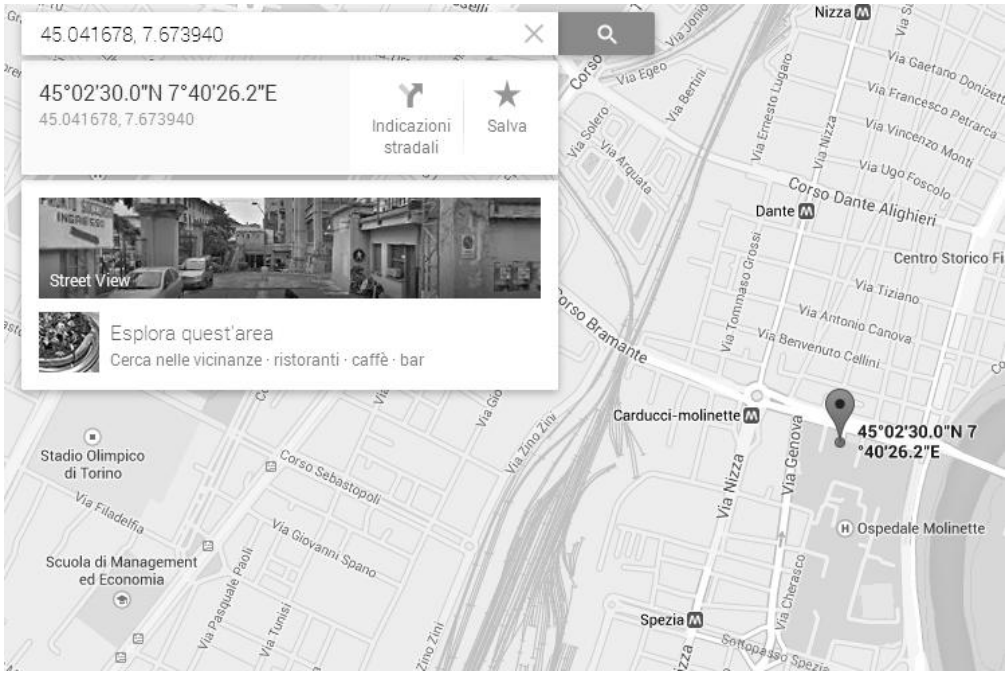
Hence, the first step in our agent-based model development consists of a meaningful and correct representation of these territorial divisions. As we have already reported in the paragraph concerning NetLogo, the world of the software is made by patches which are characterized by coordinates. The predefined settings, in general, put the origin (0, 0) on the center of the world space of the software which appears as follows to the modeler:

The axes can be modified, putting the origin in a proper way according to the environment that one wants to create, simply by changing the settings which are presented as follows:



In this window, the user can modify the origin position and the extensions of the axes in terms of patches, as well as their dimensions and size.

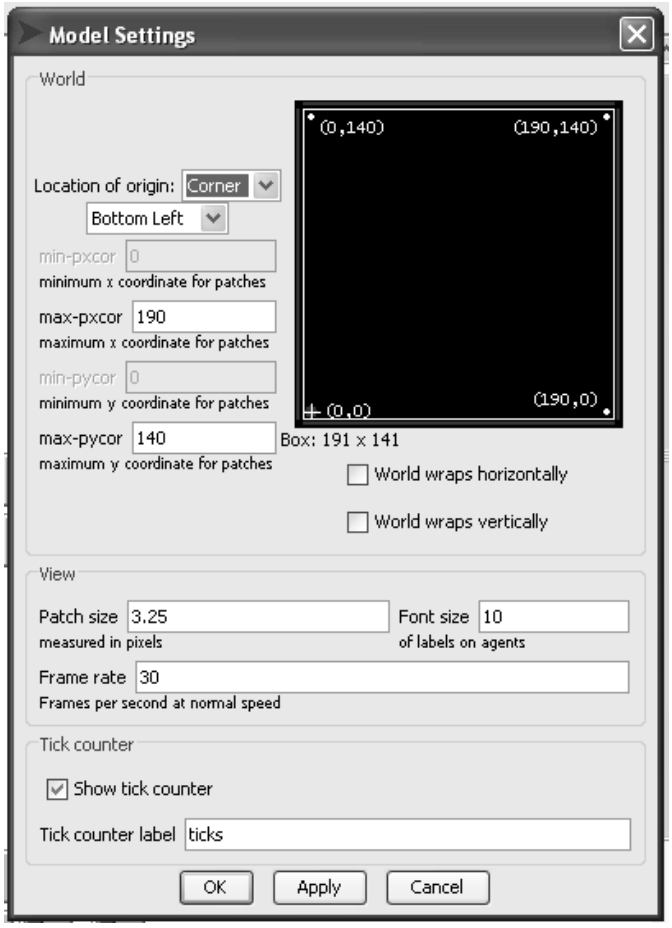
In order to develop a suitable representation of the district of Turin, we have found some reference points that have provided the geographical characterization of the entire area under analysis. Since the focus of the project is centered around a healthcare system, we have adopted the real coordinates of all the eighteen hospitals in the district as pivots for the whole world characterization.
Indeed, it is quite easy to find geographical coordinates using GIS (geographical information systems). Google maps provide precise latitudes and longitudes for each specific hospital in the area we are interested in. As a result, one can simply take the real coordinates and then rearrange the measure scale in order to find the representation in the NetLogo interface that suits best.



The picture above represents the geo-localization of the hospital “Molinette” in the city center of Turin, where the first number on the left refers to the latitude and the second number to the longitude.

So, in characterizing the NetLogo environment we have started from the geo-localization of the hospitals in the district of Turin. Taking the geographical coordinates from Google Maps for each hospital, we have proceeded by rearranging measure scales in order to have a practical NetLogo interface to deal with . We have put the origin on the down left corner of the world and we have chosen the maximum value for the x-axis and the y-axis, 190 and 140 respectively. All the characteristics of the patch size and the coordinates can be seen in the picture on the following page. Since, hospitals have to be interpreted as agents in NetLogo, we will introduce and examine them later on in the section concerning agents.
After having geo-localized hospitals as main cornerstones of our world, we have followed the already reported division of the district into “belts” identifying them with different patch colors on the NetLogo interface. In creating the belts, we have proceed by taking the hospitals as indicators of the boundaries marking the 4 zones. Thus, the world results divided as follows:

- the city of *Turin* lays almost at the center of the world and is characterized by patches colored in white.
- The *first belt* is identified by patches colored in red.
- The *second belt* is identified by patches colored in yellow.
- The *third belt* is colored in green.

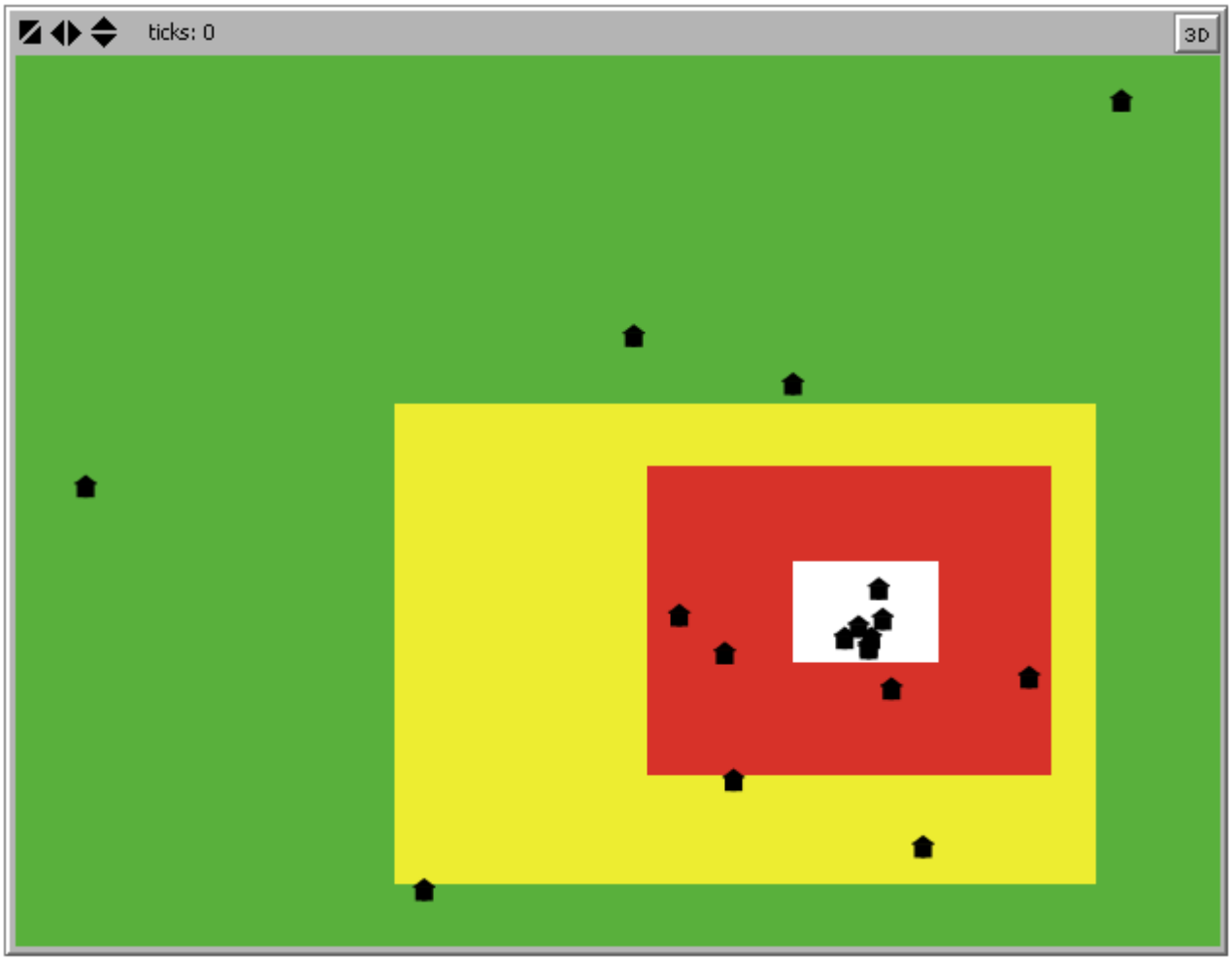


Since, each part of the NetLogo interface must be written in a programming language, we have to present the code part concerning the world creation. As a matter of completeness, it has to be pointed out that the procedures connected with the world creation are better know as "setup procedures" and differ, from a programming perspective, to the procedures connected with actions and interaction across agents.
So, the code part referring to the creation of the belts is the following:

```
to setup-canvas
  ask patches [set pcolor green]
  set Torino2 patches with [pxcor >= 60 and pxcor <= 170 and pycor >= 10 and pycor <= 85 ]
ask Torino2 [ set pcolor yellow]
  set Torino1 patches with [pxcor >= 100 and pxcor <= 163 and pycor >= 27 and pycor <= 75 ]
ask Torino1 [ set pcolor red]
  set Torino patches with [pxcor >= 123 and pxcor <= 145 and pycor >= 45 and pycor <= 60 ]
ask Torino [ set pcolor white]
  set Torino3 patches with [pcolor = green]
end
```

Each boundary is identified referring to the hospitals in the various municipalities, that serve as pivots in determining the correct values. We have to point out that the real shape of these belts is far from being a rectangle (it something irregular as it can be noticed by looking at the maps reported

above). Surely, we have simplified the shape in that the software is based on patches with cube shapes and cannot permit to represent irregular boundaries.
The overall result is presented in the picture below which gives the idea of the belts with the city of Turin almost at the center of the world and the various hospitals spread on the territory:

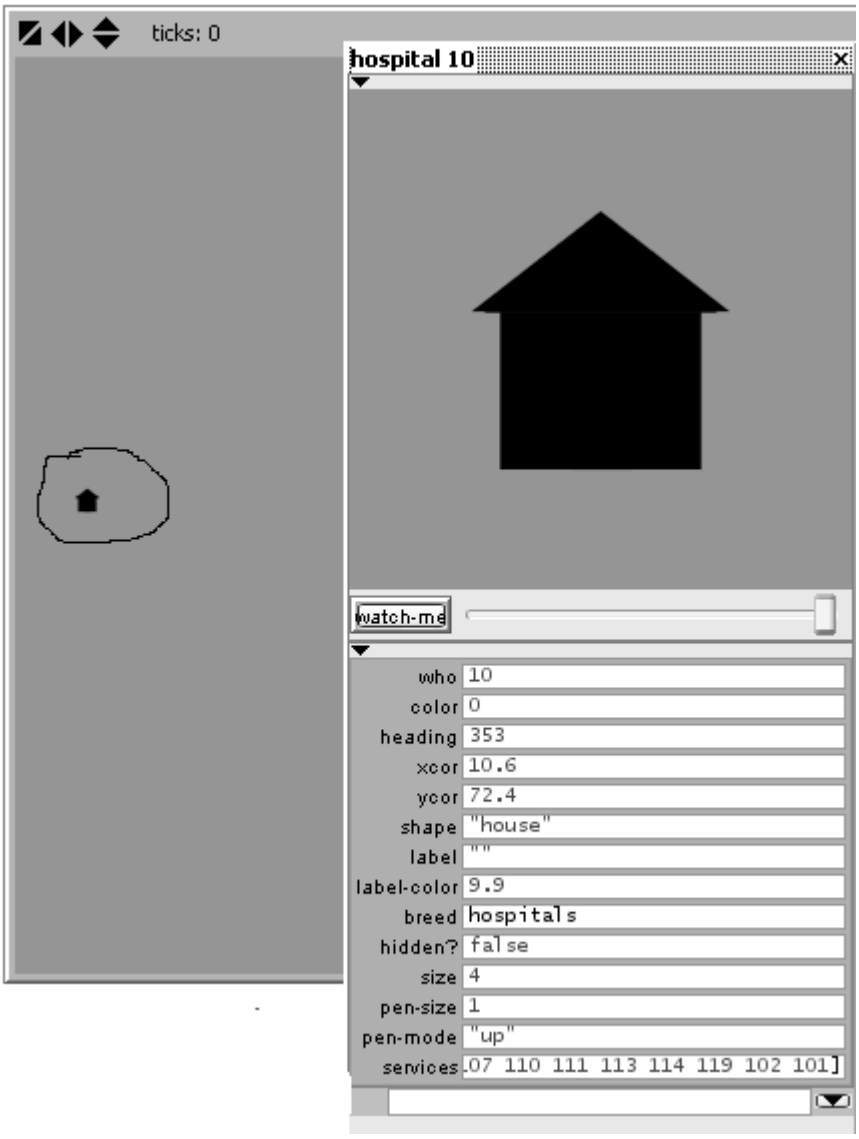


4.2 THE AGENT SET: HOSPITALS

After having presented the environment creation and its aspect on the NetLogo interface, we can now start to introduce the core part of an agent-based simulation: the agents. As we have seen in the section devoted to ABM, agents are the cornerstone of the model in that they generate interactions and networks characterizing the whole system under investigation.
To begin with, this paragraph introduces the hospitals effectively located in the district of Turin. It has to be pointed out that NetLogo identifies each agent with an ID number and the hospitals exhibit their IDs from 0 to 17 (the software counts beginning from the zero). We can report the hospitals names and their associated belt and IDs as follows:

- CTO: center of Turin (white), ID 0.
- Mauriziano: center of Turin (white), ID 1.
- Regina Margherita: center of Turin (white), ID 2.
- Molinette: center of Turin (white), ID 3.
- San Luigi, Orbassano: first belt (red), ID 4.
- IRCCS, Candiolo: second belt (yellow), ID 5.
- Koelliker: center of Turin (white), ID 6.
- Valdese: center of Turin (white), ID 7.
- Cottolengo: center of Turin (white), ID 8.
- Rivoli: first belt (red), ID 9.
- Susa: third belt (green), ID 10.
- Pinerolo: third belt (green), ID 11.
- Lanzo: third belt (green), ID 12.
- Ivrea: third belt (green), ID 13.
- San Carlo Canavese: third belt (green), ID 14.
- Chieri: first belt (red), ID 15.
- Carmagnola: second belt (yellow), ID 16.
- Moncalieri: first belt (red), ID 17.

Each hospital is correctly geo-localized by means of geographical coordinates accurately re-scaled. In order to better analyze each agent, NetLogo gives the user the possibility to inspect agents separately, opening a window that contains the characteristics of the inspected agent. In the following page we report the window that refers to the inspection of the circled hospital of Susa. From that window, the user can find each characteristic associated with this specific agent. Starting from the analysis of this particular window, we proceed by describing the main features of hospitals and their function in our model as well as the associated code parts.



Starting from the top, we find the ID corresponding to this specific hospital, number ten in this example. Then, there are the color (black for all the hospitals), the heading, the geographical coordinates for both the axis (ycor represents the latitude and xcor the longitude) and the shape of the agent on the interface. Ignoring the label which is absent, we find the breed indication. NetLogo identifies each typology of agents as breed of agents, in this case “hospitals” of course. The last indication concerning the visual property of the hospitals is the size, which can be modified by the user according to his preferences. The part of code dealing with coordinates is the following:

to setup-hospitals

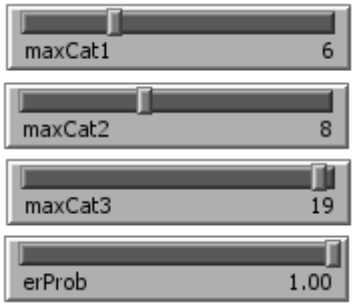
create-hospitals 18 [set shape "house" set size 4 set color black]
set cohord [[134.6 46.8][133 50.2][134.6 47.2][135 48.4][111.8 46][113.2 25.94][130.8 48.4][136.8 51.4][136.2 56.2][104.6 52][10.6 72.4][64.2 8.6][97.4 96.2][174.6 133.4][122.6 88.6][160 42.2][143.2 15.4][138.2 40.4]]

While all the characteristics explained so far are standardized by the software for each agent, the characteristic called "services" is due to our specification in the model. Indeed, with this characteristic we indicate the list of health and care services provided by the specific hospital. So, a proper explanation regarding our model characterization in terms of health and care services must be introduced.
Firstly, the services that each hospital provides derive from a general list of treatments generated by the program according to some indications given by the user through interface sliders. In particular, we have identified three typologies of health and care treatments. For each typology, we have associated a code in order to better manage the programming language:

i. *Laboratory services*: these treatments deal with laboratory exams for healthcare purposes. Their identification code is "100" and then the program adds units for each specific treatment of this category. As an example "104", "105", "106" refer to three different types of laboratory test such as X-ray test, CAT scan test and urine analysis. Note that we do not have specified any type of laboratory test so it is possible to be extremely flexible in characterizing the typologies of exams on the basis of detailed and specific data available on a medical point of view. The only exception of our medical treatments characterization consists of the so-called "blood tests" in that this type of exams are strictly identified by codes "101" and "102" denoting "blood taking exam" and "blood analysis" respectively. This element of rigidity in the program is due to the fact that, in the real healthcare system under investigation, some structures take only blood samples and then send them to other structures which proceed in the analysis. By separating the two complementary treatments we want to investigate also the effect at a network level of the blood samples passages across different structures.
ii. *Specialist visits*: this typology of health services deals with every visit or treatment that a patient has to satisfy (we will explain the characterizations of patients in the corresponding paragraph) in order to be cured. This typology is characterized by services of code "200" and can be interpreted in the same way as the codification of test services. Hence, it consists of a variety of medical treatments belonging to different medical divisions of a hospital, as well as treatments provided in private structures and so on (so, we can have dentist treatments, orthopedic treatments, cardiology services and whatever. It has to be highlighted that these treatments are not characterized by high degrees of emergency.
iii. *ER treatments*: each medical treatment characterized by high degree of emergency. We will explain better how this typology works by examining patients in the model. Their identification code is "300" and the only medical division able to provide them is the ER of the hospital.

The division reported above gives the possibility to better manage the code and to better characterize the relations that will be derived in the healthcare system under analysis. Surely, we have to stress the lack of clear medical basis, but the model can be implemented using data concerning precise treatments. Indeed, this modeling framework can be implemented in various ways with the integration of other research fields dealing with healthcare system analyses. Thus, the flexibility of ABM gives the possibility of having models in continuous development.
Going back to the treatment characterization, we have provided the user with some interface sliders, making possible to choose the maximum extension of each typology of medical services that the program can create.

By setting the slider, the user establishes the maximum amount of each typology of treatments that will enter the general list of treatments in the program code. The picture below represents the sliders on the interface connected to the three categories of medical services:

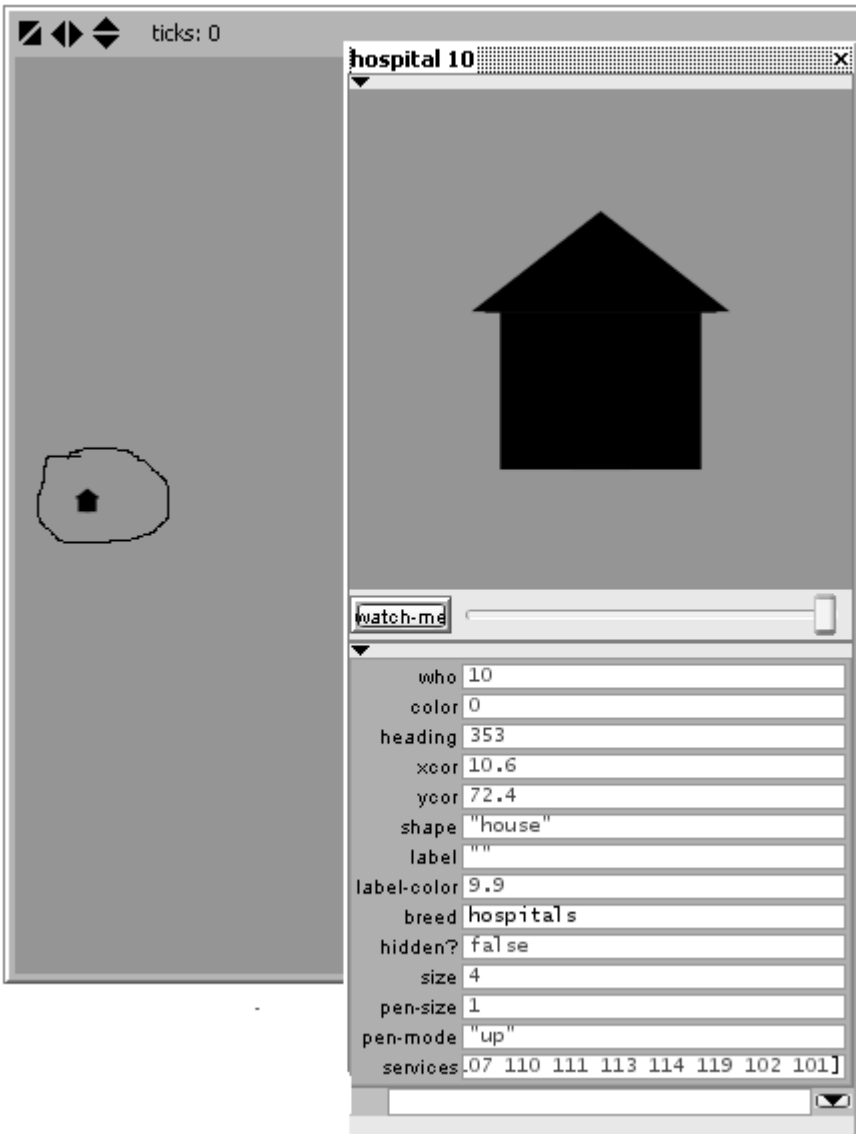


For completeness, since we are dealing with hospitals, the last slider in the picture denotes the probability according to which hospitals may have an ER among their medical divisions. If the probability is set equal to one, every hospital has an ER division and, on the contrary, if the probability is set equal to zero, none of the hospitals have an ER division. The presence or not of an emergency department may influence in several ways the final networks in the healthcare system as we will show later on.
With respect to the code part, the setup of the treatment list is denoted as follows:

```
let cat1 []
  let cat2 []
  let cat3 []
  let i 1

  while [i <= 20] [
    set cat1 lput (100 + i) cat1
    set cat2 lput (200 + i) cat2
    set cat3 lput (300 + i) cat3
    set i (i + 1)
    ]
  set treatments (list cat1 cat2 cat3)
  set maxCat (list maxCat1 maxCat2 maxCat3)
end
```

From the code part reported above, one can notice the creation of the main list containing each typology of services on the basis of the values indicated by the user through the sliders. In order to proceed as clearly as possible, we have established a maximum amount of twenty services for each typology. It has to be pointed out that the sliders determine the number of the maximum amount of services for each typology, and not the maximum amount of services that a hospital can provide. From a programming point of view, we have generated three empty lists, filled with treatments on the basis of random computations of the software. At the end of the process, the overall list “treatments” is filled in as well with the three sub-lists computed before.

So, at this point we can describe the last characteristic showed in the window devoted to the hospital inspection. We report again the picture regarding the hospital of Susa:

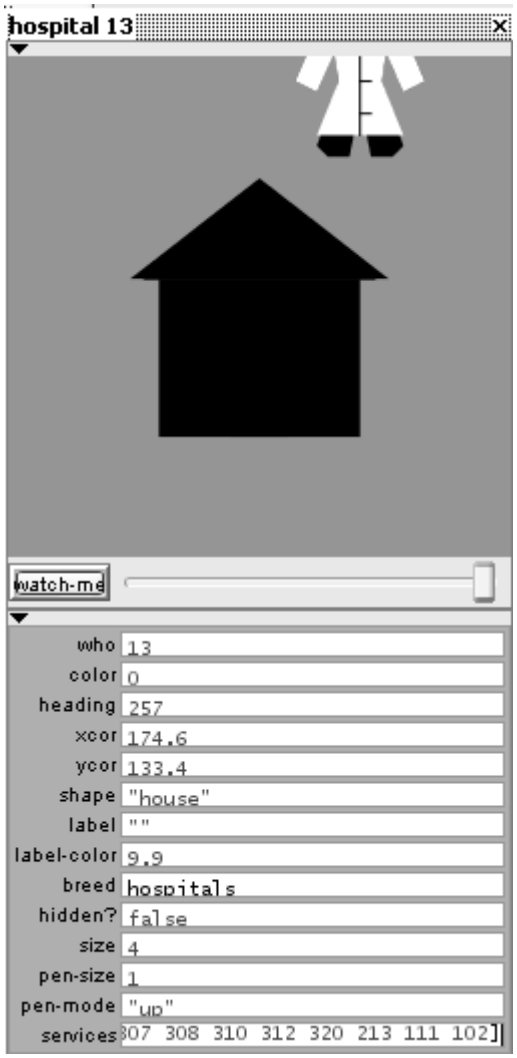


The characteristic “services” denotes the treatments provided by the specific structure, consisting of a list filled in with the various services identified by their codes. The example in the picture reports several treatments concerning the first typology of services: laboratory tests.
The code part that associates medical services to hospitals is the following:

```
ask hospitals [
   set xcor first (item who cohord)
   set ycor last (item who cohord)
   set services []
   foreach treatments [
   let maxNumber (item (position ? treatments) maxCat) + 1
   set services sentence (n-of (random maxNumber) ?) services
   if (not member? 101 services) and (random-float 1 < bloodTakingHosp) [set services lput 101 services]
   if (not member? 102 services) and (random-float 1 < bloodAnalysingHosp) [set services lput 102 services]]
```

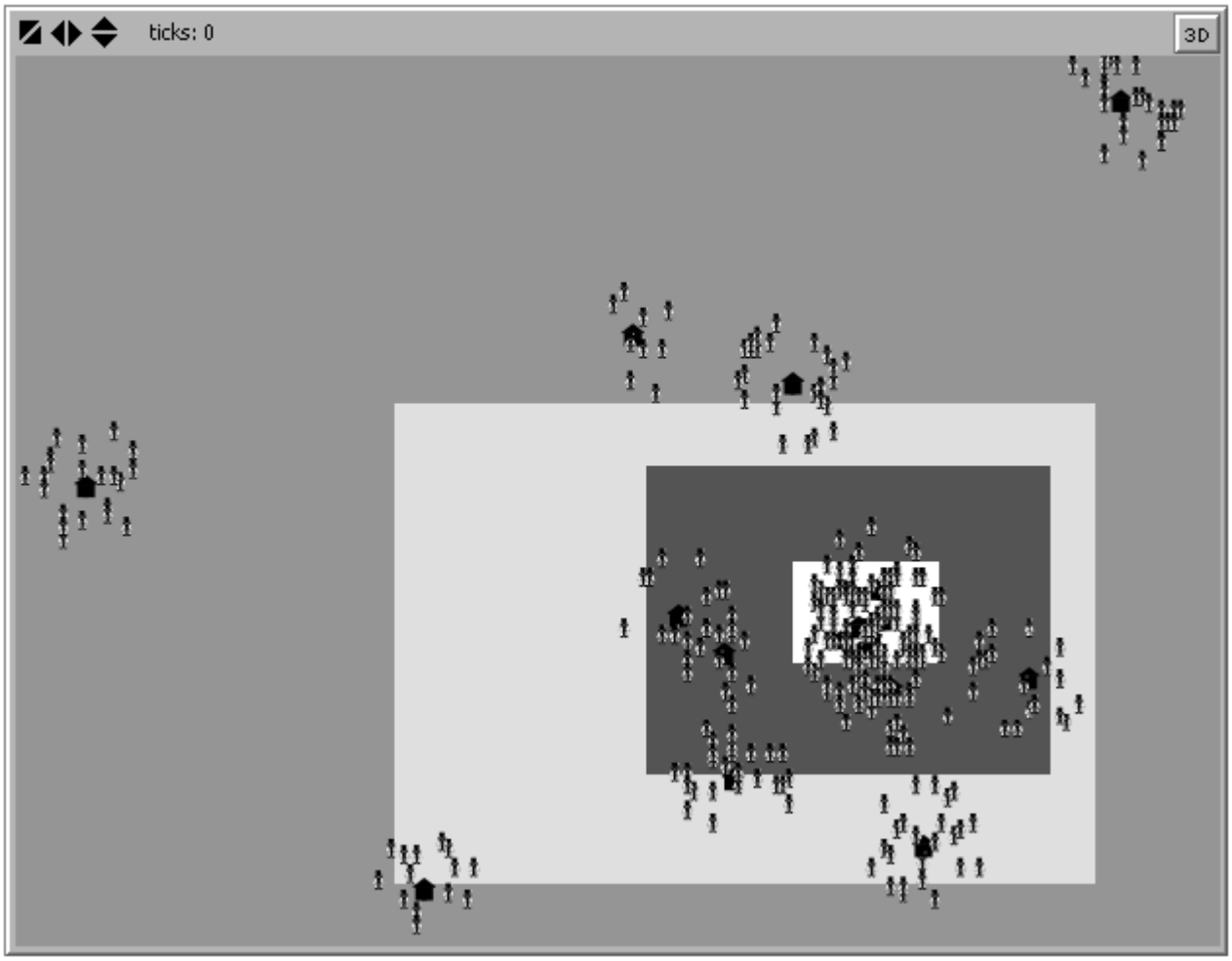
The hospitals provide services following a random process that determines their number. We can asses that the maximum amount of treatments provided by a hospital is determined in a recursively way by the interface sliders reported before. Nevertheless, the probability foundation of the computation makes the hospitals possible of providing zero treatments for certain categories. The two “if” lines of the code refer to the probabilities associated with the presence, in a specific hospital, of a blood taking center division (code “101”) and a blood analysis division (code “102”). We have already pointed out that the user, managing the correspondent sliders, establishes the probabilities that a hospital may have or not these specific tests. The picture below represents these sliders with an higher value for the probability of having a blood analysis center in the hospital than the probability of having a blood taking center. In the case of the hospital of Susa reported above, it provides both the two services.

The hospital of Ivrea on the other hand, with the same slider values, does not provide the blood taking service but only the blood analysis laboratory:



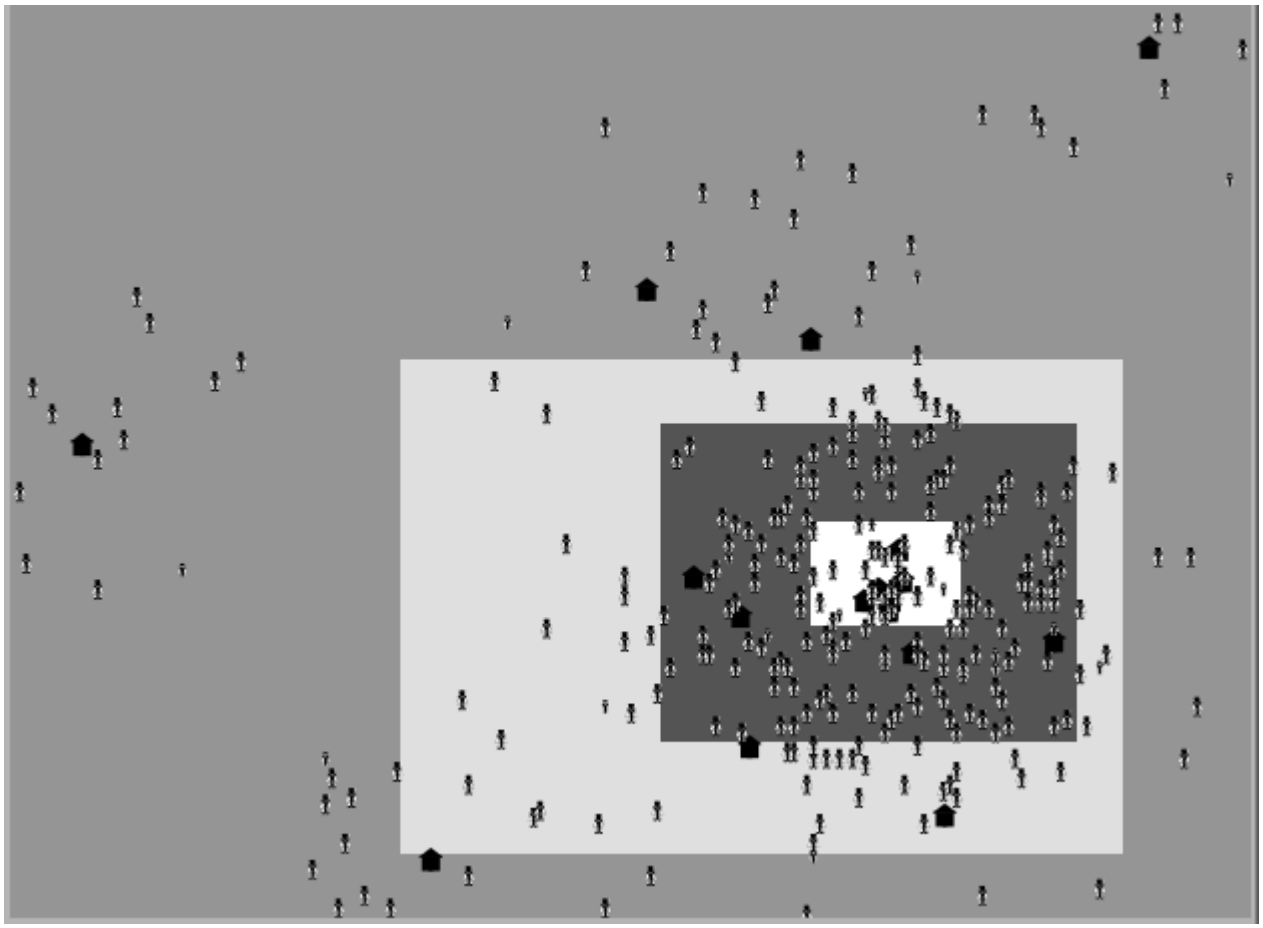
4.3 THE AGENT SET: SPECIALISTS AND ERs

The division into three typologies of medical treatments/services already explained is a cornerstone of our model in that it represents the origin of the network systems we are going to analyze. Moreover, the presence of different typologies of services has led to the creation of specific agents. In particular, we have imagined a typical hospital organization in which there is a head physician (a specialist) for each medical division. This means that each hospital provides a series of medical services, and for each of these services there is a head physician providing its specialty in its medical division of the hospital. Following this line of reasoning we have developed the "specialists": agents affiliated to their specific hospital in which they operates, providing one of the services included on the list of treatments of the specific hospital itself.
The NetLogo world with the specialists added appears as follows:



From the picture above it can be noticed the concentration of the specialists around their affiliated hospital.
In a graphical point of view, the specialists are created around the specific hospital radius. Such radius can be established by the user setting the specific slider in the interface:

For example, selecting an higher radius the overall result in the interface is shown as follows:



In this example, specialists are much more spread around the hospitals.

Looking at the programming code, the part devoted to the creation of specialists is a procedure called “to make doctors”. Since there are other types of physicians in the model, the part referred to specialists is given by the following lines:

```
 to make-doctors

set-default-shape specialists "person doctor"
  set-default-shape ers "person doctor"
  ask hospitals [
    let h who

    if (random-float 1 < erProb) [hatch-ers 1
[set color lime
 set size 2
move-to one-of (patches in-radius specialistRadius)
```

```
set affiliation h]]

   foreach services [
     hatch-specialists 1 [set color black
 set size 3
 set specialty (lput ? [])
 move-to one-of (patches in-radius specialistRadius)
set affiliation h
 set queue random 500
 set rep random 100]
   ] ]
```

Few things have to be noted from the code. First of all, the hospitals as agents create their own specialists (head physicians that manage their medical divisions) setting their affiliation which corresponds to the ID of the hospitals. Secondly, the radius is measured in terms of patches. Finally, each specialist contains some characteristics that are assigned at the moment of their creation.
In order to explore the main feature of a specialist, we have to inspect it using the corresponding NetLogo window:

The reported window refers to a specialist (head physician) belonging to the hospital of Susa because it contains the characteristic “affiliation” set equal to 10, the ID of the hospital of Susa.
We have to point out also the color and the shape of this agent. Indeed, since there are other types of physicians in the model, we have differentiate them in graphical terms according to the color and the shape. In this case, specialists are shaped as black doctors with white coat.
By examining the characteristics of a specialist agent we can find that it provides only one medical service, denoted by the label “specialty” (307 in the example above, so the specialist treats some diseases with high level of emergency). Then, we have to introduce other three important characteristics of specialists:

- *Queue*: it represents the waiting time patients have to incur in order to get cured by the specific specialist. It is expressed with a random computation that attributes a value between 1 and 500 (a specialist cannot present a queue value equal to zero). This is another element of randomness that simplify our model but is useful to establish some rules that we will explain in the course of the discussion. Surely, this characteristic may be improved with detailed data concerning for example averages of waiting times for certain treatments.
- *Cost*: this characteristic deals with the cost of the treatment provided by the specific specialist. In our model, every specialist has a cost set equal to zero in that we want to simulate our healthcare system in which health and care services provided by public structures have almost no costs for the users. We will introduce other physicians in which the cost is not set equal to zero.
- *Rep*: it represents the reputation of the specific specialist. It is associated to each specialist with a random computation which assigns values between 1 and 100. This characteristic provides some kind of quality measure to the specialist and its service.

These characteristics will participate in determining the decision processes of the patients, as we will point out in the paragraph devoted to them. Queues and costs may be improved adding precise data in terms of averages in treatment timing and costs. Such measures enter in the decision processes of patients in terms of quality of the services: trying to collect precise data about them makes the model closer to the real valuation of patients.
The last characteristic named “betw” deals with the network analysis measure of betweeness that can be only verified when the simulation runs and agents interact. We can asses that each physician agent can be seen as a node in a network of the healthcare system under investigation. Hence, each doctor presents this measure of betweeness.

Coming back to the analysis of the code part concerning the “make-doctors” procedure, it can be noticed the presence of another category of physicians: ERs. For completeness we report again the first part associated with this type of agents:

```
set-default-shape ers "person doctor"
  ask hospitals [
    let h who

    if (random-float 1 < erProb) [hatch-ers 1
[set color lime
 set size 2
move-to one-of (patches in-radius specialistRadius)
set affiliation h]]
```

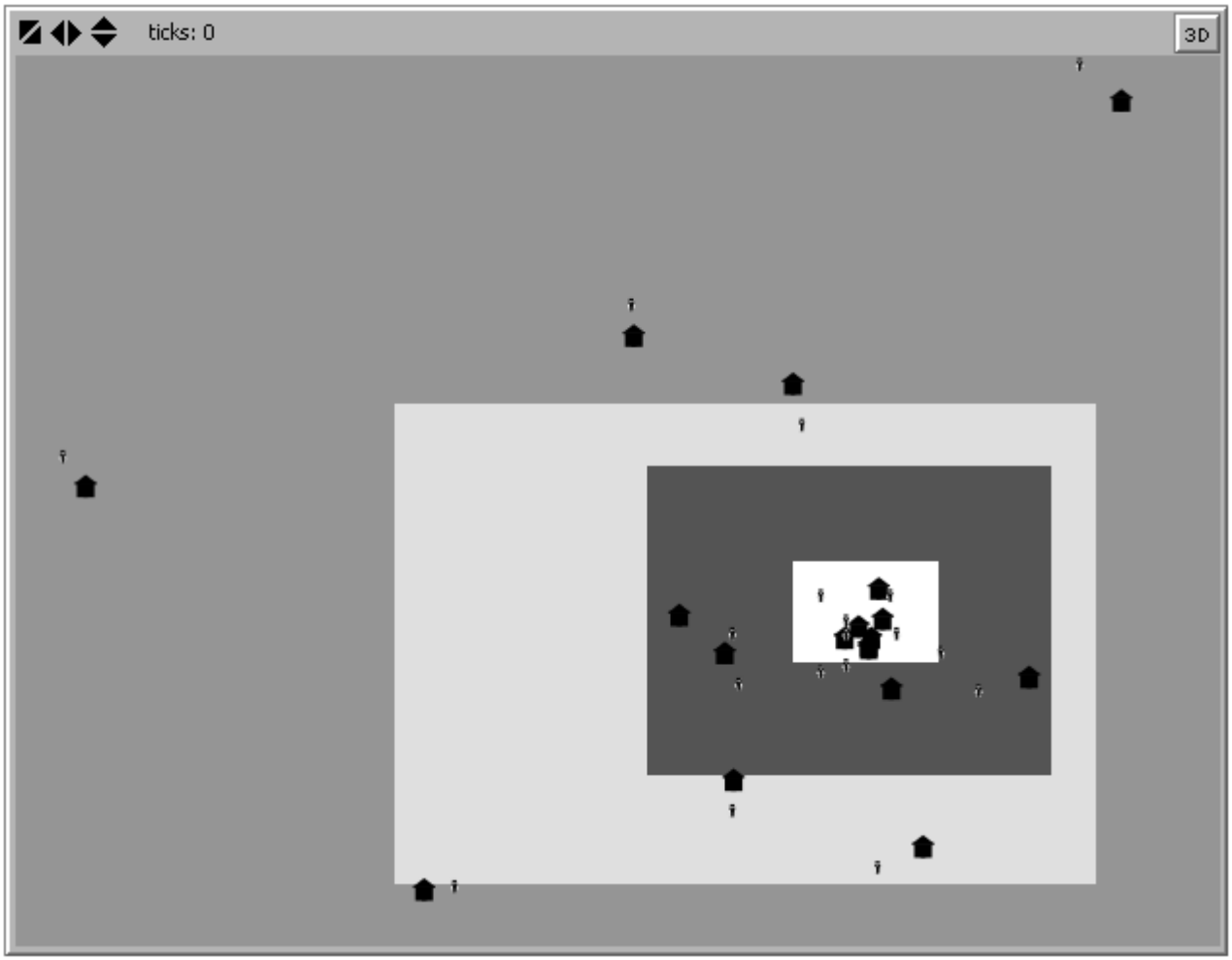
As its name suggests, ER represents the emergency department division of the hospital. They provide medical treatments characterized with high degrees of emergency.

The inspection window associated with ER doctors is the following:

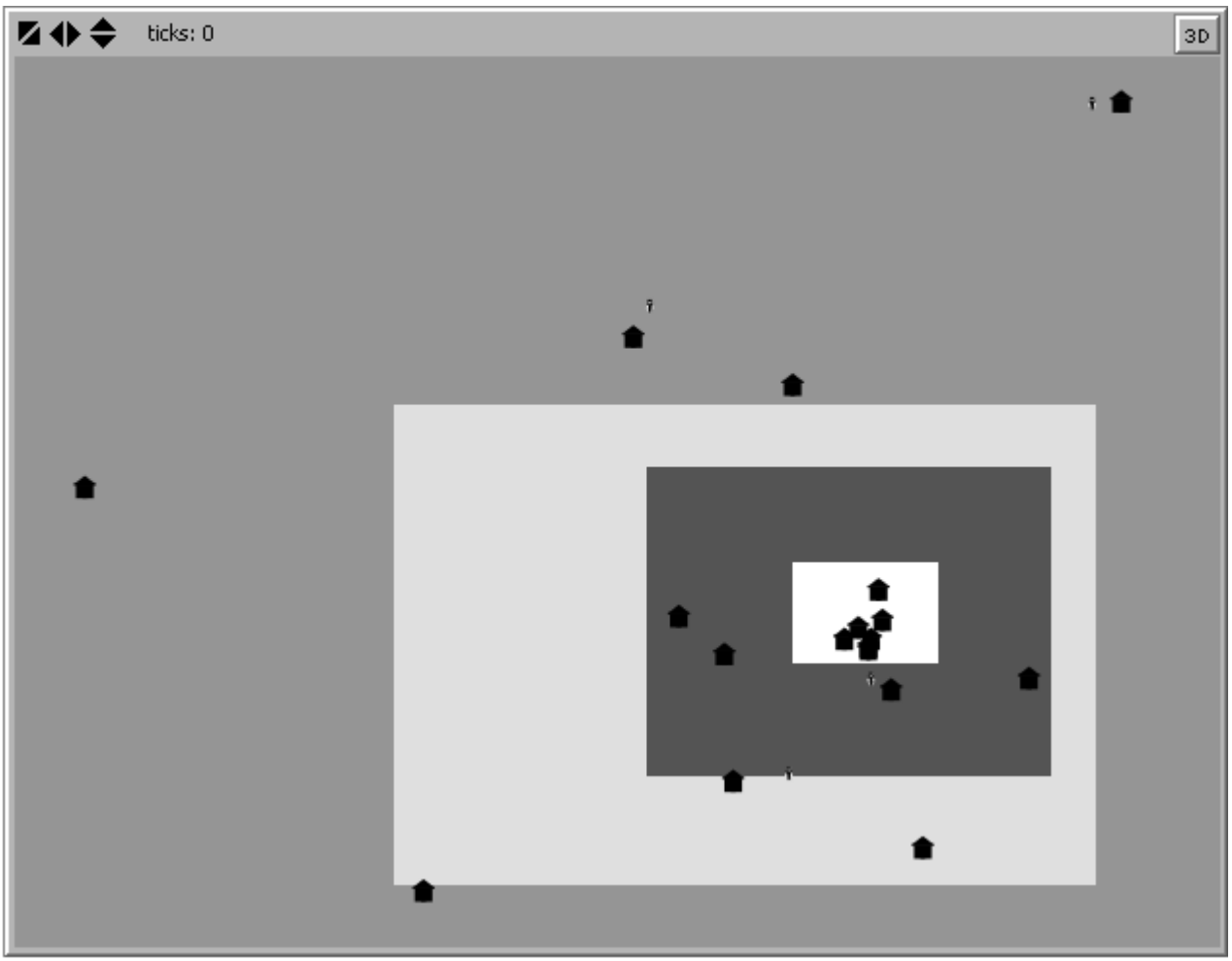
The figure shows, as an example, an ER of the hospital of Susa. Indeed, the “affiliation” label has the same meaning as the one of specialists in that it identifies the hospital in which the physician works. However, there are several differences between an ER and a specialist. First of all, the shape of the agent in the interface shows a green doctor with a white coat. Secondly, this agent lacks of all the characteristics of quality associated with specialists (queue, cost, reputation, specialty), because an ER represents always an emergency department that deals with emergencies for which patients cannot choose in terms of quality or cost. This unit is independent of the typology of service provided in that it receives emergency cases that have to be immediately treated. Hence, there are no waiting times, no queues and no costs for emergency services.

The other characteristics are the same as in the specialist case as well as the radius according to which ERs are created by the hospital.
In order to evaluate different scenarios of the model, we have added an interface slider that manages the probability of having an emergency department in a hospital. With the slider set equal to one, every hospital has an emergency department inside it (an ER). On the other hand, with the slider set equal to zero, none of the hospitals presents an ER. The slider figures in the interface as follows:

With the slider equal to one every hospital has an ER every hospital has an emergency department and so we have eighteen ERs in the scenario:



Otherwise, with a low value of the slider, the situation changes as follows (with only four hospitals providing ER services in the whole district territory):



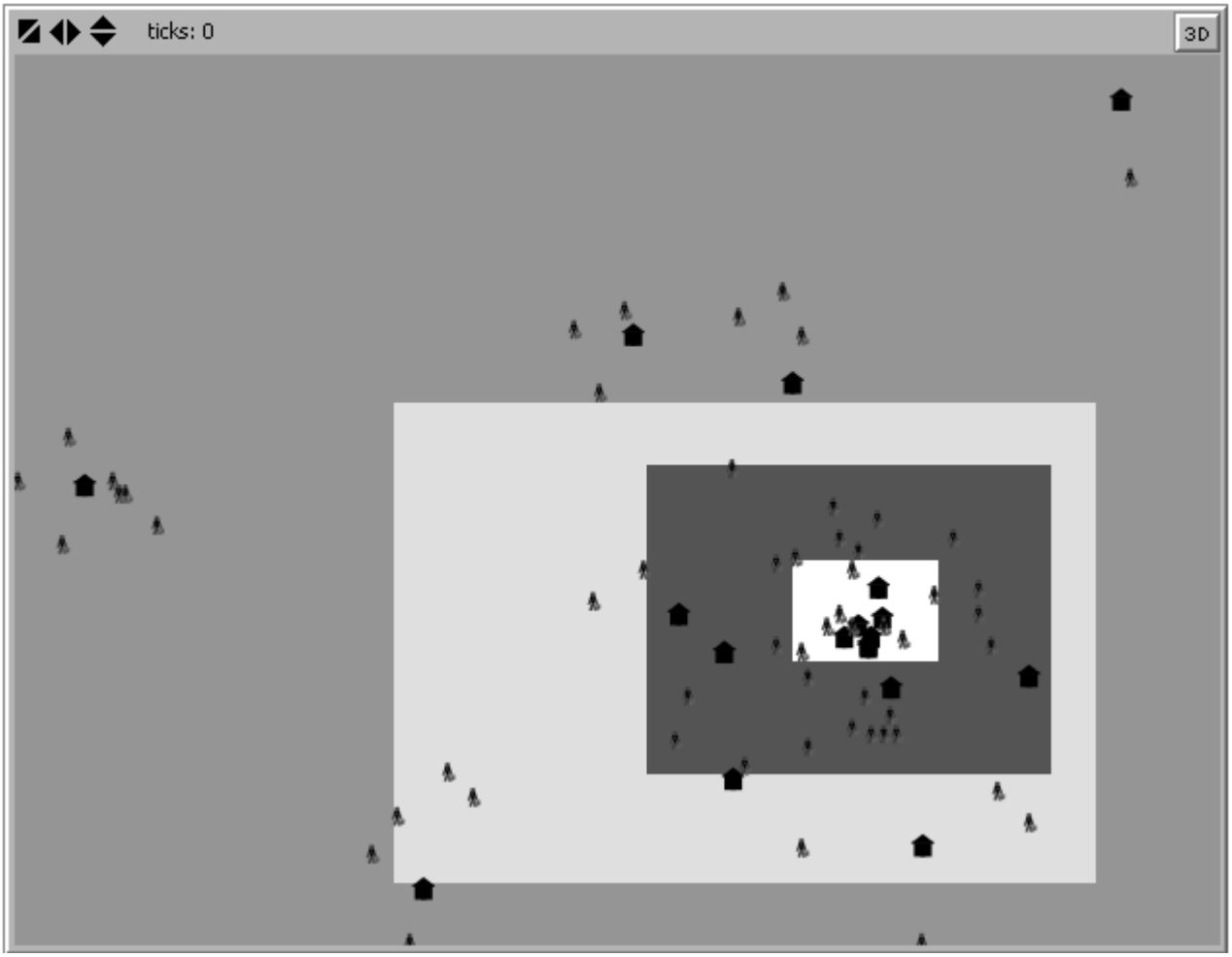
We have added the ER probability slider in order to examine possible implications at a network level by changing the number of emergency department in the territory in that emergency patients have to be treated in a particular way following different rules that we will explain later on. Thus, as in reality, having more or less hospitals with an emergency department may alter the resulting networks that patient flows generate on the basis of their needed medical services.

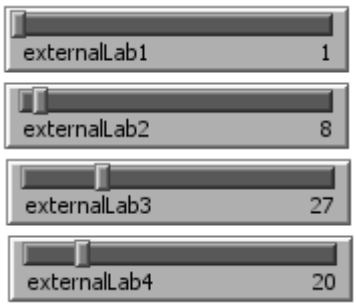
4.4 THE AGENT SET: PROFESSIONALS

In the literature review it has been highlighted the presence of two recurrent provision schemes of the healthcare services: public provision and private provision. The healthcare system of the district of Turin, as in the whole regional territory, presents a variety of licensed private structures providing different typologies of treatments. So, in order to provide a closer representation to the real system, we have developed a third category of doctors, the professionals, identifying the private structures.
To begin with, we introduce the corresponding program code devoted to the setup of these agents (procedure “to make-externals):

```
 to make-externals
    set-default-shape professionals "person business"
    create-professionals externalLab1
 [set color magenta
 set size 3
 move-to extRadius Torino
 set specialty n-of ((random 9) + 1) (one-of treatments)
set cost random 100
set rep random 100]
    create-professionals externalLab2
 [set color magenta
 set size 3
 move-to extRadius Torino1
 set specialty n-of ((random 9) + 1) (one-of treatments)
set cost random 100
 set rep random 100]
    create-professionals externalLab3
 [set color magenta
 set size 3
move-to extRadius Torino2
 set specialty n-of ((random 9) + 1) (one-of treatments)
set cost random 100
set rep random 100]
    create-professionals externalLab4
 [set color magenta
set size 3
 move-to extRadius Torino3
 set specialty n-of ((random 9) + 1) (one-of treatments)
 set cost random 100
 set rep random 100]

    ask professionals [
      if (not member? 101 specialty and random-float 1 < bloodTakingProf) [set specialty lput 101
specialty]
      if (not member? 102 specialty and random-float 1 < bloodAnalysingProf) [set specialty lput 102
specialty]
    ]
end
```

The first thing that emerges from the code is the separated creation of private health structures for each belt of the district. By means of interface sliders, the user can set the amount of private (external) structures fro each belt. This gives the possibility of modifying the scenario analysis by altering the equilibrium between public and private provision and to evaluate the choices patients given the more or less presence of private structures. The overall world representation with only professionals added (with proportion fixed by the sliders) figures as follows:

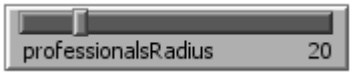




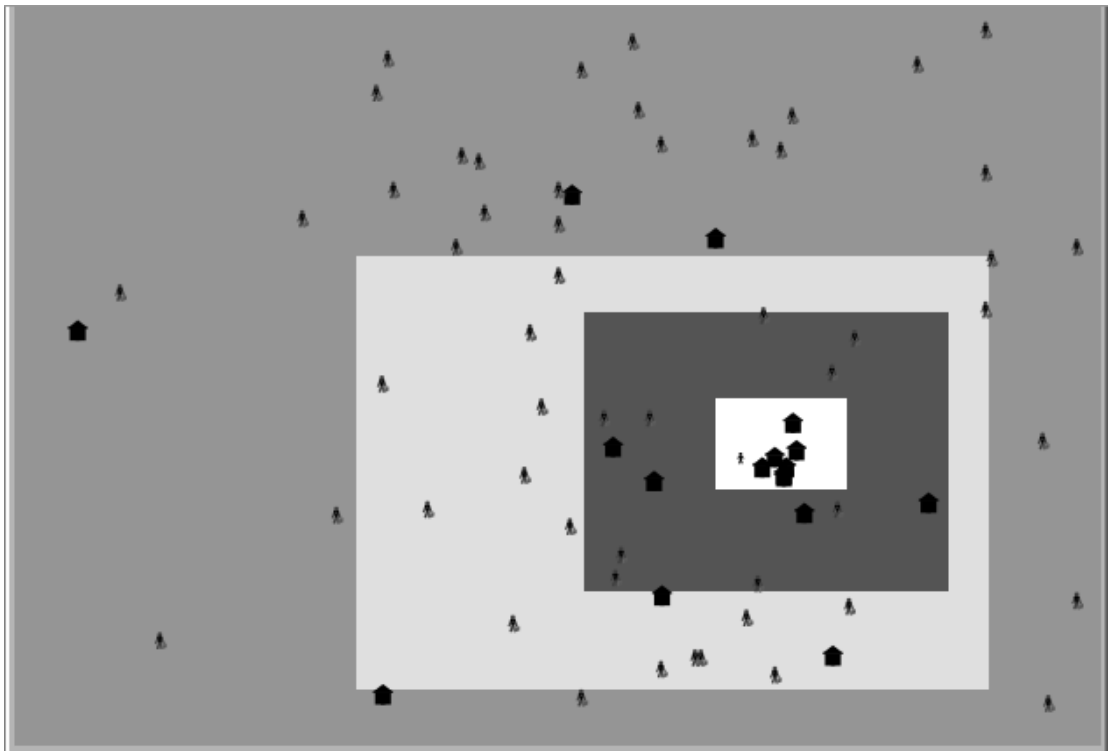
The professionals, as one can noticed, are disposed following a radius that works in the same way as the specialists. The corresponding slider regulates the size of the radius around the public structures. We have assumed private structures close to public ones because it may be reasonable to think that private health and care service centers open near public structures in order to better "capture" part of the demand belonging to the public sector. It has to be highlighted that the radius is computed around the hospitals with a simple procedure that figures as follows:

```
to-report extRadius[district]
  let location [one-of (patches in-radius professionalsRadius)] of one-of hospitals-on district
  report location
end
```

From the code we can verify that the radius is computed around the hospitals of each district. Surely, the radius computed in the case of professionals is larger than the one computed for specialists because we have to emphasize the proximity of the head physicians to their structures (because they manage their medical division of a specific structure). Private health and care service centers are totally independent of public structures, but lay next to them trying to catch that kind of patients who feel unsatisfied by the public provision.
The slider devoted to the control of the radius size figures as follows:



This value of the radius figures out the result of the previous scenario image, while the picture below represents a larger radius for professionals:



The code part regarding professionals shows almost the same characteristics attributed to specialists although there are important differences to clarify. In order to better describe them, we can visualize the inspection window referred to this typology of doctors:

In terms of shape, the professionals are visualized in the interface as business men colored in magenta with a blue overnight bag. More relevant, one can noticed that the characteristic "specialty" presents a larger amount of services provided than in the specialist case. Indeed, we have created private structures providing at least one service, with a maximum of ten services provided as specified in the following code line:

set specialty n-of ((random 9) + 1) (one-of treatments)

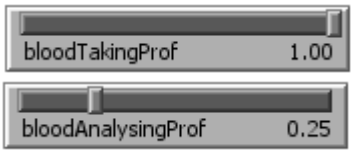
The program chooses randomly the total number of medical treatments provided by a specific private structure between a range from one to ten. At least one service must be provided. We can imagine these professionals as private clinics, some of them providing a single specific service while others providing a package of medical services.
Another meaningful difference is that private structures cannot work as emergency departments or cannot have an ER doctor dealing with emergencies. They can treat medical needs belonging to the third category of treatments (code "300"), but cannot work as emergency departments. We will stress this concept by analyzing patients and the following rules of interaction across agents.
Scrolling down the inspection window (and the code part reported before), we find the same qualitative indicators as in the specialist case: cost, queue, reputation. The explanation is the same as in the case of specialists with some important differences:

- *Costs*: the treatments provided by private clinics cannot be set equal to zero. The cost of a private structure or a professional varies following a random computation in a range from one to one hundred ("*set cost random 100"* in the code). This occurs also in the real healthcare system under investigation.
- *Queue*: we have assumed that in front of a cost patients have to face with, the advantage of a private structure is due to the absence of any kind of waiting time connected with the provided services. So, the variable "queue" is set equal to zero for this typology of agents.
- *Reputation*: the same as occurs with specialist doctors in the public health sector. The variable "rep" is expressed as a random number with the arbitrary maximum level of one hundred ("*set rep random 100"* in the code).

As in the case of public hospitals, we have introduced interface sliders managing both the probability that private structures take blood samples and the probability that these structures have a blood analysis laboratory. We report, for completeness, the code part concerning these sliders:

```
ask professionals [
    if (not member? 101 specialty and random-float 1 < bloodTakingProf) [set specialty lput 101 specialty]
    if (not member? 102 specialty and random-float 1 < bloodAnalysingProf) [set specialty lput 102 specialty] ]
```

Also in the case, we have added the opportunity of changing the composition of the two precise services in order to make comparison in the analysis of different scenarios. The importance of the two services (blood taking samples and blood analysis tests) is given by their role in the real life of every individual since these exams represent without doubts the most required health service demanded.
The correspondent sliders figure as follows:



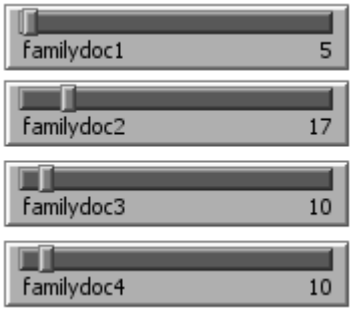
In the picture, we have set the probability that each private structure takes blood samples equal to one, so every private clinic provides this service. If we set these sliders equal to zero, none of the private structures will provide the correspondent service.

4.5 THE AGENT SET: FAMILY DOCTORS

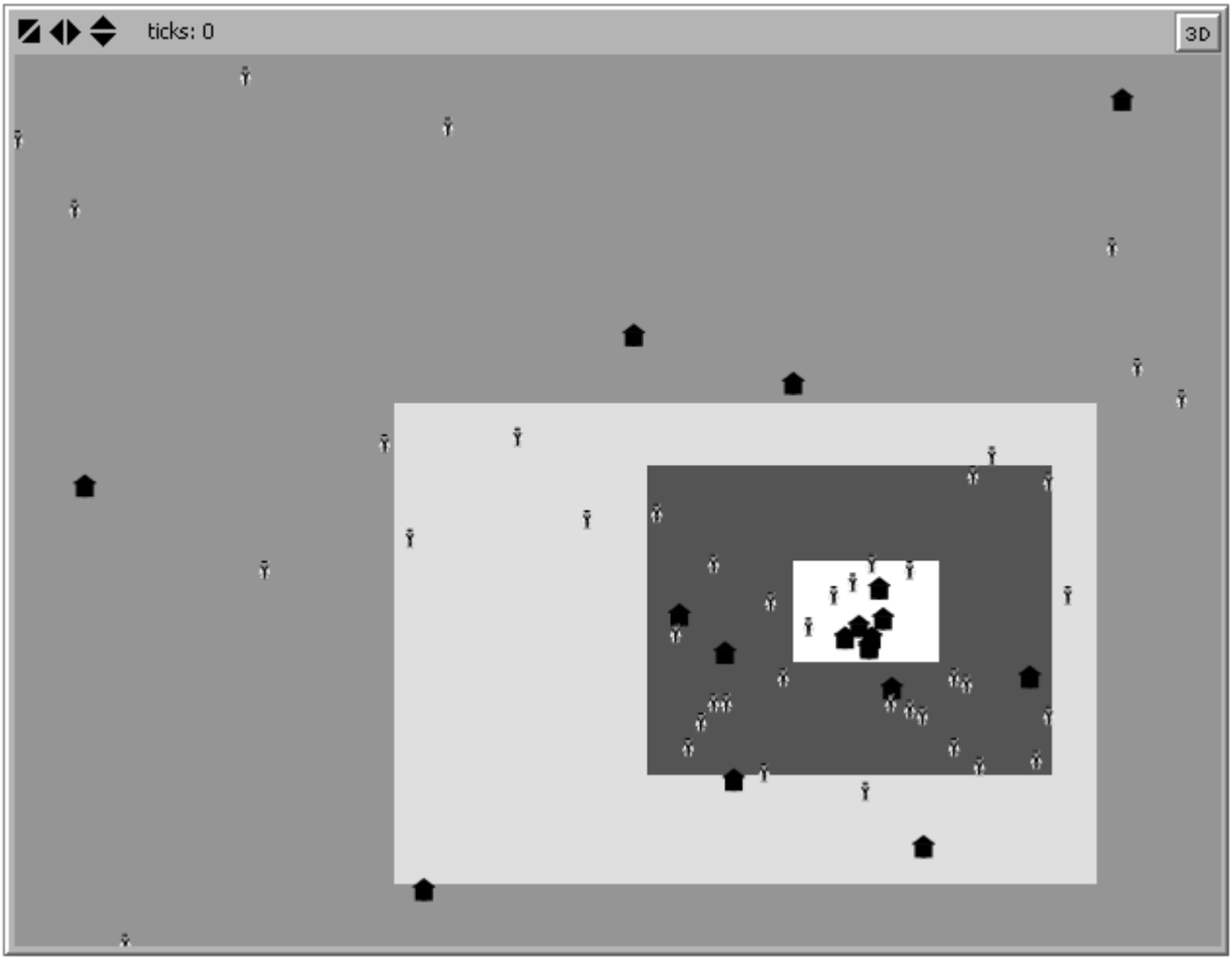
The presence of the general practitioner (family doctor) is very relevant in the Italian healthcare system. In fact, his function deals with medical prescriptions of patients and can be interpreted as an intermediate medical function between the patient and the hospitals. This last typology of doctors that we have generated in the simulation model, thus, works as an intermediate fundamental channel, through which patients have to pass in order to satisfy their medical needs.
In our model, family doctors have a huge relevance, in that they drive the patient in his decision process on the basis of some rules that we will explain better later on. We have introduced an important assumption concerning the perfect rationality of the family doctor behavior, which may totally decide the medical process that a patient must follow. This agent may be defined, like the patient too, as the most important decision maker of the whole model.
First of all, we have to show the code part devoted to the family doctor settings:

```
to make-doctors
  set-default-shape familydocs "person doctor"

  create-familydocs familydoc1 [set color pink set size 3 move-to one-of Torino]
  create-familydocs familydoc2 [set color pink set size 3 move-to one-of Torino1]
  create-familydocs familydoc3 [set color pink set size 3 move-to one-of Torino2]
  create-familydocs familydoc4 [set color pink set size 3 move-to one-of Torino3]
```

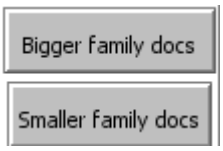
As one can notice, general practitioners are created for each belt, following the same reasoning adopted for the professionals. Family doctors, thus, are spread all over the four zones in a random way. The user can establish the amount of family doctors for each belt by setting the correspondent sliders:



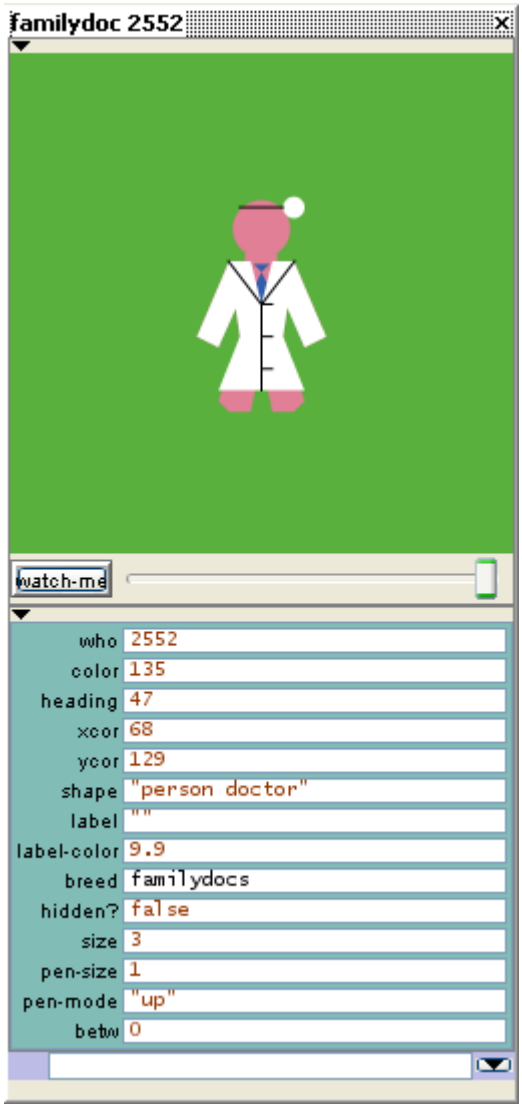
Following the values indicated by the sliders of the example, the representation on the NetLogo environment figures as follows:



The example presented in this scenario shows few family doctors in the central area of Turin with respect to the rest of the district. This may be reasonable from a logical point of view in that, in the city center, general practitioners are gathered together in big studios or offices and so, in a simulation software, this agglomeration can be figured as one family doctor agent with the same characteristics as the others. Surely, the possibility of selecting the amount of family doctors gives the possibility to make further improvements or different scenario analysis due to the presence of this typology of doctors in the territory. We have already defined these agents as the fundamental decision makers of the entire model and so, dealing with them by modifying their amount may generate important results on a theoretical point of view.
Moreover, with respect to the family doctors visualization on the interface, we have added two buttons that gives the user the possibility of enlarging or reducing the size of these agents in order to better identify them with the whole agent representation. The buttons figures as follows:



Inspecting a family doctor in NetLogo gives the following representation of this agent type:

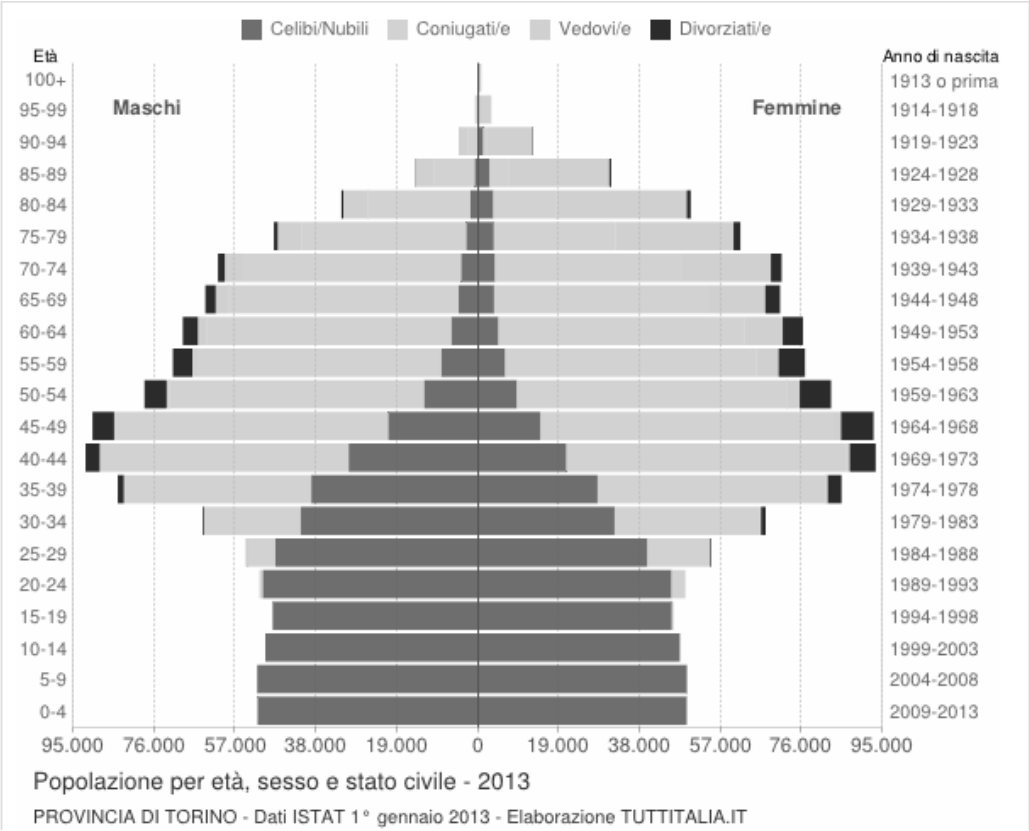


From a visual point of view, these agents are shaped as pink doctors with white coat. In terms of significant characteristics, there is nothing to point out in that they contains no non-standard variables. The importance of their role comes from the rules that the program follows and which address directly to this typology of agents. Hence, in the paragraphs devoted to procedures and link analyses we will come back to the central role of the family doctor and to the specification of its decision criteria.

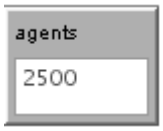
4.6 THE AGENT SET: PATIENTS

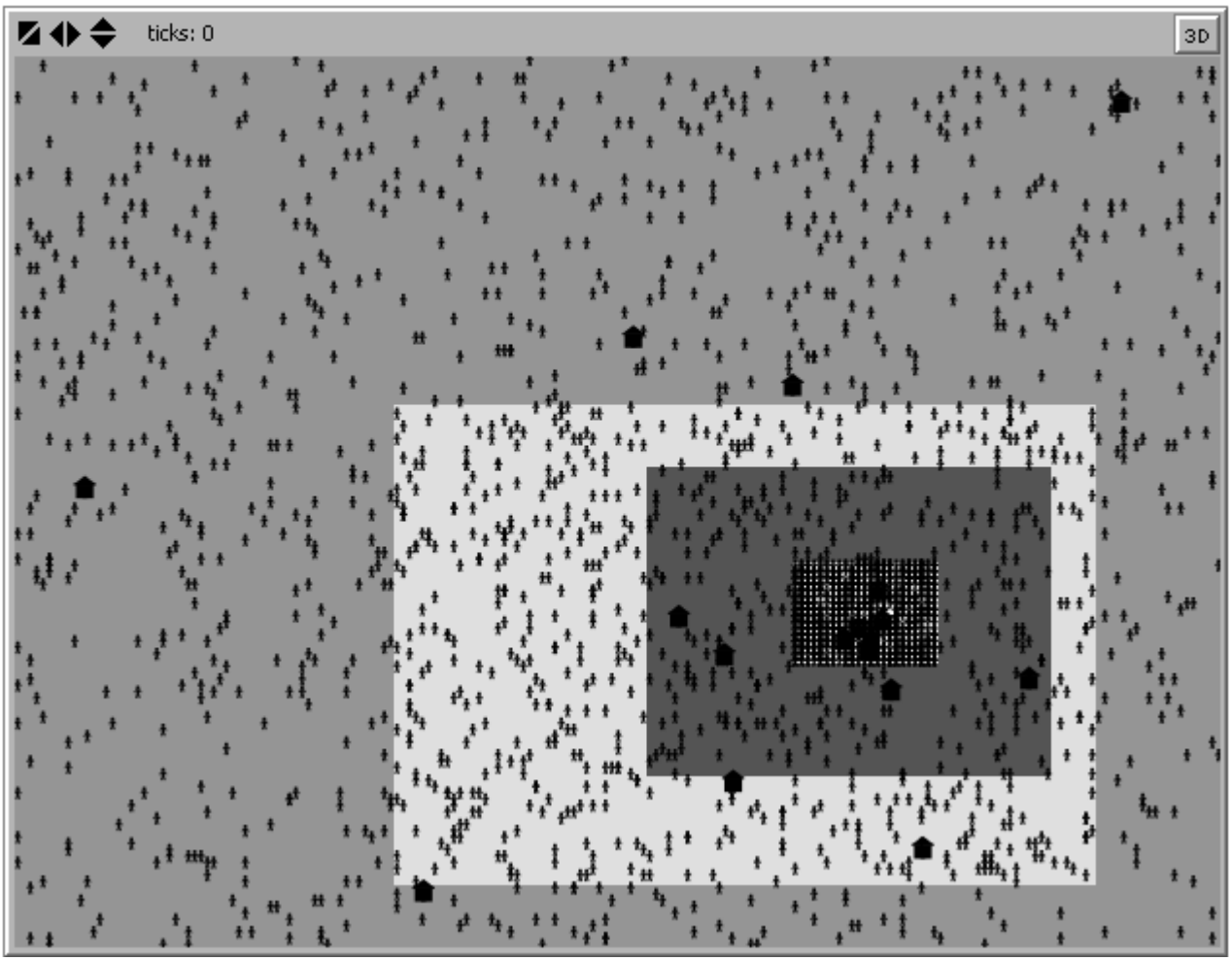
One cannot model a healthcare system without considering the users of the services provided by the system itself. Indeed, patients represent the demand side, economically thinking, and their analysis is crucial in order to capture flows, decisions, behaviors that may imply huge implications looking at the overall efficiency of the system.
It is common in the modeling language, to define patients of a healthcare system as the population of the world scenario. This is not only a theoretical definition in that real patients represent exactly the population (or part of it) of a certain area. Surely, it depends whether the modeler wants to represent only patients that have to be cured from specific illnesses or, more generally, patients whose demand must be satisfied (independent of the specific illness). Our model, focuses the attention on a hypothetical "health life" that characterizes each individual from his birth. One can imagine an entire life of an individual, characterized by periods in which he needs medical treatments as it occurs in the real world. At certain ages the individual has to get cured or has to take some medical tests. In order to model such "health lifetime" we have adopted, in programming terms, the concept of "recipe". We will deeply insist on that point in this paragraph providing also some theoretical foundations of the concept of "recipe". This last typology of agents, with family doctors, enters directly in the development of the fundamental rules followed by the program.

To begin with, since patients correspond to the population of the world, we have searched for some demographic data of the district of Turin. The web site of the Piedmont region provides several demographic databases concerning different topics. Above all, we have found the partition of the population for each age and gender in the year 2013. The dataset shows a population of the district of Turin composed by 1.109.048 males and 1.188.869 females with a total population of 2.297.917 individuals.
In order to better visualize the entire population, by means of age categories, in the district of Turin the following population pyramid may be useful (without considering the marital status):

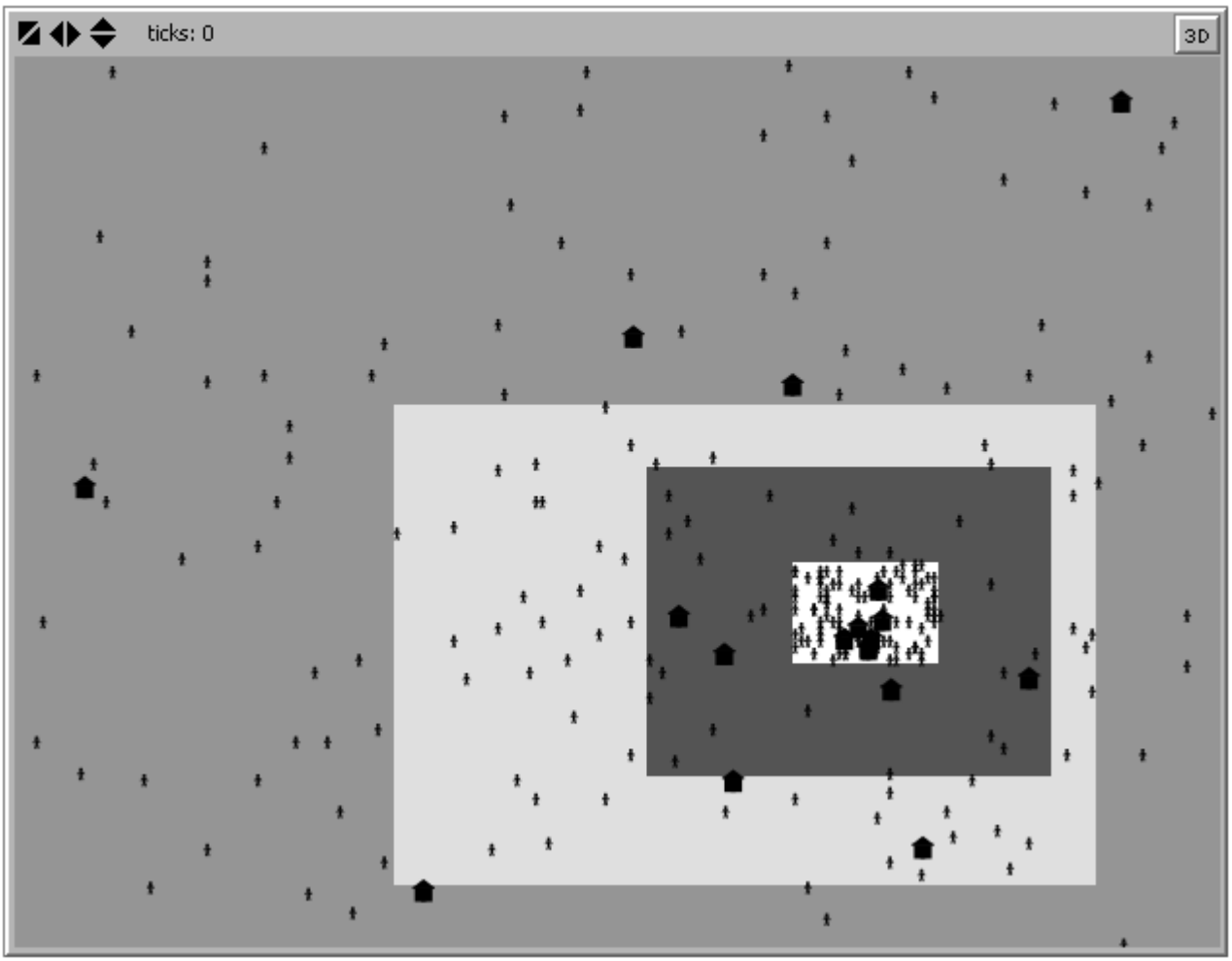


In modeling the population, we have respected the real available dataset maintaining the same proportions. Clearly, we have adopted a scaled representation, dividing all the values by a thousand with some approximations in order to deal with manageable numbers. However, the interface presents an input in which the user can choose the overall size of the population in terms of thousands of patients. The pictures below represent the distribution of patients on the world with 2,500 patients.





Changing the input number, we change the overall size of the population of patients.



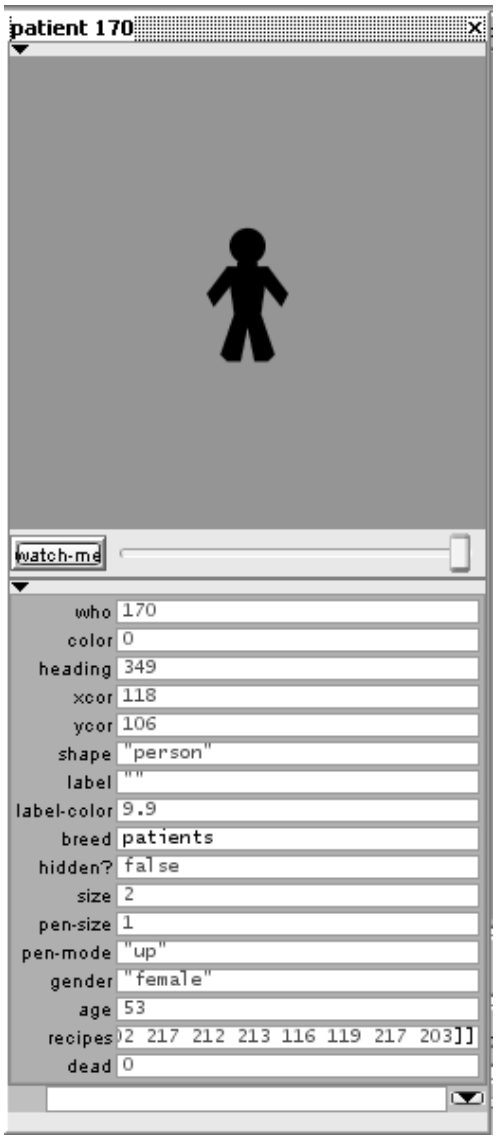
We have to point out some specifications on the program code, that are connected with the partition of patients among the various belts. Firstly, the code lines devoted to the creation of patients are the following:

```
to make-patients
  set-default-shape patients "person"
  let t1 round (0.4 * agents)
  let t2 round (0.3 * agents)
  let t3 round (0.2 * agents)
  let t4 round (0.1 * agents)
 create-patients t1 [ set size 2 set color black move-to one-of patches with [pcolor = white] ]
 create-patients t2 [ set size 2 set color black move-to one-of patches with [pcolor = green]]
 create-patients t3 [ set size 2 set color black move-to one-of patches with [pcolor = yellow]]
 create-patients t4 [ set size 2 set color black move-to one-of patches with [pcolor = red]]
end
```

The procedure “make-patients” highlights that patients are distributed in the various belts according to four fixed proportions. In particular, we have:

- The 40% of the patients belongs to the municipality of Turin, meaning that the main city is the most inhabited part of the district. The population density in Turin is higher than anywhere else in the district.
- The 30% of the patients belongs to the first belt.
- The 20% of the patients belongs to the second belt.
- The 10% of the patients belongs to the third belt.

These arbitrary percentages are invented but represent the real trend of the population density moving away from the center of Turin. The population density is then properly modeled in the simulation. Nevertheless, we do not have specified a clear geo-localization of the population in certain areas outside Turin. Hence, the population density in zones where the geo-morphological characteristics (mountain valleys) are less favorable is not considered in our model. We have modeled only a general population density with fixed proportions.
The other features that the previous code lines report concern the shape of the patients (figures as individuals) and the color (black).
The inspection window referred to a particular patient figures as follows:



Scrolling down the characteristics of a patient we find the usual ID number, the coordinates, the shape, the size and so on. The first important characteristics are the age and the gender. We have reproduced the proportion of the population from the dataset of the Piedmont demography statistic department. The dataset, reporting each age with the correspondent amount of population for that particular age and the gender, has been transferred to a notebook file. We have proceeded by cumulating the various classes of age, creating a huge list (202 elements) grouping all males from infants to one hundreds years old in the first 101 positions of the list and all females from infants to one hundred years old in the following 101 positions.
The procedures adopted to the characterization of ages and gender are the following:

```
to-report extract-probability[motherL]
 let r random-float 1
 let chosenE first filter [? >= r] motherL
 report position chosenE motherL
end


to-report age-category[y]
if (y <= 4) [report 0]
if (y >= 5 and y <= 14) [report 1]
if (y >= 15 and y <= 44) [report 2]
if (y >= 44 and y <= 65) [report 3]
if (y > 65) [report 4]
end


to giveAge

 file-open "cumulates-pazienti.txt"
 while [not file-at-end?][
 set probabilities lput file-read probabilities
 ]
 file-close


 ask patients [

 set age extract-probability probabilities

 ifelse (age > 100)[
   set age (age - 101)
   set gender "female"
   ][
   set gender "male"
   ] ]
end
```

The first two report procedures refer to the identification of the list of probabilities and to the computation of the five age categories that we have decided to adopt in order to better suit medical epidemiology dataset which usually are classified according to these five categories. Thus the classes of ages are divided as follows:

- 0 – 4 years old
- 5 – 14 years old
- 15 – 44 years old
- 45 – 65 years old
- More than 65 years old

The classification above is deeply adopted by medical statistic surveys in that these classes are useful in identifying pathologies associated to certain ages of the population.

The procedure named "giveAge" is the main procedure denoting the age and gender attribution to patients. It can be noticed how the program reads the probabilities contained in the notebook file.
So, at the very moment that the user press the setup button on the interface, the program compute the probabilities and the corresponding intervals in the huge list of cumulate probabilities. As a result, the population is divided following real proportions in terms of ages and gender.

Another important characteristic that is shown by the inspection window of a patient is the one named "recipes". The concept of "recipe" in agent-based modeling is deeply analyzed in Fontana and Terna (2014). The authors resume briefly the main elements that lead to the recipe development:

> The rationale behind it is to offer a few hints to find a framework and a grammar that are flexible and straightforward enough to encompass the widest possible range of purposeful and socially meaningful individual and organizational behavior. This is meant to meet the obvious requirement of generality but is also thought of as a way of making the simulation setting homogeneous over different types of scenarios (e.g. imagine comparing health and labor market policies in different simulations of the same economic system) thereby rendering the simulation more transparent to both scholars and policy makers.

Moreover, Fontana and Terna (2014) report a detailed characterization concerning recipes and their uses. First of all, they denote "recipes" as a variable number of steps to be taken in order to achieve a given end (the object, named "order" by the authors). Thus, agents in a simulation model are intended as problem solving cores who are able to perform one or more of the steps required to complete the recipe.

So, referring to Fontana and Terna (2014), recipes are coded, in a programming language point of view, as strings of numbers like one can notice by observing the corresponding characteristic on the inspection window of our patients in the model. Each number refers to an act, a sub-routine, of the modeled action as it can be shown in the example below (Fontana and Terna, 2014):

[3 1 7 6] means:

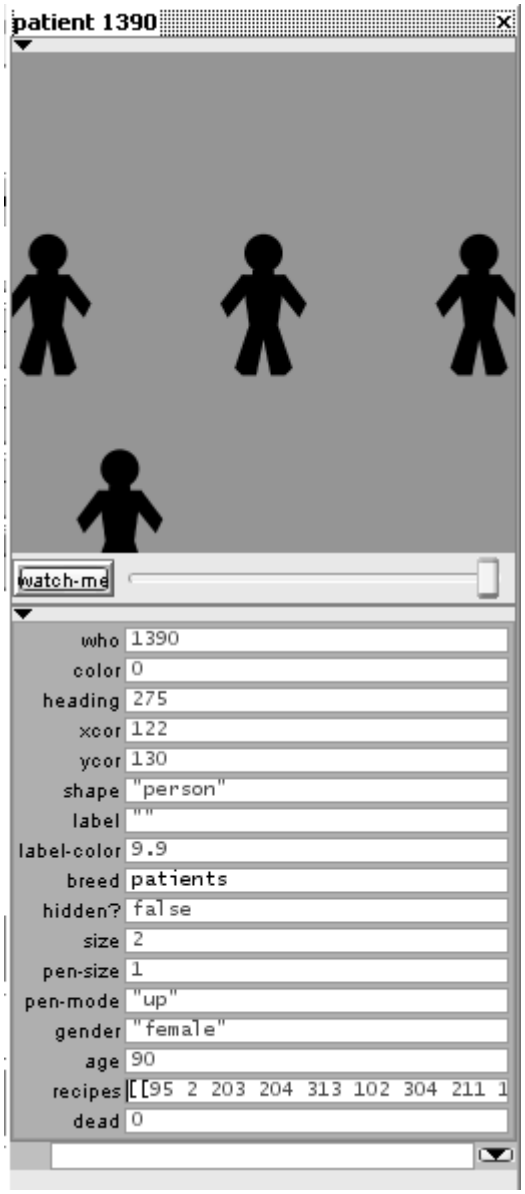
- execute step 3, then
- execute step 1, then
- ...

Referring to the recipes of our modeled patients, one can notice that they figure as lists of numbers of any length. Generally, they may also present specific natural characteristics (Fontana and Terna, 2014) denoted by lists such as: [1 4 (3 4 5) 8].
In addition to these definitions, Fontana and Terna (2014) highlight some crucial aspects of the recipe usages in healthcare as well as in other application fields. In particular, referring to healthcare, they emphasize the role of the recipes that fits perfectly our use of recipes in the model examined in these pages:

> A person (animate agent, in this case the subject launching the "order") is supposed to suffer of a few healthcare problems represented by recipes as above. Those recipes/events will be activated in different moment of these person's lifetime. In this case, the steps of the recipe are actions to be executed within the healthcare system (a medical examination, a period in a hospital, having surgery, etc.), again by animate or inanimate agents.

Hence, the quotation above is strictly linked with our modeling strategy regarding the adoption of recipes. Furthermore, as the authors suggest, the use of recipes in ABM for any economic/social kind of problems ends up with networks forming. In particular, as in our simulation model, the patients and family doctors interactions within the healthcare system create links among various doctors, hospitals, sanitary tests according to the typology of treatments needed by the patients themselves.

Now, we report again the inspection window of a patient in the model in order to better specify how the recipes are formed and the correspondent program code.



The overall recipes of this ninety years old patient is the following:

(patient 1390): [[95 2 203 204 313 102 304 211 110 214 305 302 115]
[96 8 314 214 202 315 216 313 314 308 217 302 207]
[97 1 220 311 314 111 211 310 108 103 318 307 318]
[98 3 220 101 214 220 205 101 211 110 211 213 108]
[99 8 206 311 202 218 114 315 318 215 215 117 217]]

The recipes in the example identify the whole “health lifetime” of the individual. We are assumed that each patient dies at one hundred years old (we will turn on the timing issue of the model later on), and the setup section devoted to the creation of patients creates immediately their health life, by means of a list such as in the example above. In particular, we are dealing with a list of sub-lists, each of them composed by the following elements:

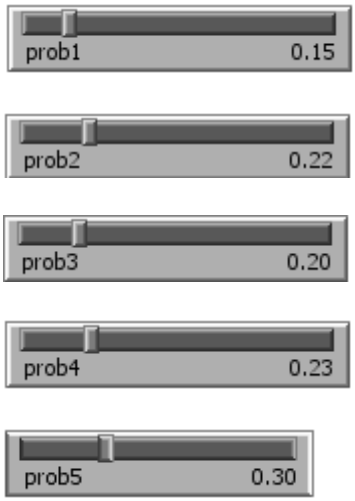
- The first number of each sub-list identifies the age at which the correspondent recipe has to be carried out by the patient.
- The second number represents the month in which the recipe starts to be implemented by the patient.
- The following numbers identify the codes of the three typologies of medical treatments that we have described before. So, these numbers are the medical services that the individual needs in order to get cured (the various step the patient has to fulfill).

The code lines devoted to the composition of these huge lists of medical treatments are identified by the procedure named “giveIllness”:

```
to giveIllness
 ask patients [
  set recipes []
  let i age
  while [i < 100] [

    let class age-category i

    if (random-float 1 < item class probAge)[
      let year []
      set year lput i year
      set year lput ((random 12) + 1) year
      let j 0
      let howManyTreatments (item class len)


      while [j <= howManyTreatments] [
      let catTreat extract-probability (item class probIllness)
      set year lput (one-of item catTreat treatments) year
      set j (j + 1)
      ]
      set recipes lput year recipes
    ]

    set i (i + 1)
  ]]
end
```

In particular, this procedure in strictly linked with the age category of a patient in that we have intended to separate treatments according to these classes of age, trying to model as close as possible the real world. Indeed, patients, in reality, are characterized by certain typology of treatments for each age category in that from a medical point of view some diseases typically occur at certain class of ages. This fact proves the adoption of the five age categories described before.
Moreover, we have associated to each age category some sliders according to which the user can choose various important features:

- First of all, the probability, for each age category, that a patient belonging to a specific age category becomes ill. So, we have five sliders in the interface, that may be useful in managing some prevention mechanisms and the overall health status of the population. The sliders figure as follows (with "prob1" denoting the probability of becoming illness for the first age category from 0 to 4 years old, "prob2" for the second category from 5 to 14 years old and so on):

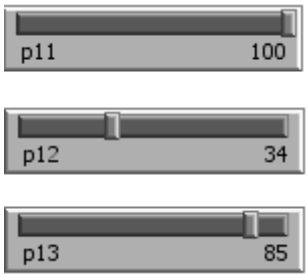


- Secondly, the user can set the length of each sub-list in terms of medical treatments that a patient, belonging to a certain age category, has to face with. This sliders provide the extension of each recipe in particular periods of time correspondent to the age categories. Hence, we have other five sliders on the interface (named "len1" for the maximum extension of the recipes in individuals belonging to the first category, "len2" for the length of recipes of individuals belonging to the second age category and so on). The following examples represents the length of the recipes of a patient belonging to the fourth age category set to two medical treatments. The program establishes at least one treatment when the patients becomes ill, so the total amount with the slider set equal to 2 is equal to three treatments:

patient 1176): [[86 2 320 211 208] [88 6 103 209 105] [89 12 305 212 215] [94 3 219 319 212] [98 8 115 219 120]]

We have to point out that a patient changes his age as time goes by, entering in the following age categories. So in the example above, the patient enters in the fifth class of age following sliders associated to that category.

- The last set of sliders manages the probabilities that refer to the composition of the recipes in terms of typologies of treatments (tests, specialist services, emergencies). Also in this case, we have these controls for each age category. So, basically we have three sliders concerning the composition of the recipes. By composition, we mean probabilities of selecting treatments from each of the three typologies of treatments. This set of sliders gives more approximation to the reality where, according to certain ages, patients generally present some typologies of treatments instead of others. For example, a ninety years old patient may incur in emergency diseases more frequently than a younger patient. The sliders (representing the first age category in the figure, with the first number representing the age category and the second one representing the typology of treatments. The others are the same.) managing these probabilities show as follows:



We want to emphasize the meaning of these probabilities because they are useful in analyzing different possible scenarios, at a network level, that the user may generate setting the sliders. For example, one may choose probabilities of becoming ill after having evaluated dataset on health prevention mechanisms. This model block represents a huge possibility of implementation by medical scientists that can provide several data related to prevention mechanisms in precise areas. For the purposes of our work, the main issue regarding these probabilities deals with modeling flexibility and scenario valuations.
The code lines referred to these probability sets show that we have proceed by normalizing them in order to make the program easier to develop. In particular, the code figures as follows:

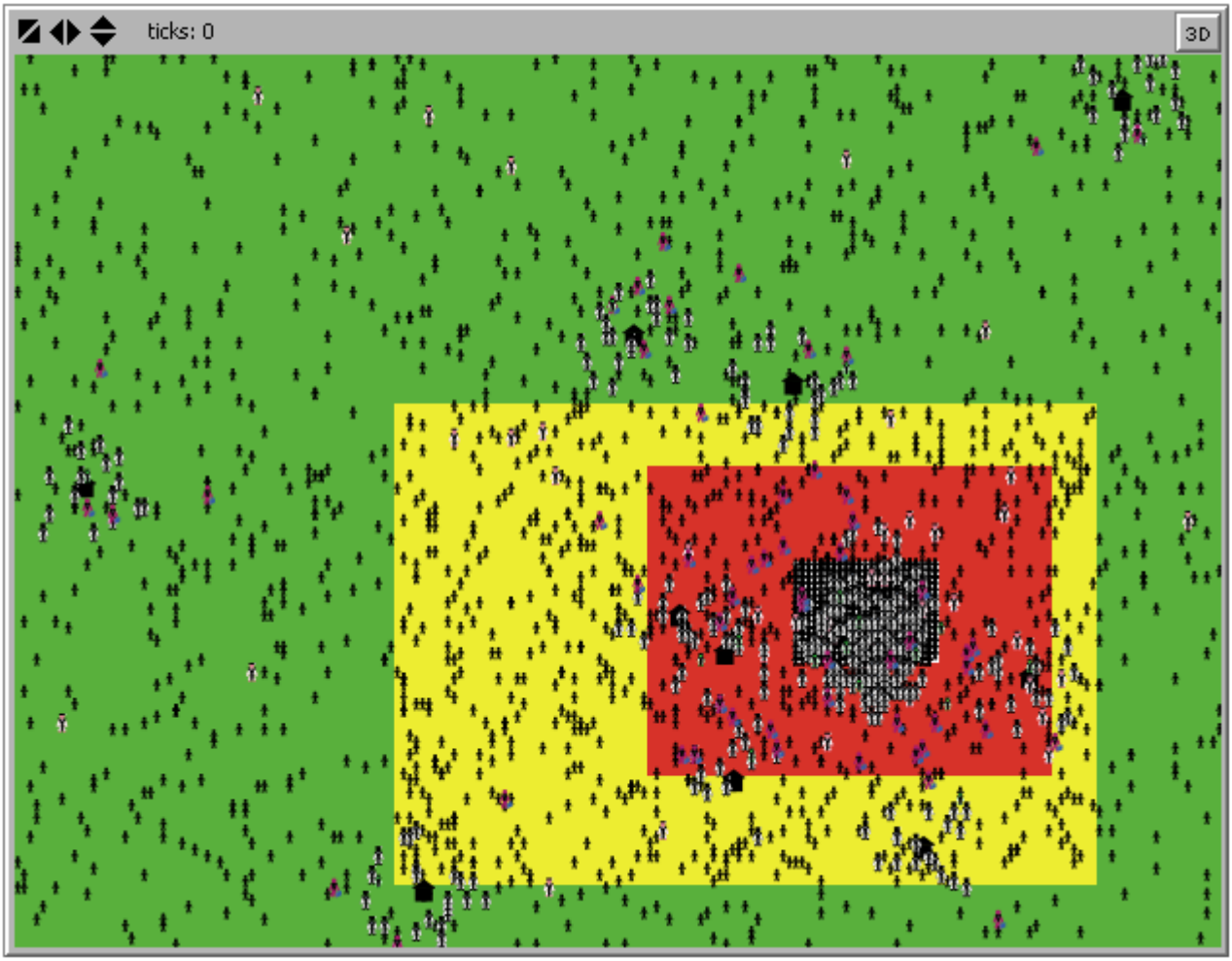
```
to normalize-prop

let p11n (p11 / (p11 + p12 + p13))
let p12n (p12 / (p11 + p12 + p13)) + p11n
let p1 (list p11n p12n 1)


let p21n (p21 / (p21 + p21 + p23))
let p22n (p22 / (p21 + p21 + p23)) + p21n
let p2 (list p21n p22n 1)
```

```
let p31n (p31 / (p31 + p32 + p33))
let p32n (p32 / (p31 + p32 + p33)) + p31n
let p3 (list p31n p32n 1)


let p41n (p41 / (p41 + p42 + p43))
let p42n (p42 / (p41 + p42 + p43)) + p41n
let p4 (list p41n p42n 1)

let p51n (p51 / (p51 + p52 + p53))
let p52n (p52 / (p51 + p52 + p53)) + p51n
let p5 (list p51n p52n 1)

set probIllness (list p1 p2 p3 p4 p5)
set len (list len1 len2 len3 len4 len5)
set probAge (list prob1 prob2 prob3 prob4 prob5)

end
```

The first number of these probabilities reflects the correspondent age category while the second number, if it is present, identifies the three typologies of treatments.

4.7 THE AGENT SET: OVERALL REPRESENTATION

After having explained each type of agents generated in our model, the overall view in the NetLogo interface may provide a general idea of the entire world creation. Although this paragraph gives only a single representation of the typical scenario generated by the simulation, we have to stress the fact that the user may change several variables, adding significant modifications to the overall scenario representation. One of the primary goals that our model tries to achieve, in fact, deals with the experimental capabilities it may provide.
Anyway, the world scenario including all the elements in the agent set figures as follows:



This example refers to a district of Turin composed by 2,500 patients spread all over the district area according to the percentages previously described, eighteen hospital structures with affiliated specialists and emergency departments, external private structures (professionals) and family doctors. As one can notice, the city center of Turin is the most populated area with a high population density. As a result it appears quite chaotic and difficult to interpret looking quickly at the NetLogo interface. The other belts are better manageable in visualization terms and it can be observed the presence of “health-radius” areas with specialists and professionals gravitating towards. On the other hand, family doctors are spread over each belt randomly.
Now, since we have explained the first pillar of an ABM (the agents), we can proceed by examining the rules that control the model and generate the mechanisms of the emerging networks.

4.8 THE FUNDAMENTAL RULES OF THE SIMULATION: PATIENTS AND FAMILY DOCTORS PROCEDURAL BEHAVIORS

During the discussion about patients and general practitioners, we have highlighted the importance of these two types of agents. In this paragraph we expose the fundamental behavioral procedures that these agents follow when the program runs. In modeling these procedures, following a methodology quite common in economic theory, we have undertake some strong assumptions that refer to agent preferences driving the behaviors of individuals.

First of all, in our model, patients incur in some health diseases that have to be cured. Each disease is identified by a precise medical sequence of treatments that the patient has to follow, the so-called "recipe". When a recipe starts functioning, the program immediately checks the first treatment the patient has to undertake. This means that the program checks the third number in the list that characterize the recipe entering in function. Indeed, due to the different nature of the three typologies of medical treatments, the program needs to know if the patient has to be cured as soon as possible because of an emergency or not. In other words, if the first medical treatment that a patient has to undertake coincides with a treatment belonging to the third typology of medical services (emergencies), then the associated medical routine imposes to bring the patient to the nearest hospital. The code part concerning the valuation of the first medical treatment in a recipe of a patient is the following procedure named "to get cured":

```
to getCured
  ask patients with [not hidden? and length (filter [first ? = age] recipes) = 1 and (item 1 first (filter
[first ? = age] recipes) = currentMonth)] [
    let treats but-first but-first (first (filter [first ? = age] recipes))
    let choice floor (first treats / 100)
    ifelse (choice = 3) [
      let doc choose-er
      if (see-er doc treats = 0)[hide-turtle set dead 1]
      ][
      let doc choose-family
      if (see-family doc treats = 0) [hide-turtle set dead 1]
      ]
  ]

end
```

As one may notice from the code lines, the program selects the first treatment of a recipe and divides it by one hundred in order to consider only the resulting integer (1, 2 or 3). If the result is 1 or 2, then the patient takes a visit to the family doctor. Otherwise, if the result is 3, then the patient must be sent immediately to an emergency department (an "ER" in our model). We stress the fact that the computation occurs only for the first treatment in order to identify emergency cases. An important assumption that we have introduced in the model deals with the possibility that none of the hospitals or private structures provide certain treatments needed by a specific patient. If this patient cannot find structures able to treat him for a specific disease then he "dies" (disappearing from the simulation). The procedure before shows some lines about this assumption although it is presented in specific procedures of ERs and family doctors. We have introduced this strong

assumption because the list of treatments selected by the program is randomly generated as well as the services provided by the units of hospitals and by professionals. Hence, there may be the case that certain treatments may not be offered by the healthcare system, which metaphorically "loses" the specific patient.
The first lines of the "get cured" procedure regard the timing check of the recipe in that the program verifies when a recipe has to start being implemented in terms of age of the patient and the precise month.
Hence, a patient, according to what we have explained so far, may be routed on two different paths:

Visiting the general practitioner when the disease is not immediately dangerous for the life of the patient (treatments of typology 1 and 2).
Admission to an emergency department of the nearest hospital because of an emergency that has to be immediately treated.

We have to discuss these two paths separately in that they present several important issues of the model under analysis.

The emergency department

The procedure associated to the ER's visit is characterized by a computation of the distance in terms of patches of the nearest hospital with an emergency department with respect to the specific patient that needs to be cured as soon as possible. The reason under this process comes directly from the reality, in that the process of admission in an emergency department is always characterized by a proximity criterion. The "report" computation is the following:

```
to-report choose-er
  report min-one-of ers [distance myself]
end
```

Then, we have the core procedure managing the ER's visiting mechanism. After the admission into the ED division, the patient must be cured with all the treatments included in his recipe. The following procedure aims at explaining this mechanism:

```
to-report see-er[doc treats]
  rush doc
  let flag 1
  ask doc [
    let lab1 one-of (specialists with [affiliation = [affiliation] of myself and member? 101 specialty])
    if (lab1 = nobody) [set lab1 min-one-of (specialists with [member? 101 specialty])[distance
myself] ]
    let lab2 one-of (specialists with [affiliation = [affiliation] of myself and member? 102 specialty])
    if (lab2 = nobody) [set lab2 min-one-of (specialists with [member? 102 specialty])[distance
myself] ]

    if (lab1 != nobody) [
      take-tests lab1
      if (lab1 != lab2) [ask lab1 [take-tests lab2]]
    ]
    let process []
```

```
  foreach treats [
     let targetDoc one-of specialists with [affiliation = [affiliation] of myself and member? ? specialty]
     if targetDoc = nobody [set targetDoc min-one-of (specialists with [specialty = ?])[distance myself] ]
     set process lput targetDoc process
    ]
    set process remove-duplicates process
    ifelse not(member? nobody process) [
      take-visits-to first process
      while [length process > 1] [
        ask last process [take-visits-from last (but-last process)]
        set process but-last process
      ]
    ][set flag 0]
  ]
  report flag
end
```

The procedure above denotes three important features:

- Blood taking exams (code “101”) and blood analysis tests (code “102”) are treated separately. In particular, if one or both of these services are not provided by the hospital in which the emergency department works, then the patient is sent to the nearest hospital providing these services. The program follows again the proximity criterion in selecting the nearest specialists (medical divisions) providing the two precise services.
- Generally, all the treatments composing the recipe of the patient are implemented by the hospital in which the patient is sent with an high degree of emergency (i.e. the hospital having the emergency department). There may be the case that not all the services are provided by the hospital, and, if so, the program selects the nearest hospitals again on proximity criterion basis. This feature of the ER behavioral procedure represents a good approximation of the real healthcare system under analysis in that it is quite common that the hospital takes care of its patients cured in its emergency department, providing them in all the medical tests and specialist visits needed with its own medical divisions. It may occur that in some cases the patient has to be transferred, for certain exams or treatments, in other structures offering specific services in better ways.
- As we have already reported before, patients that cannot find services provided in any structure die, disappearing from the simulation.

Another thing that has to be noted deals with the creation of duplicates in the program that is strictly forbidden by the procedure above. In other words, when the patient enters in an emergency department for the first time, he establishes a link that will be no longer created in other future possible passages.

The general practitioner

As we have pointed out in the course of the exposition of the model, the family doctor is a central figure in our agent-based simulation. Indeed, he is the decision maker driving his patients in choosing the hospitals or professionals that will cure them. In economic science terminology, we can address the family doctor as the perfectly rational subject of our model.
Due to the same proximity criterion, we have established that patients make visits to their nearest family doctor belonging to the same area (belt). As for the ER case, the procedure is a simple "report" computation of the distances in terms of patches:

```
to-report choose-family
  let area pcolor
  report min-one-of (familydocs with [pcolor = area] ) [distance myself]
end
```

The procedural rules that characterize the interaction between patients and family doctors are contained in the following code lines:

```
to-report see-family[doc treats]
  go-check doc
  let flag 1
  ask doc[
    let structures turtles with [breed = professionals or breed = specialists]
    let lab1 min-one-of (structures with [member? 101 specialty])[dist * (distance myself) + waitlist
*  queue + cost - quality * rep]

    let lab2 min-one-of (structures with [member? 102 specialty])[dist * (distance myself) + waitlist
*  queue + cost - quality * rep]

    if (lab1 != nobody) [
      take-tests lab1
      if (lab1 != lab2) [ask lab1 [take-tests lab2]]
    ]
    let process []
    foreach treats [
      let targetDoc nobody
      ifelse (random-float 1 < stubborness)
      [set targetDoc one-of structures with [member? ? specialty] ]
      [set targetDoc min-one-of (structures with [member? ? specialty]) [dist * (distance myself) +
waitlist *  queue + cost - quality * rep] ]

      set process lput targetDoc process
    ]
    set process remove-duplicates process
    ifelse not (member? nobody process) [
      take-visits-to first process
      while [length process > 1] [
        ask last process [take-visits-from last (but-last process)]
        set process but-last process
```

```
    ]
   ][set flag 0]
  ]
  report flag
end
```

The procedure is another "report" computation that refers to the list of medical treatments in a patient recipe. In particular, it emphasizes some important aspects:

- Economically speaking, the patient behaves like a sort of "consumer" with precise preferences with respect to three variables: quality of the services, waiting times, distances of the hospitals or clinics. In other words, we have modeled the patient as an agent with few informational knowledge but with individual preferences that must be taken into account in choosing the health and care providers. Hence, the final decision regarding the choices of the structures in which the patient finds his cures is highly influenced by his own preferences. This feature of the model may be reasonable by analyzing typical behaviors of real patients. Generally, they search for medical services with high quality, but they often valuate queues and distances as well. Nevertheless, our simulation interface is provided with a set of sliders managing these three variables in order to give the user the possibility of arranging the weights of such patient preferences as well as verifying implications on a network level:

- The family doctor, on the other hand, can be defined, in economic science terminology, as the rational agent in the model. Contrary to the patient, the general practitioner has more informational knowledge with respect to health and care providers in the territory. As a result, he valuates the preferences of the patient and then send him to the healthcare structures (public hospitals or private clinics). In doing so, the family doctor compute a precise rational formula composed of variables indicating the patient preferences. The choice of family doctors is given by the lowest value provided by the formula computation. The formula is the following:

  distance + waiting time (queues) + costs – quality of the service

  The formula represents the rationality characterizing family doctors, who firstly evaluate preferences of their patients and then decide where to send them. Behind this formulation, thus, there is a precise assumption to be pointed out: the family doctor has complete information about the main characteristics of health and care providers in the model (queue, costs, quality and distance) and he is the decision maker of patient movements. We have to highlight that the quality of medical treatments is valued by means of the attribute "reputation" addressed to the physicians (specialists and professionals).

Analyzing the code lines, we can notice that the formula is expressed with some weights, indicating the association of the variables to a precise patient with precise geographical coordinates and preferences.

- The hypothesis of a family doctor as the main decision maker may be softened. Indeed, ethic in medicine science refers to the freedom of choice of the patient in any case. This principle is quite adopted in real healthcare systems and, as a result, may impact in the overall patient flows and their decisions. In order to model the freedom of choices that patients posses, we have introduced a further variable called "stubbornness". It is controlled by a specific interface slider which can assume values from zero to 1. The code lines report the logical computation that the program undertakes: the program extracts a random number between zero and one, then it compares the number with the value indicated by the slider. If the extracted number is less than the slider number, then the patient chooses on his own, while, on the contrary, if the extracted number is higher than the slider value, then the patient follows the family doctor. As a result, with the slider set equal to zero, all the patients will follow the family doctor decisions, while, on the other hand, with the slider set equal to one, they will decide on their own choosing randomly the health and care providers. The "stubbornness" slider figures as follows:

- Two more things have to be highlighted. First of all the specific indication on the code of the blood taking and blood analysis tests. Again, the purpose of this work is to focus also on the laboratory networks that may derive in the healthcare system, so we want to isolate these two services that must work in pairs but can be implemented by different providers. Secondly, it is important to point out that, when deciding health and care providers for patients, family doctors as NetLogo agents create links with the chosen providers after having computed their valuations. This links are created immediately following a cascade process according to the treatments that the patient has in his recipe.

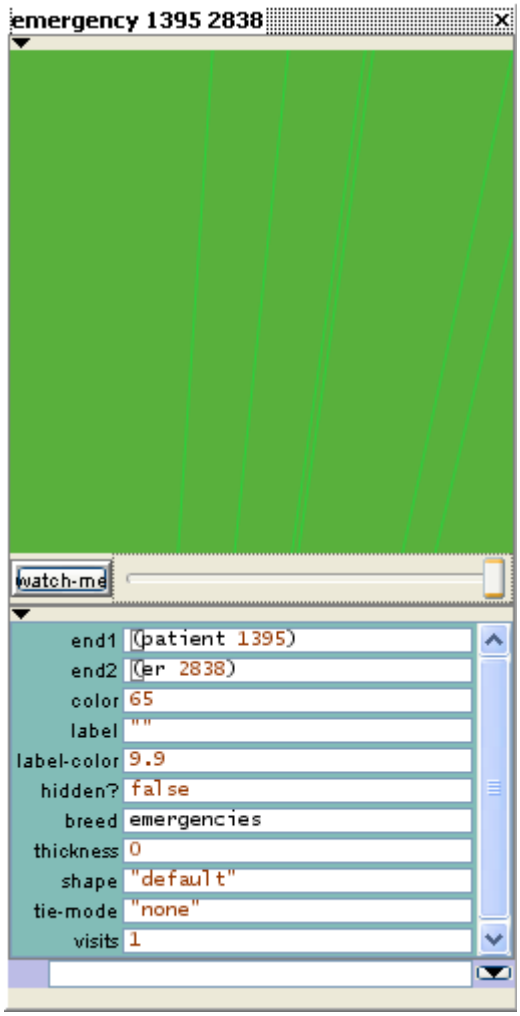
The last point serves as introduction for the following paragraph devoted to the link identification in our NetLogo code. First of all links are considered agents in NetLogo. We have decided to treat them separately from the agent set explanation in that they identify connections among agents after their interactions and so they are a result of the different procedures.

4.9 AGENTS CONNECTIONS: LINKS CHARACTERIZATION

As we have reported before, NetLogo identifies links as agents with precise attributes. A link defines a connection between two other agents in the simulation interface. We have decided to treat this typology of agents separately from the agents presentation in that links are generated as an emergent consequence of agents interactions. Indeed, they are the result of patient interactions with doctors and doctors connections with other doctors. Hence, every single link in the simulation connects two ends: the first end, from which the link starts, may be referred to a patient, a family doctor, a specialist, a professional or an ER while the second end may address a specialist, a family doctor, a professional or an ER (but never a patient).
Since we have modeled several typologies of physicians, we have identified four typologies of links characterized by different colors: ER link, family doctor link, professional link, specialist link. We proceed by analyzing each typology and the corresponding procedures written down in the code.

ER Links

This typology of links defines the emergency operation that characterizes a patient transferred to an emergency department. Since links are agents, we can analyze them using the inspection window:



As one can notice, links are characterized by two ends that represent a kind of ID for the specific link. The example reported in the inspection window refers to a link connecting patient number 1395 with an ER doctor number 2838. The ER links are colored in green and present arrows pointing towards the ER doctors.
As it occurs in all the other typologies of links, the attribute "visits" reports the passages executed by a patient when he is admitted to the same emergency department. In other words, patients can enter in an ED many times during their "health lifetime" as well as they can visit same doctors more than one time. In order to analyze the whole system at a network level, we have introduced the variable "visits" to count the number of passages carried out between two agents and to verify what links present several visits at the end of the simulation. This may be useful at the end of a simulation, in that we can "prune" the interface considering only those links with high number of visits.
The procedure associated with the ER links creation is characterized by the following code lines:

```
to rush[doc]
  ifelse (out-emergency-neighbor? doc)
        [ask out-emergency-to doc [set visits visits + 1]]
        [create-emergency-to doc [set visits 1 set color lime]]
end
```

We have to highlight again that the patient with high level of emergency is directly admitted in the nearest emergency department without passing through any family doctor check up.

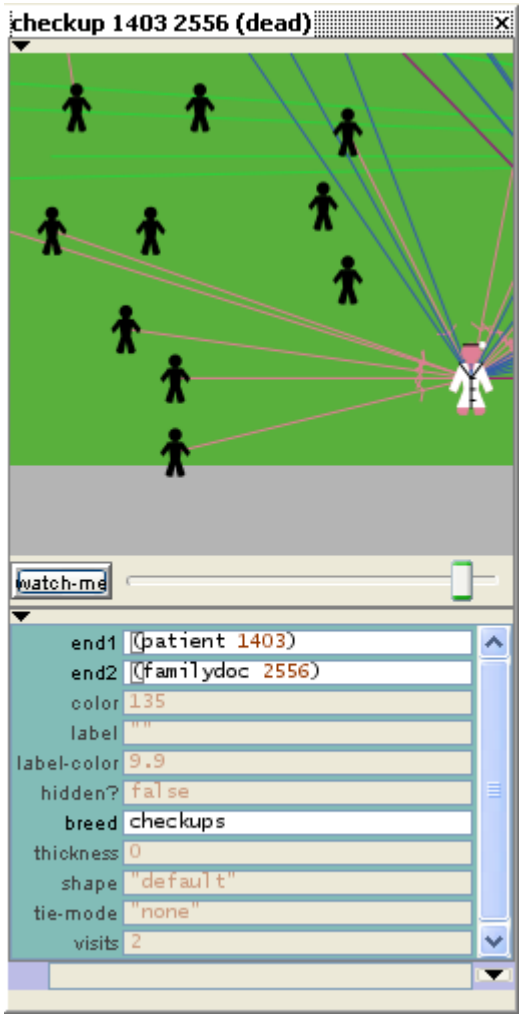
Family doctor links (check up visits)

This typology of links identifies the connection between patients and general practitioners. We have called "check up" the visit provided by family doctors and thus, the name of the corresponding link. The characterization of these links is the same as in the previous typology with the only difference that they are shown in pink color on the NetLogo interface. The procedural code part devoted to "check up" links is the following:

```
 to go-check[doc]
  ifelse (out-checkup-neighbor? doc)
        [ask out-checkup-to doc [set visits visits + 1]]
        [create-checkup-to doc [set visits 1 set color pink]]
end
```

Also in this case the links contain the number of visits referred to a specific patient interaction with a specific family doctor.

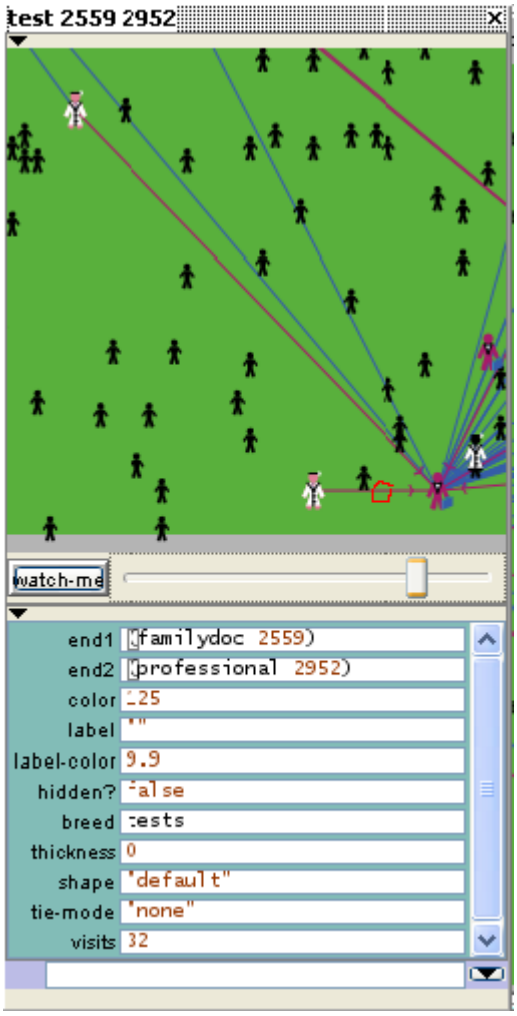
The inspection window is the following:



This typology of links connects always patients with family doctors. The figure above shows clearly the direction of these pink links with the arrows pointing towards the family doctor. It is interesting to notice that the example above reports a link which is “died”. This proves the fact that links are agents. We will explain how it can be possible to “kill” links as a result of a “prune” operation with some interface commands.

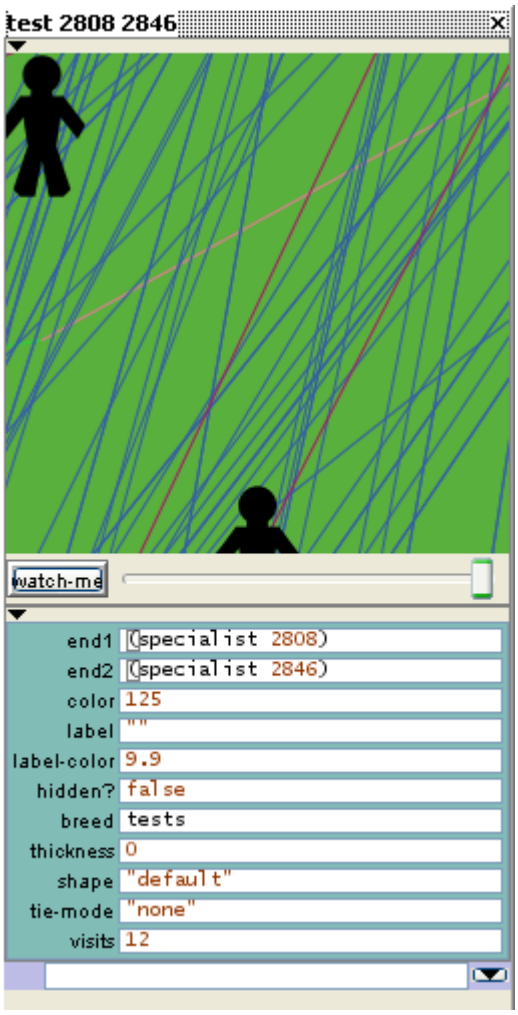
Tests links (laboratory exams)

So far the previous typologies of links have been a consequence of the precise agents involved: patients and ERs in the first typology, patients and family doctors in the second one.
However, this typology differs from the previous ones in that it refers to a specific class of treatments: the laboratory exams(code “100”). Here, what drives the creation of these links is the typology of treatments. This explains the reason why we have characterized separately the two services “blood taking tests” (code 101) and “blood analyses test” (code 102) in the previous part related to the procedures and the code lines. In other words, these links named “tests” refer to these two types of treatments and give the user the possibility of managing and studying separately the emergent network of the “blood circuit”.
These links figure as follow:



The link is marked with a red sign in order to identify it. The example refers to a link connecting a family doctor and a professional (a private clinic). The amount of visits is very relevant in this example. The color used for this typology of links is the magenta.
However, the connection generating this typology of links may be derived from various doctor interactions such as specialists-specialists, professionals-professionals, specialists-professionals or professionals-specialists, ERs-professionals, ERs-specialists.

The example below refers to a specialist-specialist “tests” link:

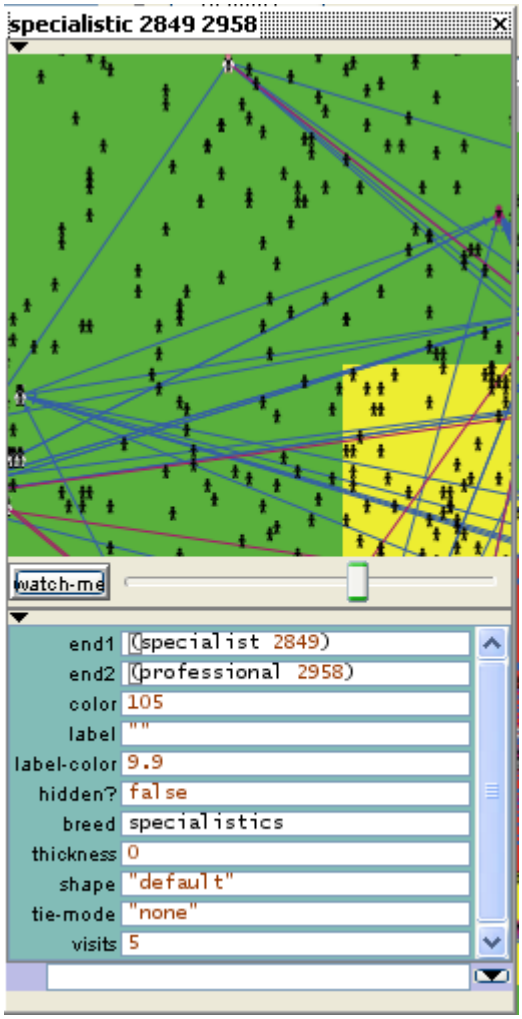


The corresponding code lines devoted to the definition of those links are the following:

```
to take-tests[lab]
  ifelse (out-test-neighbor? lab)
        [ask out-test-to lab [set visits visits + 1]]
        [create-test-to lab [set visits 1 set color magenta]]
end
```

Specialists visits

As for the “tests” case, these links result from the typology of medical treatments provided by the doctors. In particular, they identify all the treatments except the blood taking/blood analysis tests. Also pathologies belonging to the third category may be presented by those links in that they not always are figured in the first position of a patient recipe (the emergency case). Again, as the “tests” links, they may identify connection of different doctors combinations. Surely, they are the most abundant links at the end of the simulation in that they result from several different treatments. The emergent network originated by specialist visits represents the other target of analysis we want to focus on.
The inspection window figures these links colored in blue as follows:



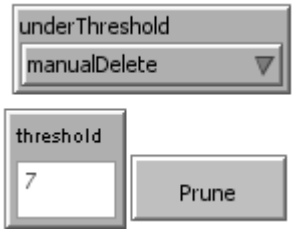
The example shows a connection between a specialist and a professional. Anyway, as we have pointed out, we can have relations of various type: specialist-specialist, professional-professional, professional-specialist, family doctor- specialist, family doctor – professional, er-specialist, er-professional.

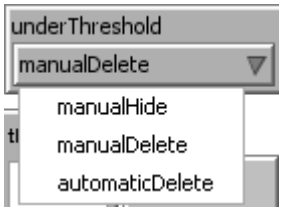
For these links the code lines present two separate procedures identifying the orientation of the connection from or to other doctors.

```
to take-visits-to[doc]
  ifelse (out-specialistic-neighbor? doc)
        [ask out-specialistic-to doc [set visits visits + 1]]
        [create-specialistic-to doc [set visits 1 set color blue]]
end

to take-visits-from[doc]
  if not (doc = myself)[
    ifelse (in-specialistic-neighbor? doc)
        [ask in-specialistic-from doc [set visits visits + 1]]
        [create-specialistic-from doc [set visits 1 set color blue]]
  ]
end
```

4.10 FURTHER PROCEDURES AND COMMANDS

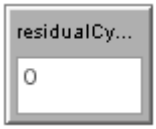
We have made some references to the possibility that links may die or hide in the simulation interface in the previous paragraph. These possibilities are not scheduled by the program, but they are left to the user discretion in that there are some buttons in the interface. The set of commands devoted to links figures as follows:



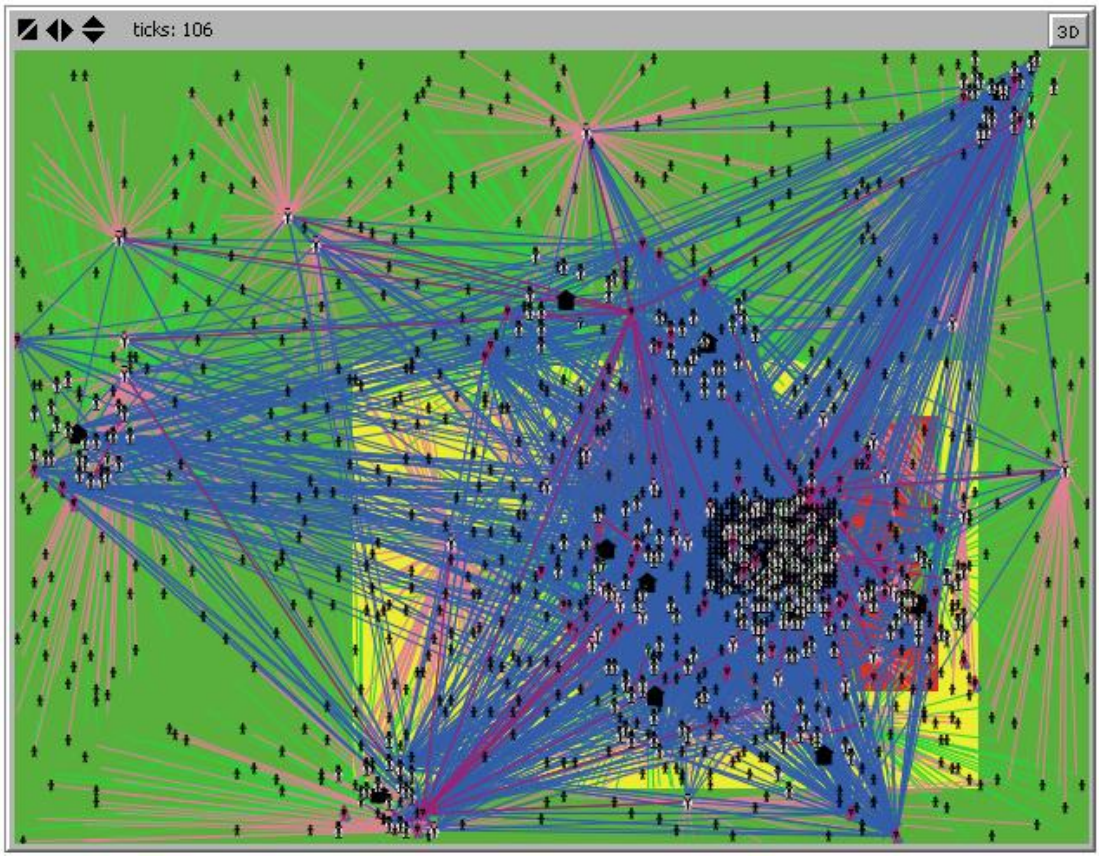


The input named "threshold" gives the user the possibility of choosing the minimum number of "visits" that links must possess in order to be not deleted. Indeed, the user can choose what links to preserve in the simulation in order to better manage the resultant networks and to valuate only those links with a significant number of passages. The associated button related to links cancellation is the "under threshold" command which in turn may offer three possibilities:

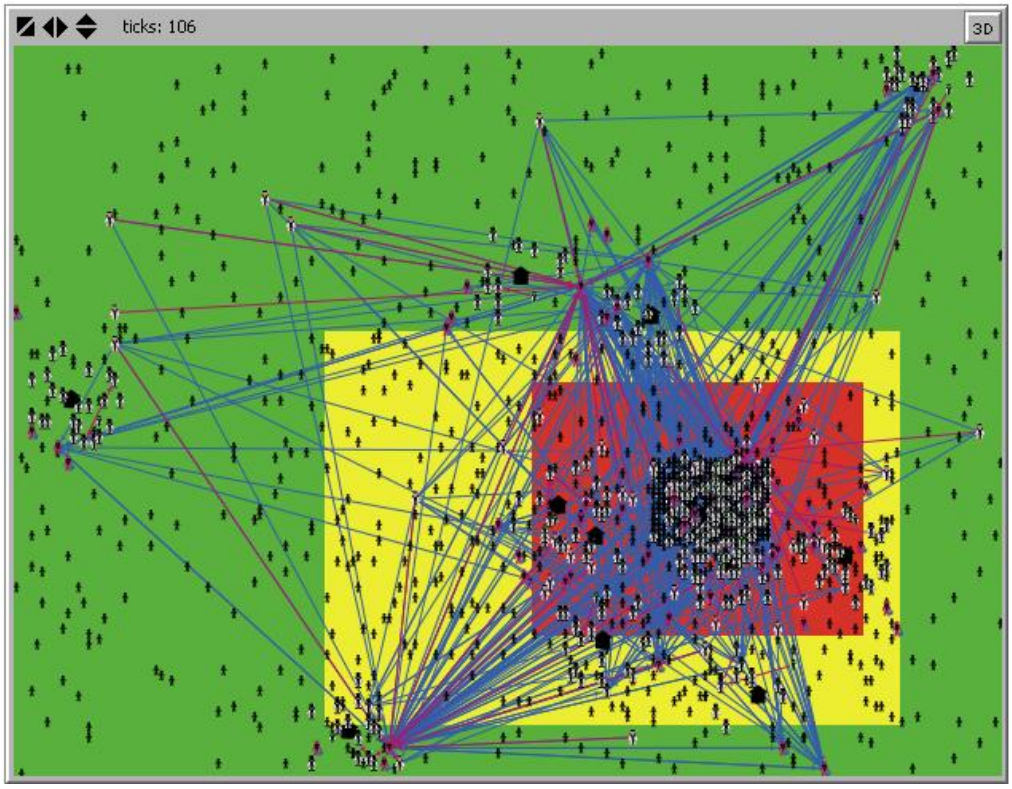
- Selecting "manualHide", the user can hide (and not "kill") all the links with a number of visits less than the value indicated in the threshold input. In order to hide the links, the user has to press the button "prune".
- Selecting "manualDelete", the procedure is the same as in the "hide" case but it "kills" the links that do not satisfy the chosen threshold level. Also in this case, the user has to press the button "prune".
- Finally with "automatic delete", the program deletes links on its own when there are more than one cycles of simulation. Indeed, we have added another interface input enabling the user to choose the number of simulation cycles in order to compare various populations at the same time. The input named "residualCycles" gives the number of simulations be left by the program (i.e. if the input reports a value of 1, then the program has to run one more simulation) and figures as follows:



We can provide a quick example, showing the usage and the effect of a manual cancellation of links. Firstly, we run the program in order to visualize a general view which it usually figures as chaotic and difficult to be interpreted. Clearly, these buttons deal only with "specialist" and "tests" links in that the family doctor visits and ERs links usually do not present an high number of passages.



As one can notice, managing with a similar scenario is not an easy task. However, selecting a threshold value of seven passages and using the button “manualDelete” the result will be a cleaner interface world with only those links which present at least seven visits:



The corresponding code lines characterizing these links controls are given by the following two procedures with the first standing for the “automaticDelete” selection while the second standing for the “manualHide” and “manualDelete” options:

```
to checkPopulation
  if (all? patients [hidden?]) and (residualCycles > 0)
  [
    if (underThreshold = "automaticDelete")[ask links with [visits < (threshold * cycle)][die]]
    ask patients [show-turtle set dead 0]
    giveAge
    giveIllness
    set cycle cycle + 1
    set residualCycles (residualCycles - 1)
  ]
end

to modLinks
  ask links [show-link]
  if (underThreshold = "manualHide")
  [ask links with [visits < threshold][hide-link]]
  if (underThreshold = "manualDelete")
  [ask links with [visits < threshold][die]]
end
```

Another important feature of the model is the time characterization. Patients have certain ages and present recipes starting at some ages in their lifetime making, thus, a precise characterization of the passing of time a fundamental issue to be persecuted. The following procedures denote the passing of time and the aging process of patients:

```
to timeGoesBy
  set currentMonth currentMonth + 1
  if (currentMonth = 13) [getOlder set currentMonth 1 set currentYear currentYear + 1]
end

to getOlder
  ask patients with [age = 100][hide-turtle set dead 1]
  ask patients with [not hidden?] [set age age + 1]
end
```

First of all, NetLogo identifies the passing of time with “ticks” reported on the world scenario up on the left corner. We have associated ticks with month, so a tick represents a month and twelve ticks represent a year. Hence, after 13 ticks the year increases by one. This time characterization is then associated to the recipes activations that identify months and years in which they start entering in function. On the other hand, the passing of time increases the ages of patients who live since they reach one hundred years old. If they reach this age limit, they die and the simulation cycle ends when all the patients disappear from the interface. In case of more than one simulation cycle, the population is set up again with new patients satisfying always the same proportions in terms of ages

and a new simulation begins. The limit of 100 years old is consistent with real data on the population of the district under analysis.

Further interface buttons are related to the hiding of patients and to the enlarging or reducing size of family doctors. These controls serve as visualization tools in order to deal with some agents immediately and to quickly recognize them on the interface.

The corresponding code lines are the following procedures (with the first identifying the hide/show patients button and the other two related to the family doctors size):

```
to hideShow
  ask patients with [age < 100 and (dead = 0)][set hidden? (not hidden?)]
end

to bigFamilyDocs
  ask familydocs [set size size + 1]
end

to smallFamilyDocs
  ask familydocs [set size size - 1]
end
```

Moreover, since an agent-based simulation program generates new scenarios all the times one presses the setup button due to the probabilistic computation it has to implement, we have added the possibility of saving a particular random computation in order to generate always the same scenario settings. This is done by saving the so called “random seed”, identified by a monitor on the interface and that can be saved through its correspondent on/off switcher.

This control may be useful in the experimental trials that can be implemented with the model. The program code shows the corresponding procedures as follows:

```
to startup
  set randSeed new-seed
```

```
end

to setup
  clear-all
  if (not keepSeed?) [set randSeed new-seed]
  if (abs randSeed) > 2147483648 [ set randSeed new-seed ]
  random-seed randSeed
```

This lines refer to a setup configuration of the random seed. In particular, if the user adds a value of the seed that goes out of the range, the program immediately corrects it (look at the "if" line with a specific range set).

4.11 NETWORK PROCEDURES AND BUTTONS

The healthcare system modeled in our work is analyzed by means of two fundamental typologies of network: the "tests" network and the "specialist" network. NetLogo provides useful tools devoted to network analysis, with a specific extension that is characterized by network measures and commands related to this specific purpose. Hence, in order to give some results in terms of number and quantities, we have added three measures concerning network analysis, some of them already reported in the literature review section.

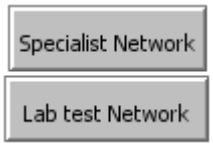
- *Betweenness centrality*: NetLogo computes this measure related to a single agent taking every possible pair of agents (doctors in our case), and for each pair calculates the proportion of the shortest path between members of the pair that passes through the current agent itself. The resulting betweeness centrality of a single agent is the sum of these and will be visualized in the attribute "btw" figured in each doctor inspection window.
- *Eigenvector centrality*: this measure can be referred to a node, and is defined as the amount of influence a node has on a network. In other words, agents that are connected to a lot of other agents that are themselves well-connected (and so on) get a higher Eigenvector centrality score. We have to highlight this definition in that our model will lack some connections most of the times. Indeed, eigenvector centrality is only defined for connected networks, and the primitive will report "false" for disconnected graphs. Moreover, in this implementation, NetLogo normalizes the eigenvector centrality such that the highest eigenvector centrality a node can have is 1.
- *Closeness centrality*: this measure referred to an agent can be defined as the inverse of the average of the agent distances to all the other agents. The more central a node is, the lower its total distance to all other nodes. Note that NetLogo takes into account only the distances to the agents that are part of the same component as the current agent, since distance to agents in other components is undefined. The closeness centrality of an isolated agent is defined to be zero.

Looking at the program code, the procedures concerning the network analysis are distinguished for each typology of network considered in our model (tests network and specialist network):

```
to spNetwork
  ask links [hide-link]
  let structures (turtle-set familydocs specialists ers professionals)
  let connections (link-set specialistics)
  ask connections [show-link]
  nw:set-context structures connections
  ask structures [set betw nw:betweenness-centrality set eigvec nw:eigenvector-centrality set
weighted nw:closeness-centrality]
  layout-circle sort-on [betw] structures with [betw != 0] 65
end
```

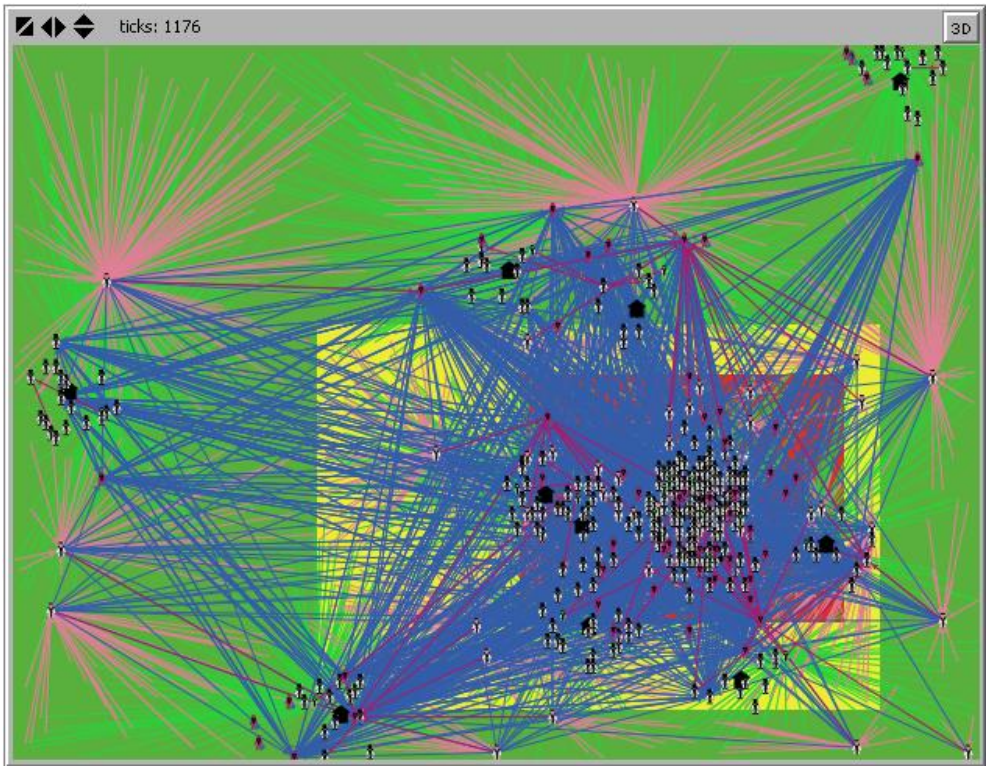
```
to testsNetwork
  ask links [hide-link]
  let structures (turtle-set specialists ers professionals familydocs)
  let connections (link-set tests)
  ask connections [show-link]
  nw:set-context structures connections
  ask structures [set betw nw:betweenness-centrality set eigvec nw:eigenvector-centrality set
weighted nw:closeness-centrality]
  layout-circle sort-on [betw] structures with [betw != 0] 65
end
```

As one may notice, the so-called “turtle set” defines the agents involved in the network identification (the agents that posses the network measures as attributes). In our case, the agents involved are all the typologies of doctors in the model.

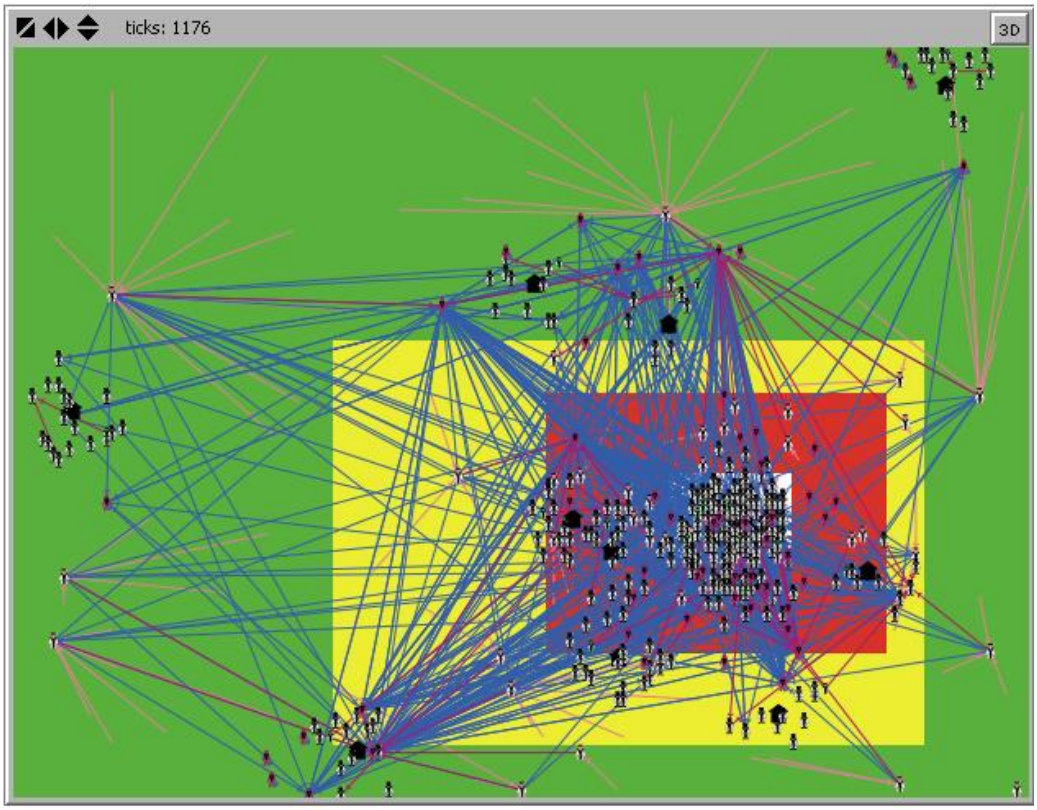


The interface buttons above initialize the network visualization process on the NetLogo interface.
We can show an example of network visualization, starting from a full simulation cycle of 1176 ticks (circa a hundred years).

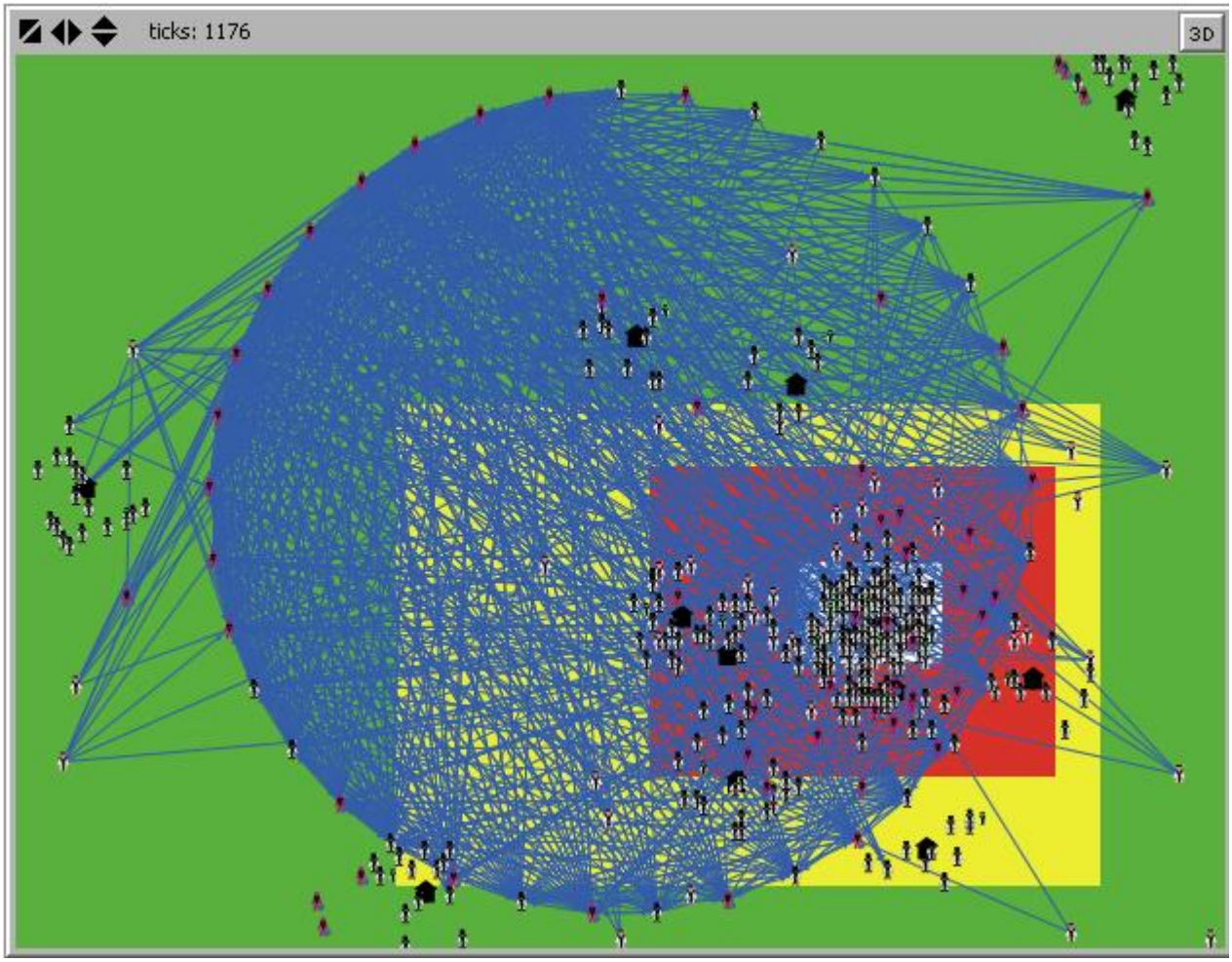
The overall representation without pruning any link is the following situation where all the patients have ended their lifetime:



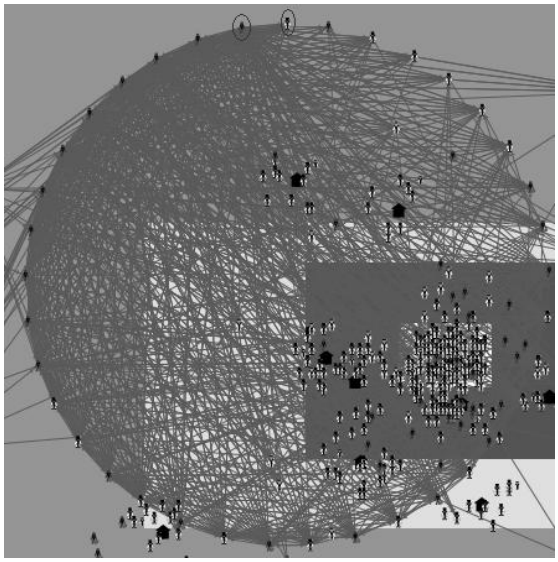
The amount of links is extremely relevant in that each patient movement is represented, covering all patients health lifetime. One can consider only those links with a consistent number of passages and so the situation, with a threshold of 7 visits, changes as follows:



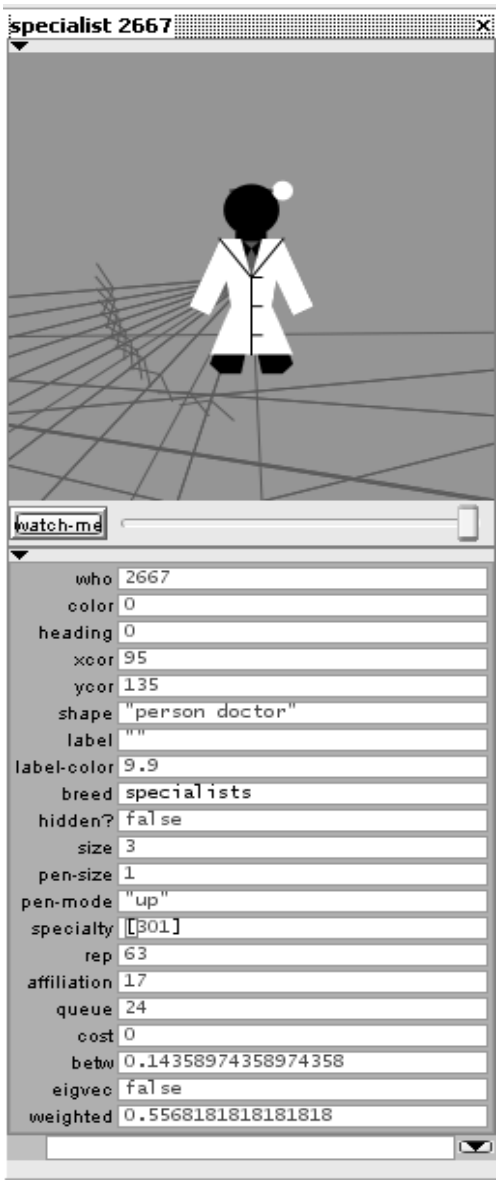
The scenario, with pruned links, is much more manageable and, then, it is possible to analyze the specialist network pressing the correspondent button:



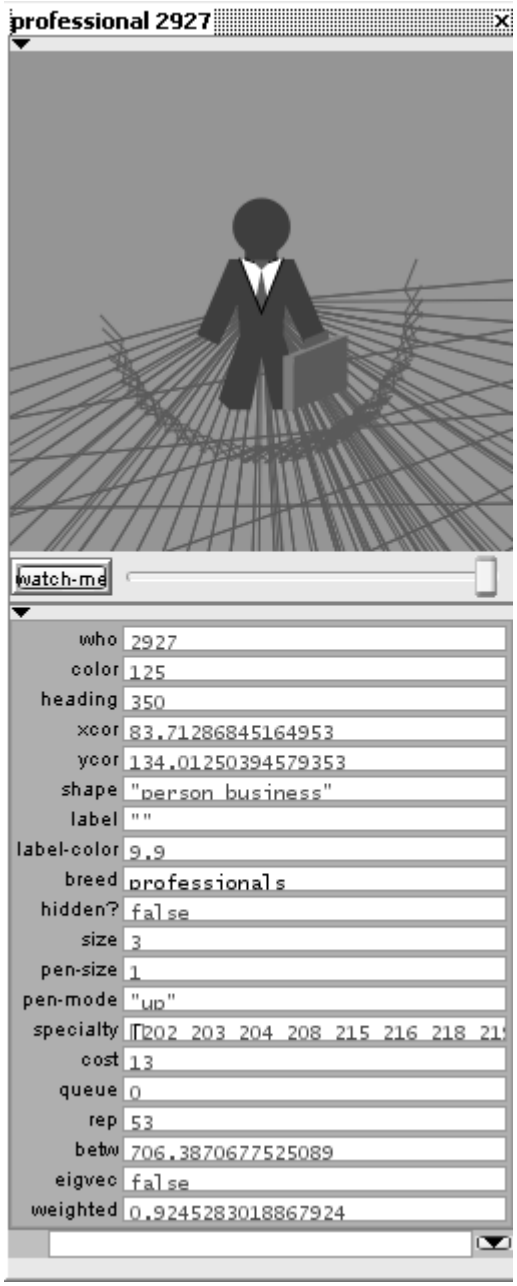
The picture above represents the specialist network in our simulation model. NetLogo lays out in circle agents involved in this network, focusing on professionals and specialist doctors, while family doctors enters in the network indirectly by standing away from the circle. This layout representation provides a clear visualization of the structure of a network. It is interesting to notice that, in this simulation experiment, some professionals and some specialists do not provide the minimum threshold of seven visits and are taken away from the network.
The circle layout is also useful in identifying the betweenness values of each agent in the network. In particular NetLogo disposes agents in circle in increasing order of betweenness value. So, agents are disposed in a clockwise order according to their betweenness value that can be verified from the inspection window of each doctor composing the network. The following pictures refer to the inspection of the less relevant agent in the network in terms of betweenness and the most relevant one.



The two agents circled above show as follows:



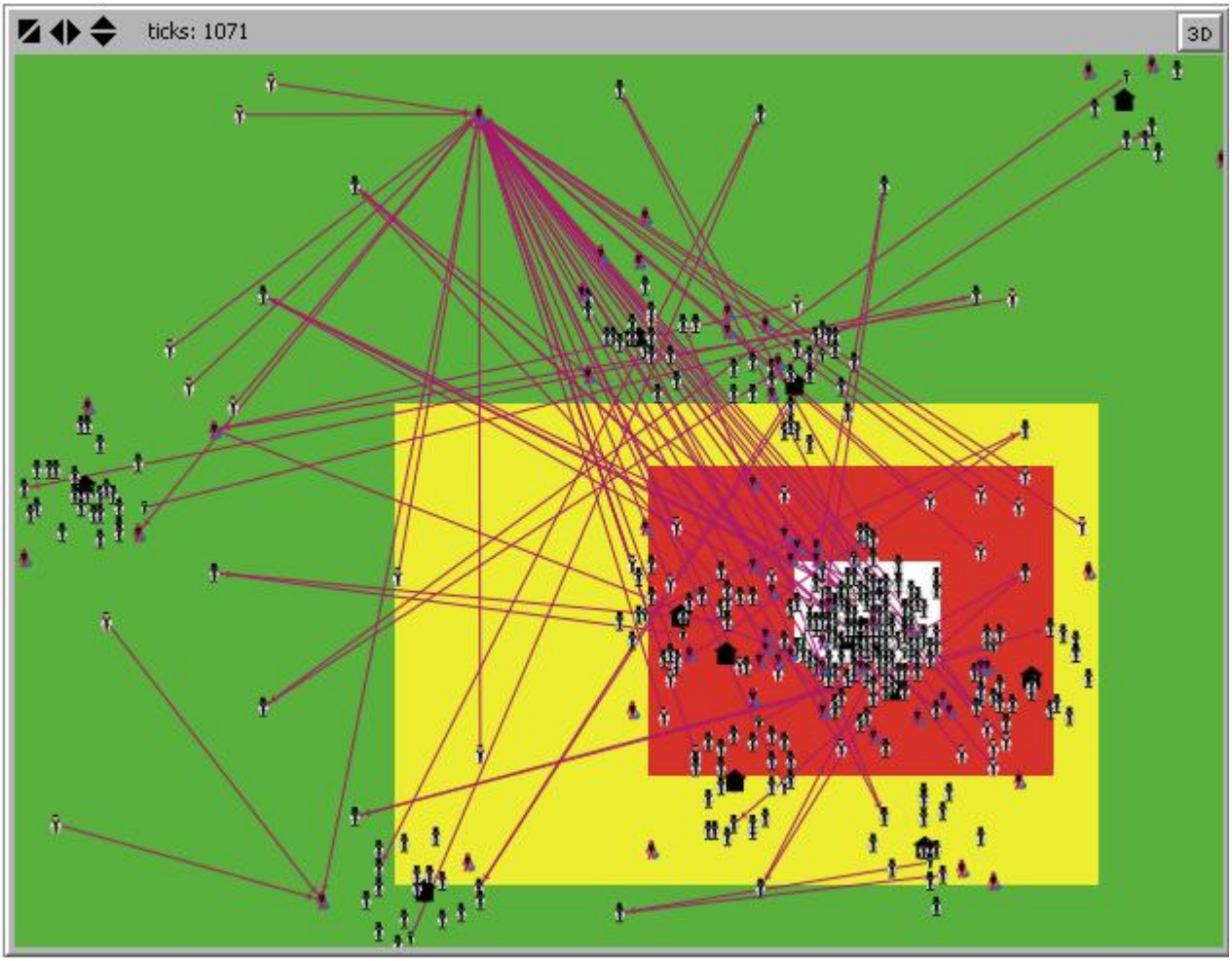
The specialist number 2667 is the located exactly at twelve o'clock in the circle representation. Indeed it shows a low betweenness value (0.14 circa). Then, this specialist affiliated to the hospital of Moncalieri works mainly inside its public structure without interacting with other health and care providers.
On the other hand, the most important agent in terms of betweenness is the professional on the left of the previous one:



As it can be noticed, both betweenness and weighted centrality show large values, meaning that this private clinic is deeply engaged by several agents in the whole healthcare system. This agent is highly used by other interacting pairs of doctors as intermediate step and, so, it is a central figure in many patient movements. Because of its relevance in the specialist network, the weighted centrality

is highly significant and close to 1 (because it is the inverse of the average distances), meaning that the agent has a strategic position in the network.

Looking at the laboratories network, the overall situation is represented as follows (magenta links in this case):



The network structure in this case is less regular than before in that blood tests represent specific treatments while in the specialist case, we consider a huge variety of treatments, resulting in a higher level of connection. The disposition of the agents in the network follows the same criteria adopted in the specialist case.

4.12 EXPERIMENTING WITH THE MODEL: THE LABORATORIES NETWORK

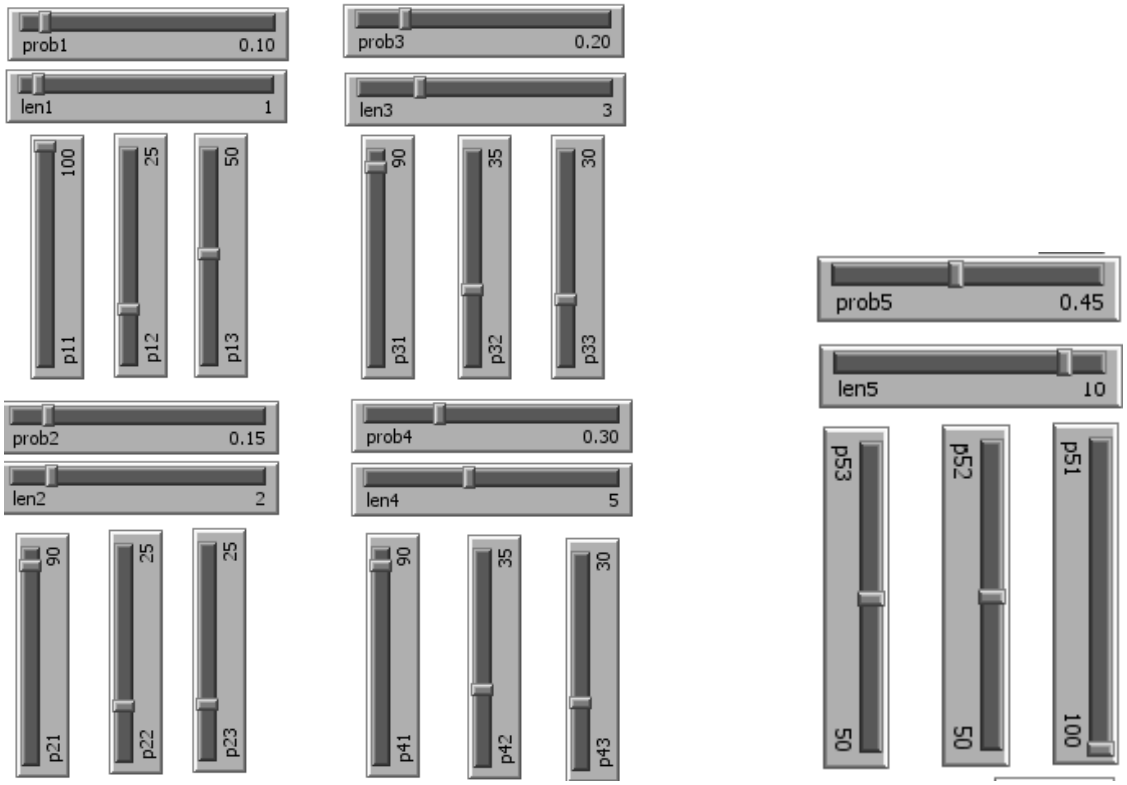
These paragraphs focus on the model usage and on the analysis of different healthcare scenarios that it can generate. We can proceed by representing a variety of possible situations that may occur in an healthcare system, simply by changing values and settings in the NetLogo interface. In order to provide some kind of benchmark, we will keep a specific random seed.

Experiment n°1

To begin with, we start to simulate a situation in which all patients follow their family doctor in choosing the health and care providers of the district. Hence, the slider "stubbornness" in the interface is set equal to zero. Introducing this compulsory rule, we want to evaluate networks generated by rational computations of the family doctors. The patients preferences are set choosing a high weight for the distance of the health and care providers, lower values for waiting times and qualities of the services.

So, as it usually occurs in reality, distance is the dominant variable taken into account by patients (especially those inhabiting rural areas of the second and third belts).
In order to compose the recipes each patient will incur in during his lifetime, we have tried to respect some differences in medical treatments that address the five age categories. Great relevance in probability terms is assigned to laboratory exams for all the five age categories in that most of the health and care provisions patients need regard medical tests and analyses. Moreover, the probability of incurring in "illnesses" is increasing with respect to age categories as well as the length of the recipes. With respect to treatments characterized by high degree of emergency (code "300"), we have assigned higher probabilities for infants because they may be more involved in emergency diseases at their birth.

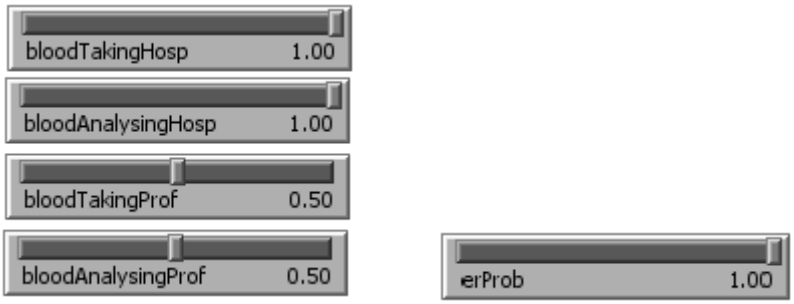
In particular, the composition of the recipes for each age class is determined following the proportions:



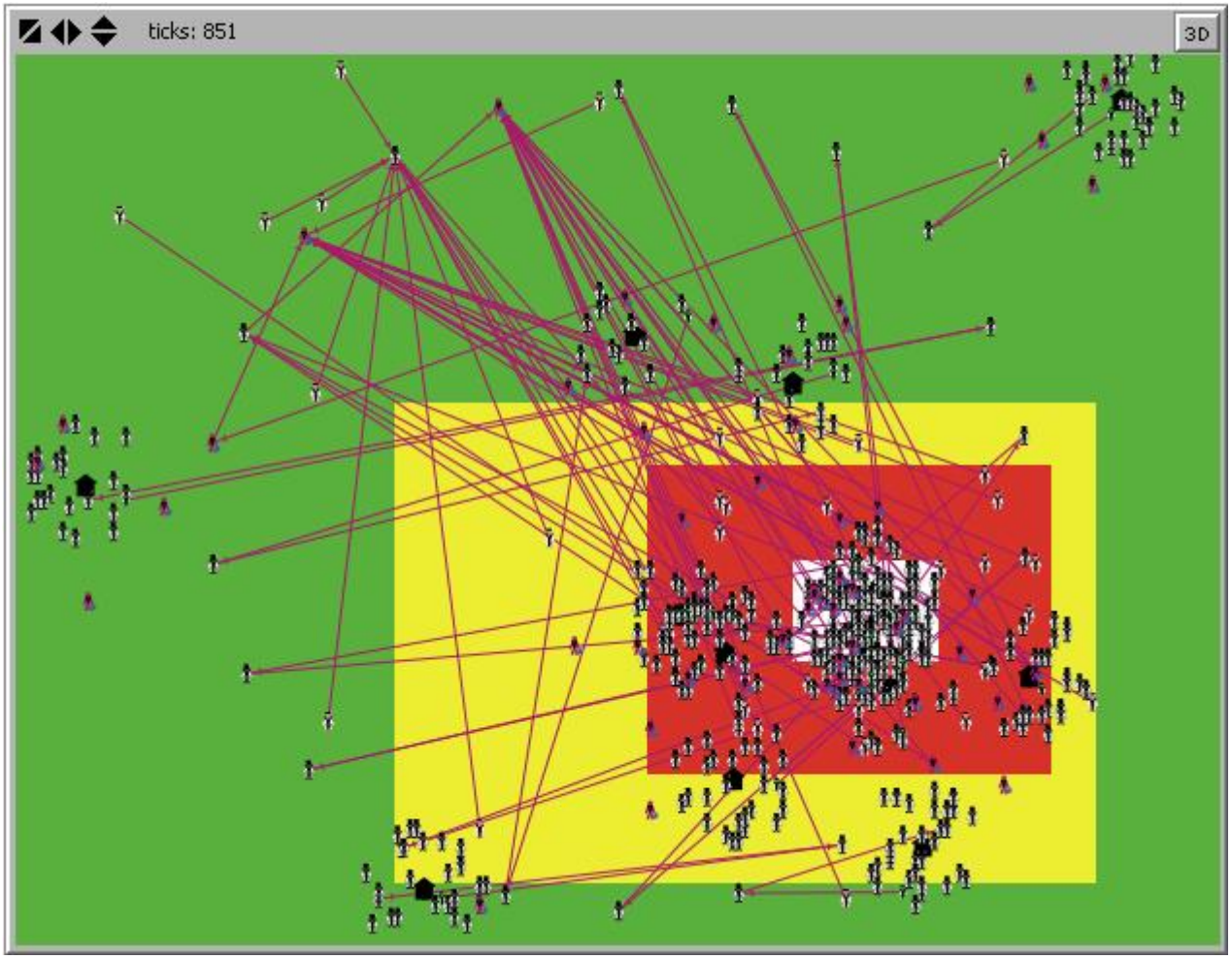
The amount of medical treatments for the three different typologies of treatments is established as follows:

External private structures and family doctors distribution among the four areas are established as follows:

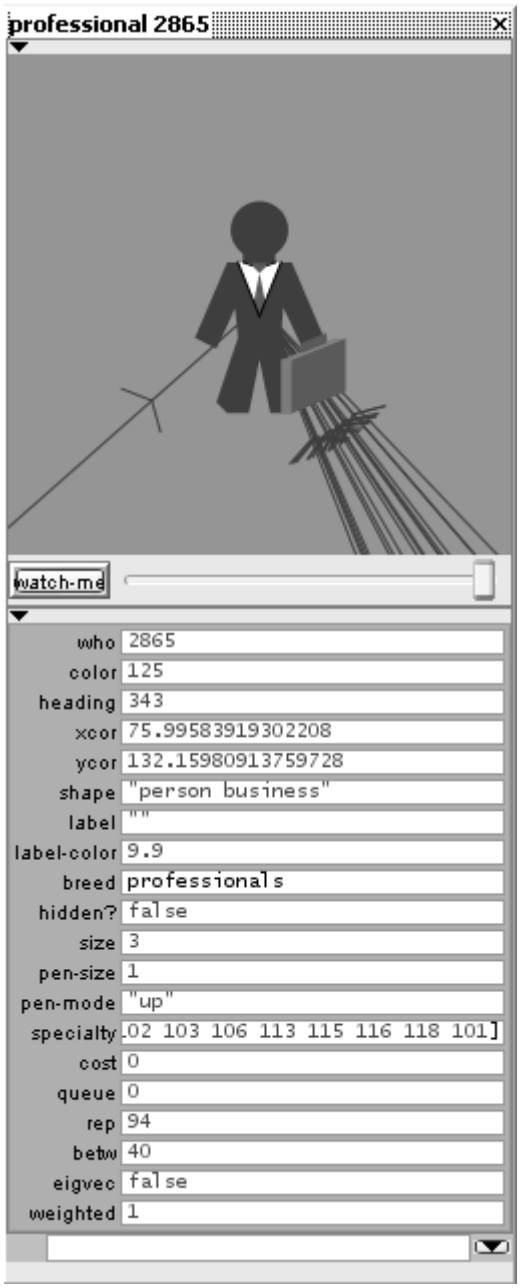
The sliders concerning the emergency departments and the blood test centers for hospitals and private structures represent the reality in the healthcare system under investigation. Each hospital has an emergency department and a blood analysis center as well as a point of taking blood samples. Private clinics have the 50% of possibility of having these two typology of services (blood taking and blood analysis).



The resulting “blood tests” network figures as follows at the end of a simulation cycle:

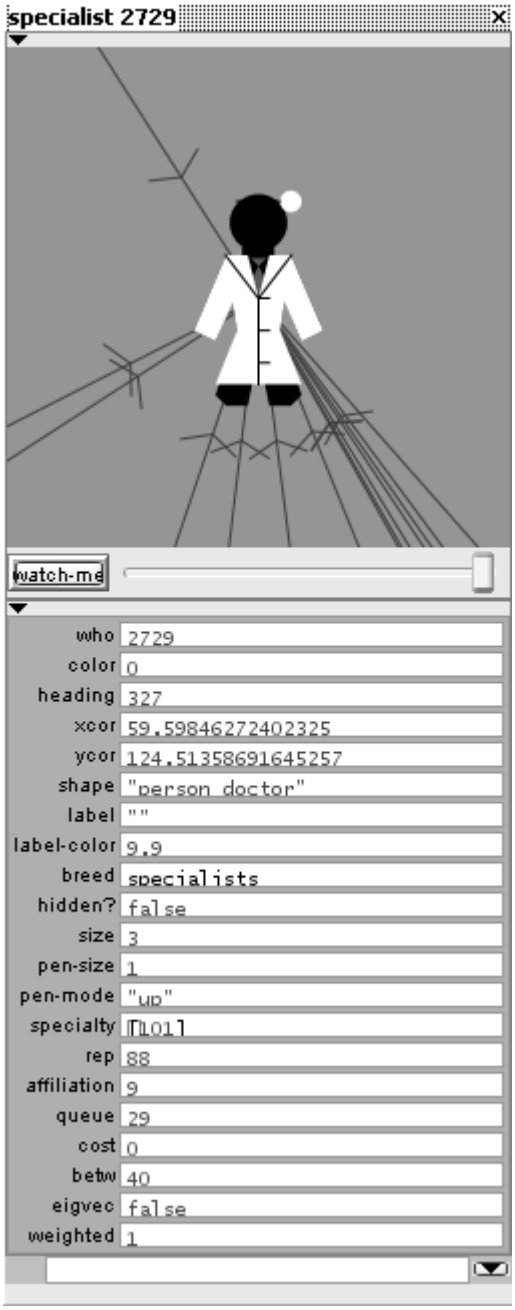


We have adopted a threshold value of at least two passages for each link. First of all, we have to note that there are circa twenty nodes in the laboratories network. Most of these doctors are specialists. However, it is important to highlight that the agents with higher betweenness and weighted centrality are the so-called “professionals” (the private structures). The resulting network structure representing the “blood circuit” is given by a clear random graph (see the section devoted to network analysis) and will recur in all the experiments made in these pages. It is important to notice that these emergent networks are not characterized by a complete connection across agents. This feature will imply that, with respect to the blood circuit, the eigenvector centrality of the various nodes will be zero in all the experiment sets. The main node of the network presented above is presented in the following figure.



Indeed, the services provided by this professional are mainly characterized by medical analyses and laboratories. We can think about this agent as a relevant private laboratory center which may be also used by public health structures. Nevertheless, inspecting the various links involving this agent, we assess that most of the medical orders come from family doctors and other professionals. In particular family doctors orders dominate above all. This phenomenon may be associated with the high reputation rate presented by this private structure although we have imposed a lower probability weight for the variable “quality” in the patients preferences. A possible explanation may be derived from the geographical position in the scenario of this agent. It can be located in a zone where there are few hospitals (in external belts) and family doctors direct patients towards this structure for blood tests. However, resetting the scenario with the same random seed, we notice that the professional is located in the city center of Turin, receiving orders also from external belts. Hence, this private structure has a central position and provides quality tests that also capture external demand.

The other agent with high relevance in terms of betweenness and weighted centralities is a specialist:



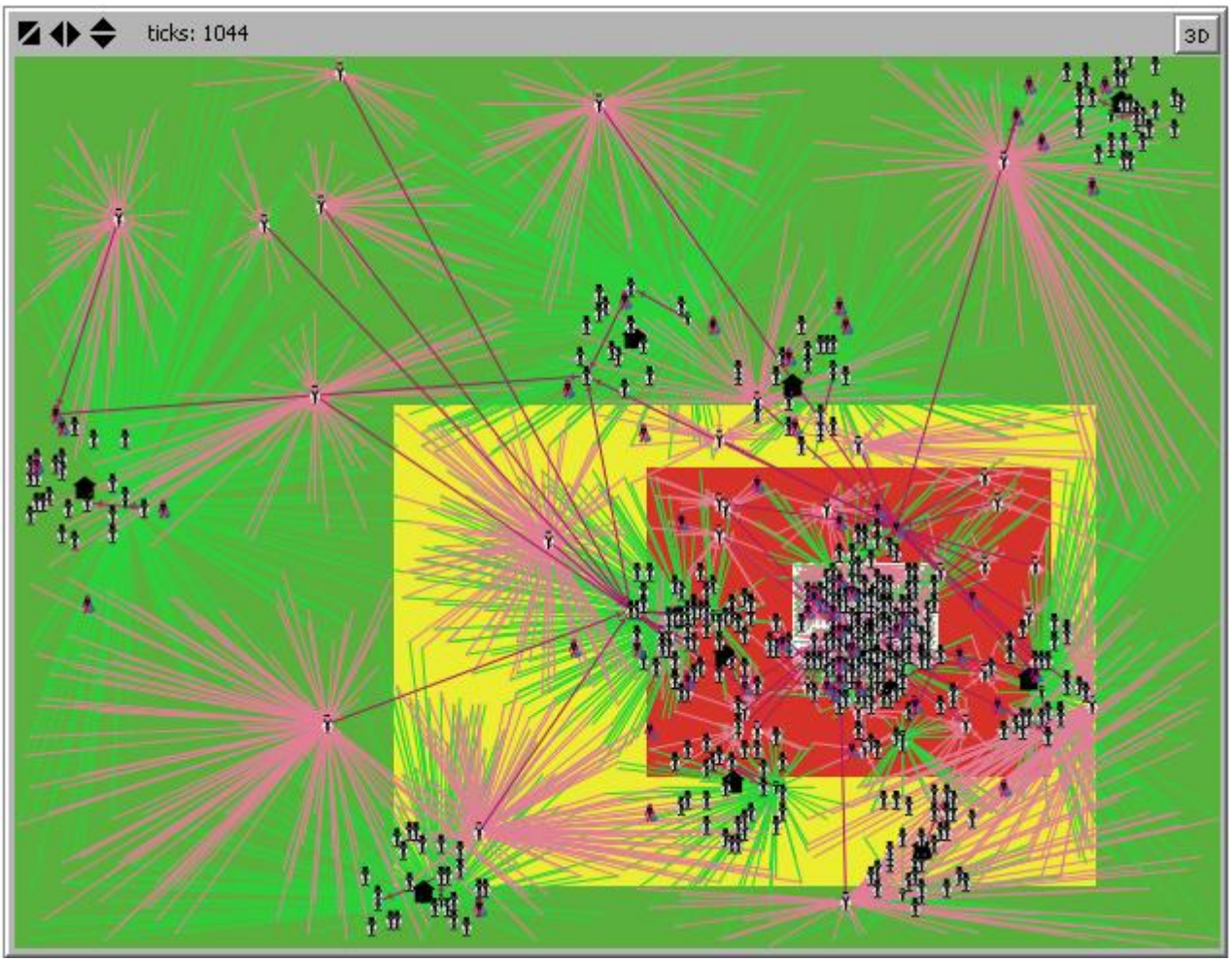
It is interesting to notice that the “quality” of a service has a huge impact on the choices of the family doctors (here, the decision makers of the system). Moreover, this specialist works for the hospital of Rivoli in the first belt, but some links come from other external belts, meaning that the distance of the patients does not always prevail.

Generally, from this first experimental scenario, we can conclude that specialists with lower values of betweenness and weighted centralities belong to hospitals located in external belts. Specialist doctors determine the majority of the laboratory-network nodes, but the three professionals located on the left of the circle structure exhibit high values of network relevance. Hence, hematology divisions in public structures work mainly for their own hospital and do not interact with other structures. This results also from the fact that every hospital in this scenario provides both the services. It seems that public structures work isolated from other agents in a laboratory network point of view. Probably, the emergency department plays a crucial role in "capturing" patients with high emergency diseases (code "300" at the first position of a patient recipe) inside the public structure. Then patients are entirely treated inside the private structure with all the needed specialist visits and medical tests. The hospital of Rivoli is the only exception in that it is also used from patients belonging to other belts, whose family doctors consider the high level of reputation of the blood taking center inside this hospital. In this case, family doctors surely value the distance in the formula, but the weight of the reputation assumes a huge importance in the final decision of family doctors who operate rationally. In other words, distance does not always value much than reputation when there are some services provided with high quality. We can apply the same reasoning to the private structures that work as fundamental nodes in the network of this experiment. The higher degrees of reputation of these structures reduce the "distance" effect in the formula computed by family doctors, prevailing on their decision. Furthermore, we have to take into account that these private clinics operate in the metropolitan area of Turin, the most densely populated. Here, the distances between patients and health and care providers are minimal and, as a consequence, family doctors decisions are driven mainly by the two other variables (quality and waiting times). However, the case of the professional number 2865 explained above shows that also the number of services provided plays a crucial role in the final decision of family doctors. Indeed, looking at the specialties offered by the private structure, we can notice a variety of different types of laboratory analyses (various types of treatments with code "100"). So, economically speaking, it can be also that the supply is a fundamental driver as well as the geographical position.
As we have pointed out at the beginning of this scenario characterization, the assumption of the family doctor as the only decision maker deeply impacts on the overall result of the simulation.

Experiment n° 2

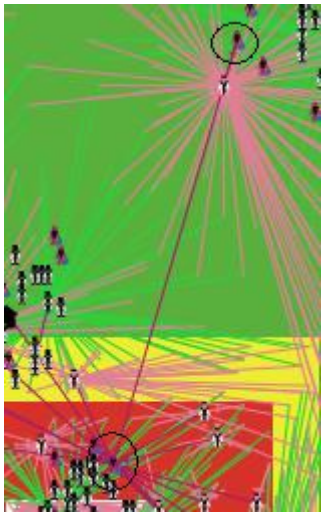
We now want to verify possible changes that may be driven by eliminating the strong assumption regarding family doctors as main decision makers. We repeat the same experiment with the same scenario settings, but with the opposite case in which all patients decide on their own where to be attended. This occurs setting the slider "stubbornness" equal to 1:

We want to focus on the laboratory network, so, in order to better visualize the entire scenario after a full cycle of simulation, we have hidden specialist links (the blue links). The overall representation figures as follows:



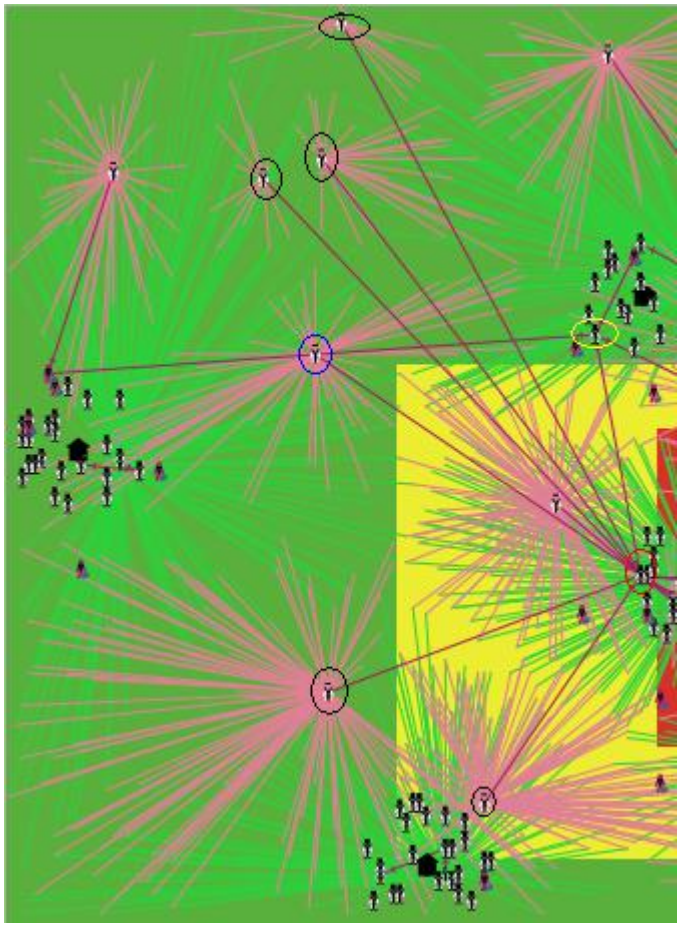
We can immediately observe the importance of the emergency departments that "capture" patients in the public structures (all hospitals have an emergency department in this scenario). The general practitioners, although totally absent in the decision making process, continue to visit patients as first passage in the recipe if the disease is not an emergency and so they "capture" patients too according to their geographical location. However, from this initial view, the blood-laboratories network is not immediately recognizable. There are few magenta links that start from family

doctors (although they have not implemented their formula), and the “distance” as main patient preference seems to have a marginal role.
As an example, we can examine this link connecting two private structures circled in black:



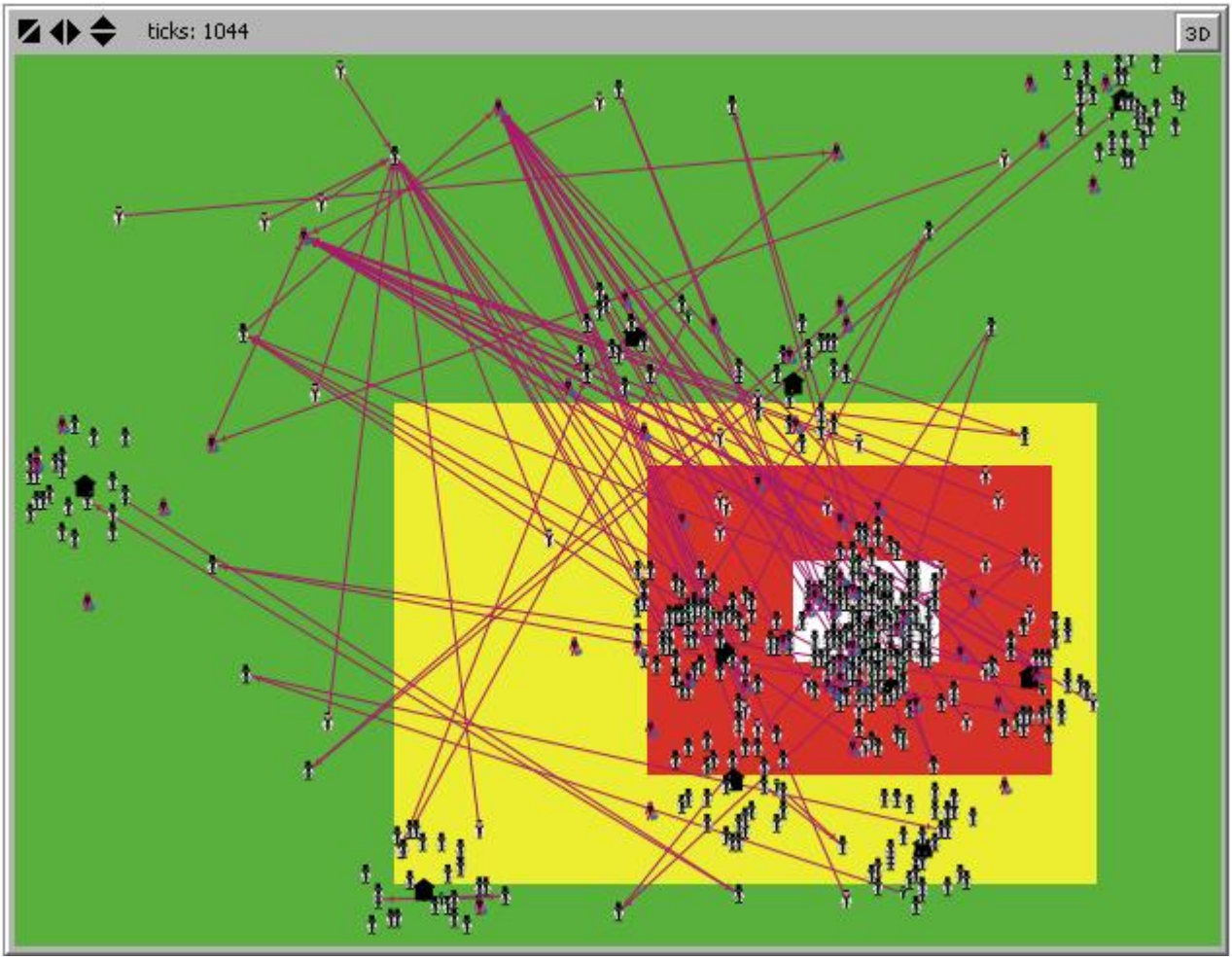
This link connects a private clinic in the area of Ivrea to another private structure in the first belt of Turin, meaning that the distance weight of the patients do not account so much in their final decision. Indeed, this link contains a huge number of passages (490 visits):

Another example that may clarify the randomness characterizing patients decisions, may be referred to the hospital of Rivoli. As in the previous experiment with family doctors as main decision makers, this public structure provides an important center for taking blood samples with an high degree of reputation (quality). We will analyze this structure looking at the network structure, but from the general scenario representation it emerges that it serves patients from every side of the north-western part of the district (Susa and Lanzo above all). The laboratory center in the hospital of Rivoli is circled in red and figures as follows:



The picture is the western portion of the world scenario. One may notice the importance of the laboratory in the hospital of Rivoli simply by observing the provenience of its incoming links: they come from family doctors (circled in black) located far away from the first belt in which the hospital is located. Moreover, the family doctors circled in blue has visited patients who have decided to choose different centers for their blood tests. In particular, someone has decided to go to a private structure located near the hospital of Susa and providing both blood taking tests and analyses of the samples. On the other hand, someone else has decided to opt for the public provision in the hospital of Rivoli. However, the randomness in the decision making process of patients cancels out the effect of the distance in that after the blood taking tests in the hospital of Rivoli, some blood samples are analyzed by the laboratory in Lanzo circled in yellow. So, the random choices of patients determine huge connections on a network level.

Now we want to check the laboratories network structure, using the corresponding interface commands. The result figures as follows:

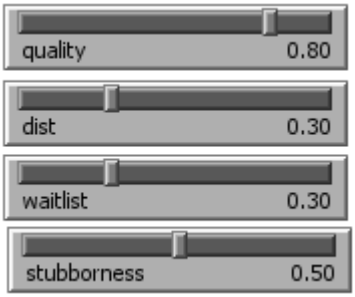


The resulting network seems quite similar to the previous case when family doctors acted as decision makers. There are always three professionals with higher betweenness and weighted centralities values. However, there is an additional professional entering in the network structure (the first professional clockwise). Due to the randomness of patients decisions, we have that some links connect structures very distant to each other as we have already pointed out.
The overall implications for the network structure regard mainly the connections among different and distant health and care providers. A meaningful phenomenon that occurs in this experiment as well as in the first one deals with the "incorporation" of the greatest quantity of blood tests by the private structure located in the city center of Turin (professional 2865). So, as a result, the structures with the lowest number of blood tests and analyzes are the ones located on the right-hand side of the circle, which represent mainly laboratories of the public hospitals in the area (CTO, Regina Margherita, Mauriziano, Molinette). Hence, the biggest hospitals in the city of Turin, according to the modeled scenario, are underused with respect to their capacity of taking the blood samples and analyzing them (remember that in this scenario every hospital provides both the two services). Nevertheless, comparing the two experiments, we find that in the second one the evidence of the phenomenon is much consistent. The complete "stubbornness" of the patients has a huge impact on the overall network structure while the rationality of the family doctors, on the other hand, takes into account the three patients preferences giving more importance to the hospitals of the city

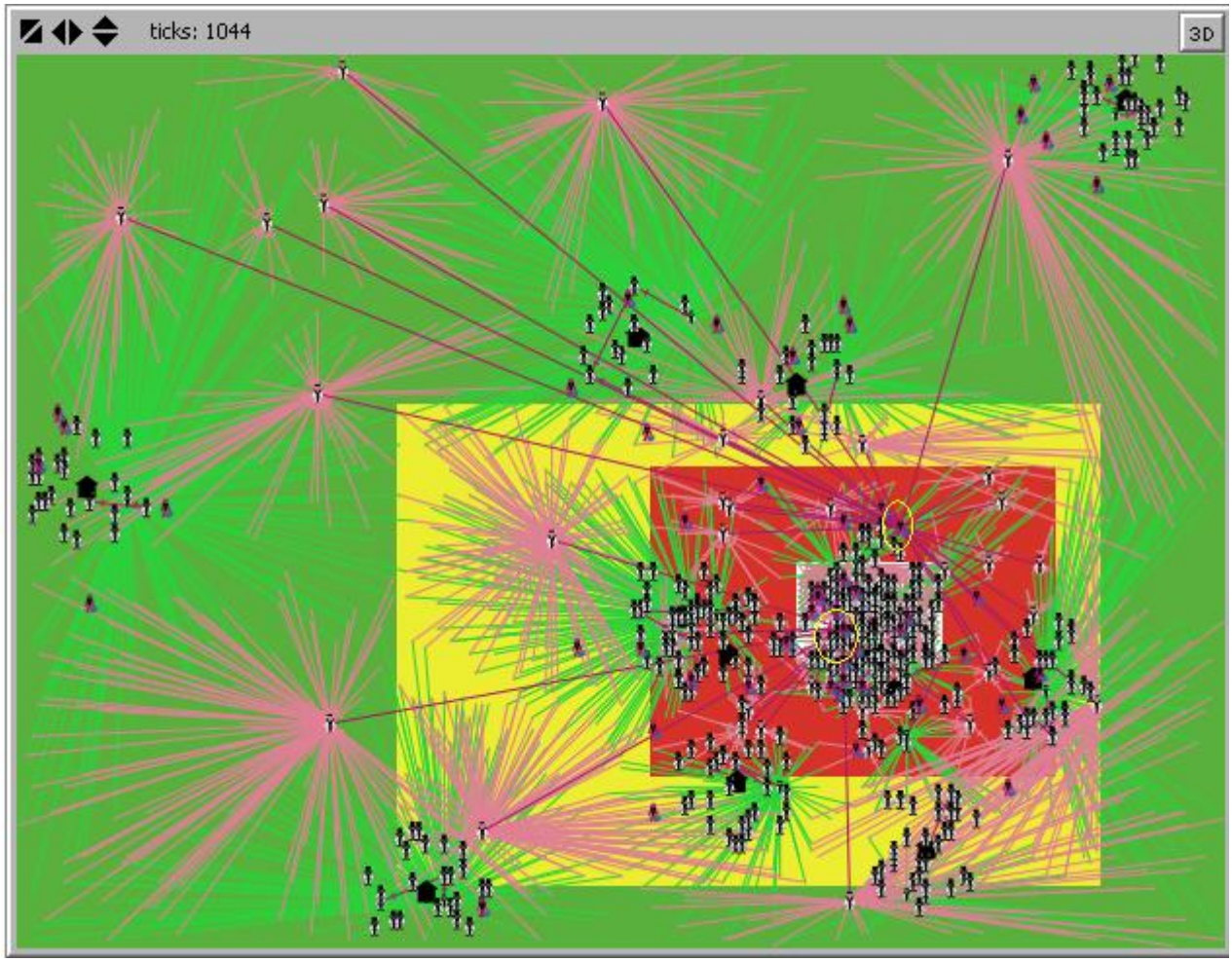
center. In the first experiment, in fact, we have observed that hospitals in the city center of Turin are not so underused from a blood tests point of view. Many other public structures are underused in the first experiment such as laboratories in the hospitals of Ivrea and Carmagnola. However, the overall results of the two experiments give the same intuition: the hospitals of Turin are quite underused as blood taking centers and laboratories of analyzes while a huge part of the demand is satisfied by private structures despite the lower weights associated to the variables “quality” and “waiting list”.

Experiment n° 3

So far, we have changed only one variable regarding patients behavior: the “stubbornness”. It can be useful to consider the other three variables (distance, waiting lists and quality) no more fixed, introducing changes in the behavioral rules adopted by family doctors in their decision formula.



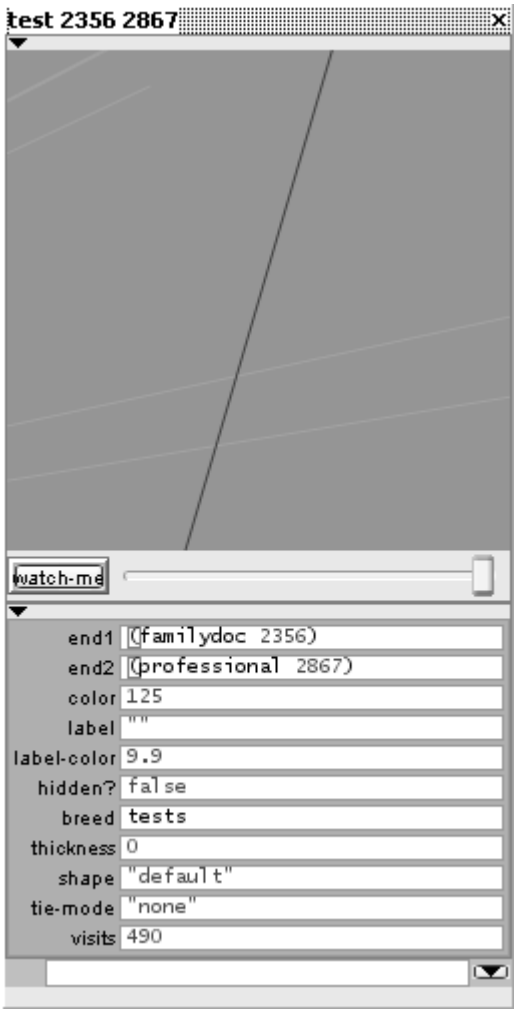
The figure above presents the first set of settings regarding patients preferences. All the other settings are equal to the first experiment, preserving also the same random seed.
So, as a first step, we can assume that distances are no longer relevant in choosing the health and care providers. On the other hand, we put some emphasis on the role of the quality of the medical services. Clearly, we expect that the attribute “reputation” of the doctors will play a crucial role in the final network structure composition. It has to be highlighted that the attribute “reputation” assumes random values and so, changing the random seed, one may identify different structures with high quality services. However, we are taking the first experiment as a benchmark scenario. The variable related to the waiting lists assumes a lower weight in this first step of the experiment. With respect to the decision making subjects of the simulated experiment, we will have half of the patients choosing randomly while the other half following the family doctor instructions.
The scenario representation that comes from these new specifications is shown in the next page. The lower importance of the distances between the patients and the health and care providers is immediately verifiable by looking at the magenta links coming from the third green belt and ending in structures located in the city center. The central structures of convergence are circled in yellow.



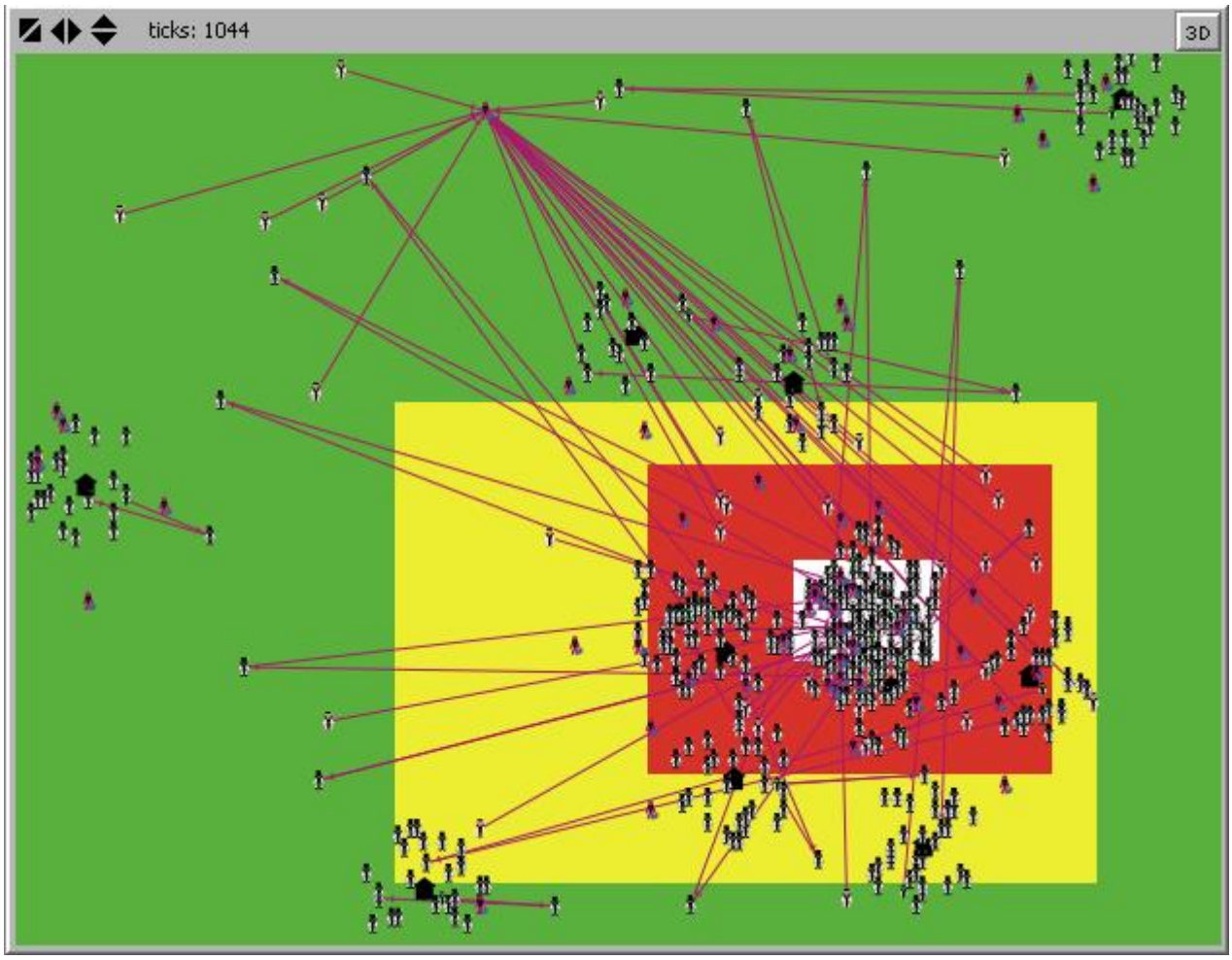
We can infer that this network presents a more compact structure in that there are few links characterized by many passages.

The link presented in the picture above, for example, captures all the patients coming from the area corresponding to their family doctors. Analyzing the entire scenario representation, we can identify one link colored in magenta for each family doctor . This means that the “quality” variable has a huge impact on the overall results in terms of network, identifying few pivot structures.

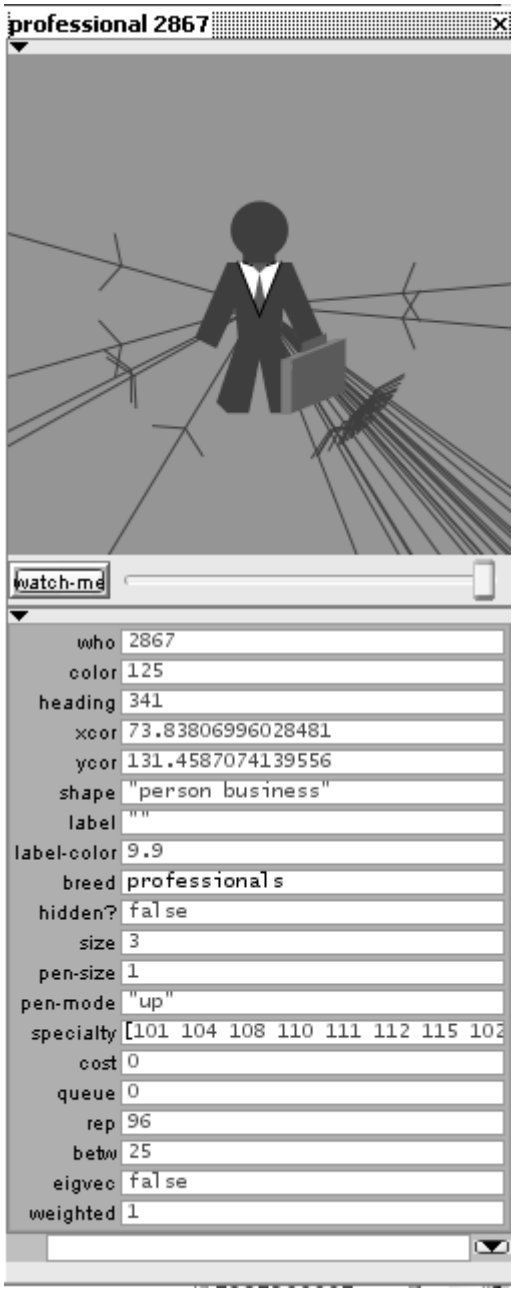
In particular, the link shown above presents these features:



The number of visits represented by this link is extremely significant. The family doctor from which this link starts is located near the municipality of Ivrea and the majority of its patients are sent to the same private structure (professional 2867) for taking blood samples and analyzes. Inspecting these magenta links, we find that the number of visits can be expressed as an interval between 50 and 650. So, we can theorize, under this scenario settings and random criteria, that some kind of centralization of the blood circuit occurs. The resulting blood laboratory network seems to be mainly centered around few nodes.
In the next page we present the overall network structure that reveals network measures and provides more insights.



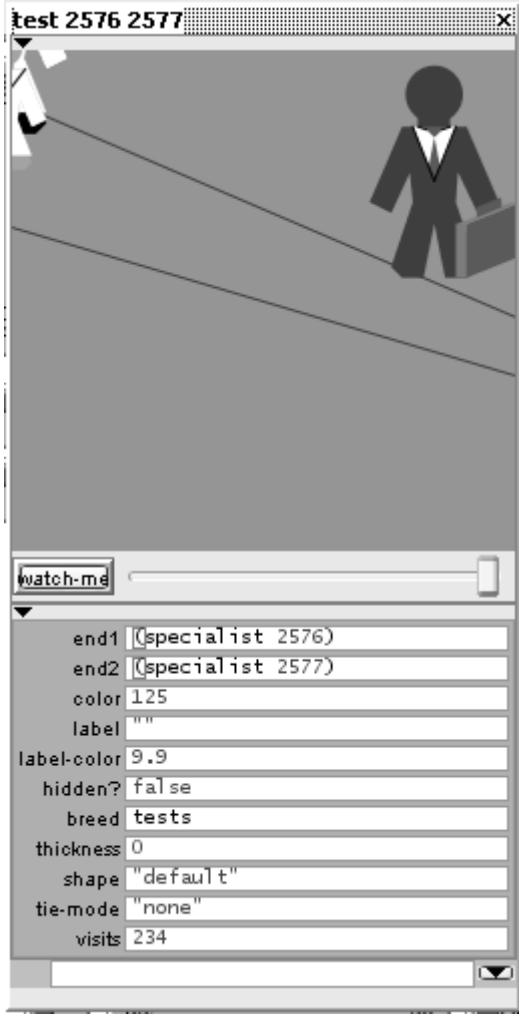
The network structure emphasizes some aspects of the experiment. First of all, the main node of the network is the professional previously indicated (professional 2867). Note that, in this experiment, the professional is not the same as the two experiments explained before because the importance of the “quality” variable is emphasized in the decision making processes. The inspection window related to this agent is shown in the next page and describes it as a private clinics centered on laboratory exams and analysis It provides both the blood analyses (code 102) and a center taking blood samples (code 101). The level of “reputation” randomly generated is extremely high in this case and so it drives family doctor decision formula.



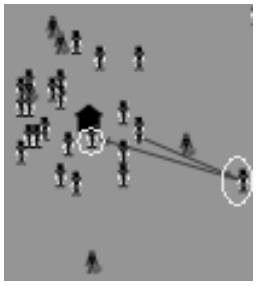
An interesting characteristic of the agent is its, apparently low, betweenness value. A possible reason may regard the services offered by the agent. It provides both the services associated with both the blood “taking” and “analyzing” activities. So, patients may undertake these activities in this structure without passing through other hospitals or doctors, especially those young patients characterized by high probabilities of taking medical exams and low probabilities of incurring in pathologies requiring specialist visits or emergencies. In this case, the private structure (professional 2867) is directly used by patients without connecting several doctors.

On the other hand, there may be patients who demand only one services of the two related to blood, and that come from hospitals. Indeed, examining incoming links, we find many connections with specialists affiliated to some hospitals mainly associated to the first belt (the one in which the professional is located).

Furthermore, the other agents displayed in circle and forming the network structure are all hospital centers that take blood samples and present a low betweenness centrality value. Analyzing their links, we can see how they work with the corresponding analysis laboratory of the same hospital structure.

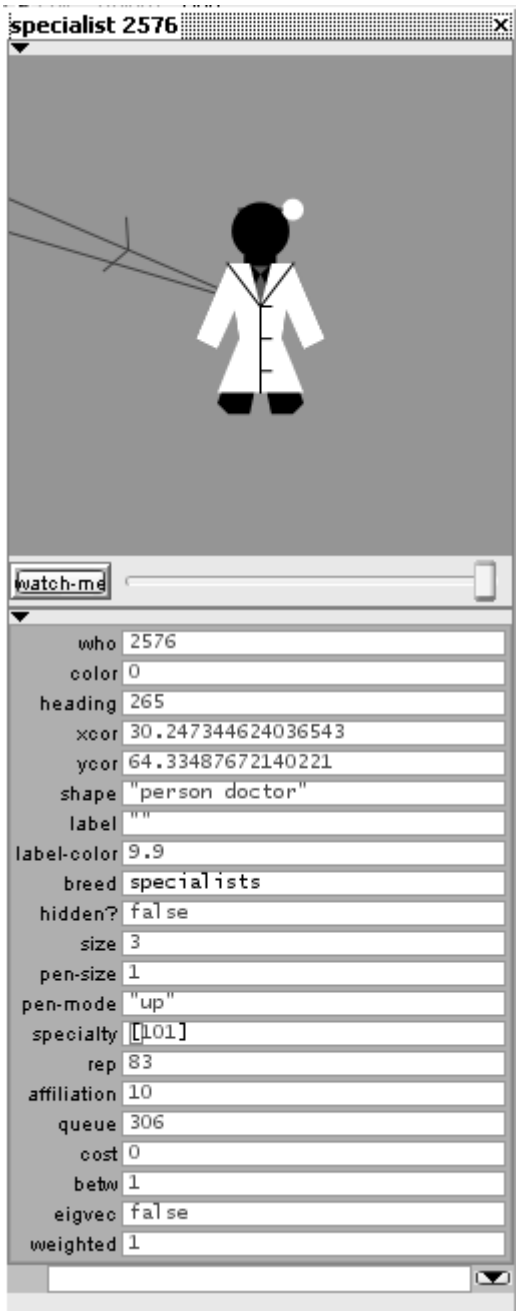


The link inspected above refers to the connection between the blood taking medical division and the analysis laboratory in the hospital of Susa.

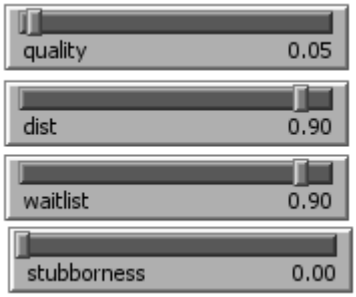


This is a clear example of how hospitals tend to work on their own creating isolated networks. The number of visits presented in the above link reveals public hospitals are used by significant amounts of patients, but they tend not to cooperate with other structures. We have to point out that the reputation level these blood taking centers exhibit is significantly high, and so, they may be chosen

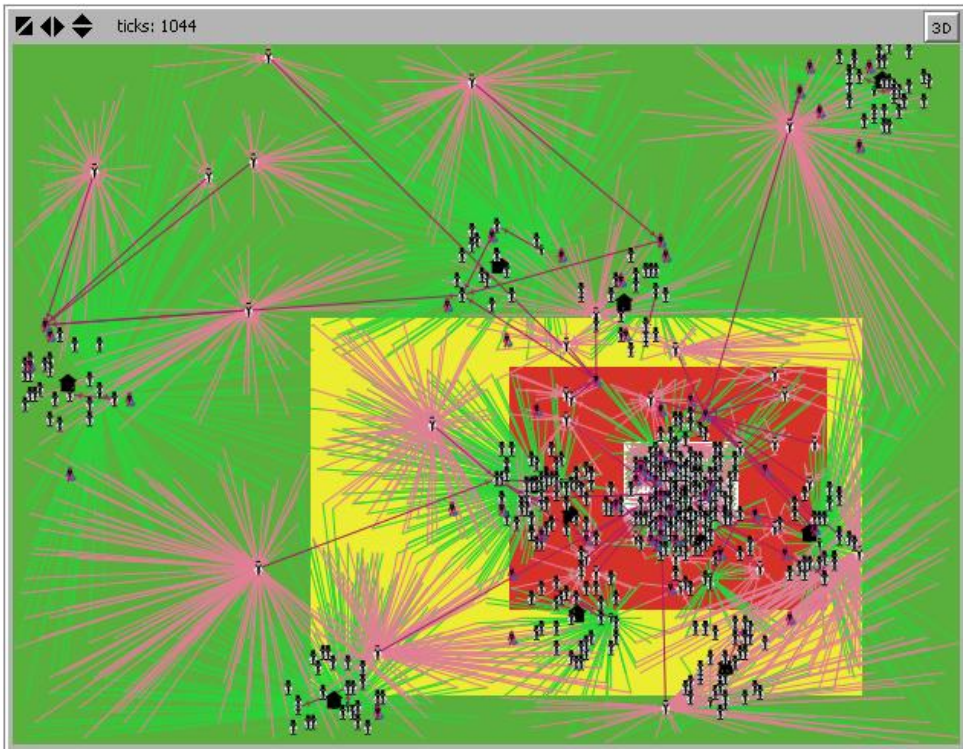
by family doctors as well, depending on the computation of the decision formula that family doctors undertake. Moreover, some patients may decide on their own, choosing to be treated in a single structure instead of going where the services present high quality. The blood taking center of the hospital of Susa, reported in the figure above, shows a high level of quality of the service provided:



With respect to the waiting lists that patients have to face with when they opt for the public provision of health and care services, we have assumed that professionals (private clinics) present null waiting times while specialists in public hospitals show positive queues assuming random values. Hence, imaging a scenario where the "waiting list" variable has huge impact on the family doctor decisions means endorsing private structures. Nevertheless, we may experiment a situation in which patients value both distance and waiting lists more than the quality of the health and care services provided. Indeed, in the real world, the two variables (distance and waiting lists) assume a crucial role in patients decisions when they have to deal with blood taking tests and other medical exams. We have to take into account that the program will generate some patients, belonging to certain age categories, with extremely high probabilities of having recipes characterized only by medical examinations. So, as it occurs in reality, a patient that does not present any pathology but has to undertake some check up visits (for example visits for agonistic sport disciplines, routine check ups for aged patients or other routine check ups) will usually value distance and waiting times much more than the quality of the service. We can impose this patients preferences set:

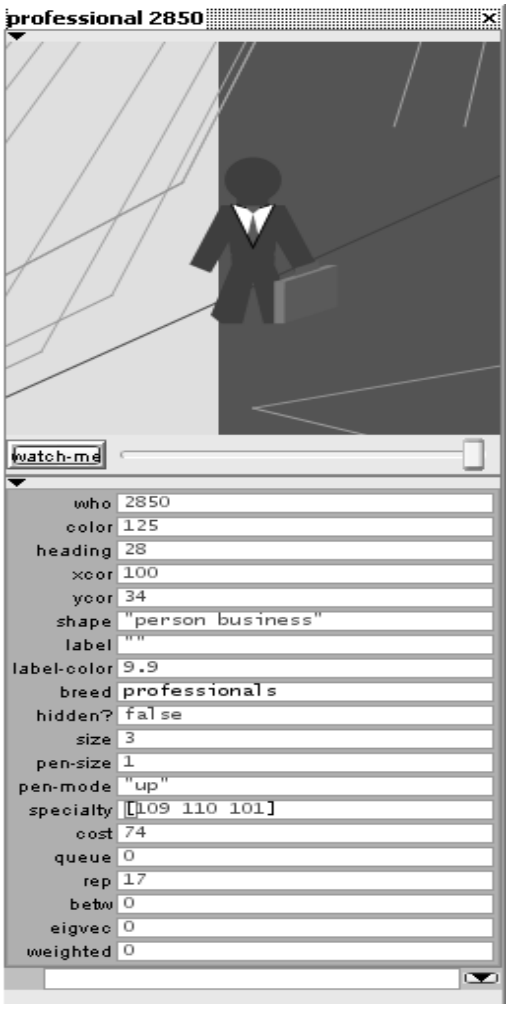


Since we want to emphasize the patients preferences changes, we have chosen to delegate all the decision making process to family doctors. Other settings remain unchanged as in the previous experiments.
With the patient preferences identified as in the figure above, we expect that laboratories and structures with high level of quality of the services provided will not prevail on others.
The overall representation in the world scenario is the following:

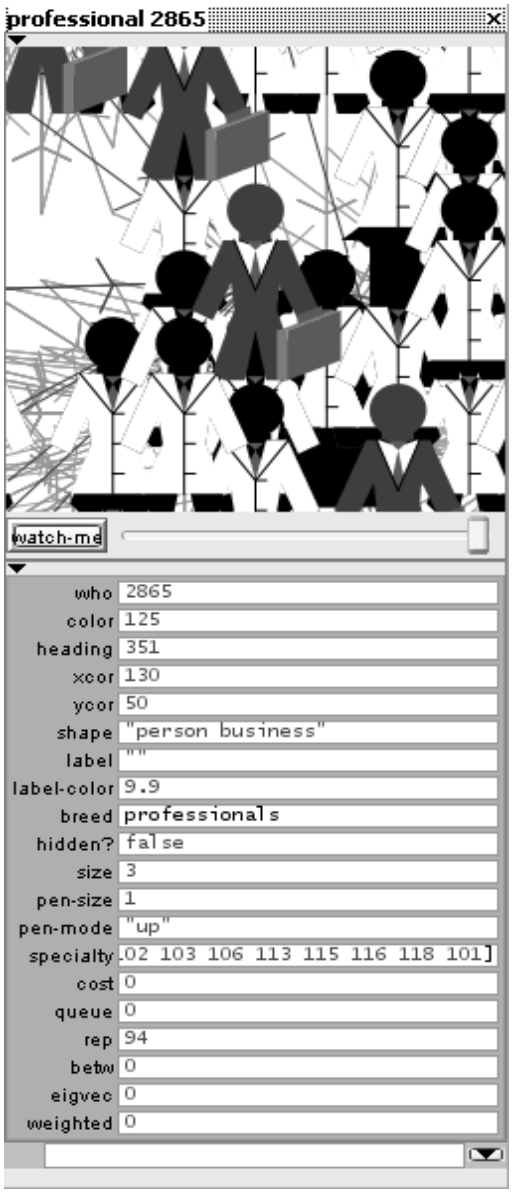


A quick view on the agents involved in the “blood circuit” reveals that, as we expected, private clinics prevails on public hospitals because of their null waiting lists. However, there is a particular case that merits consideration.

We want to focus the attention on the link coming from the family doctor circled in blue and the professional (private structure circled in yellow) located in the city center and that has already been analyzed for its relevance in previous experiments. It is curious to notice that the professional, circled in blue, located in the middle of the two agents is totally ignored from patients that live in the second belt (the yellow one) and are visited by the family doctor circled in blue. Indeed, we have assumed high probability for the preference regarding the distance of patients to the structures as well as the waiting times they have to face with. Nevertheless, the professional circled in blue in the middle is totally ignored by patients despite its proximity in terms of patches.
This professional has the following characteristics:

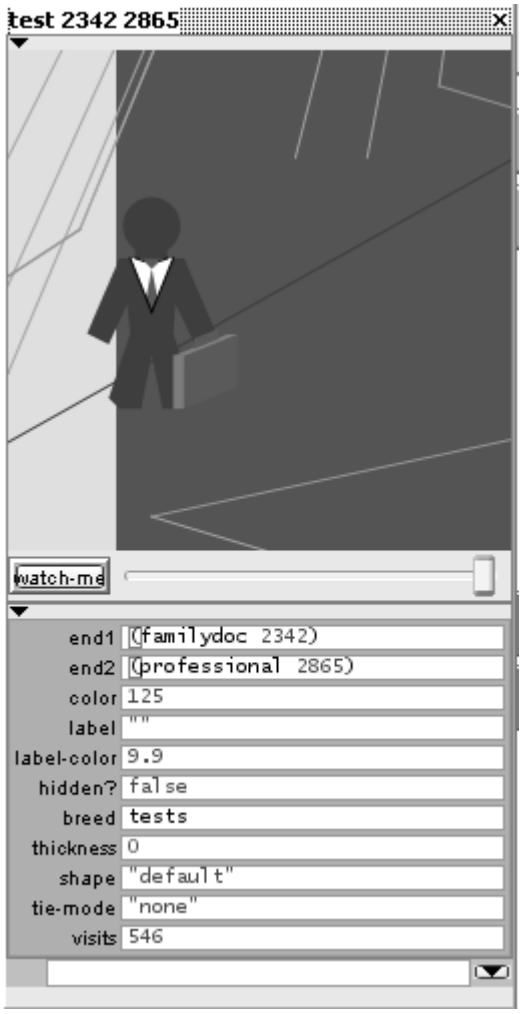


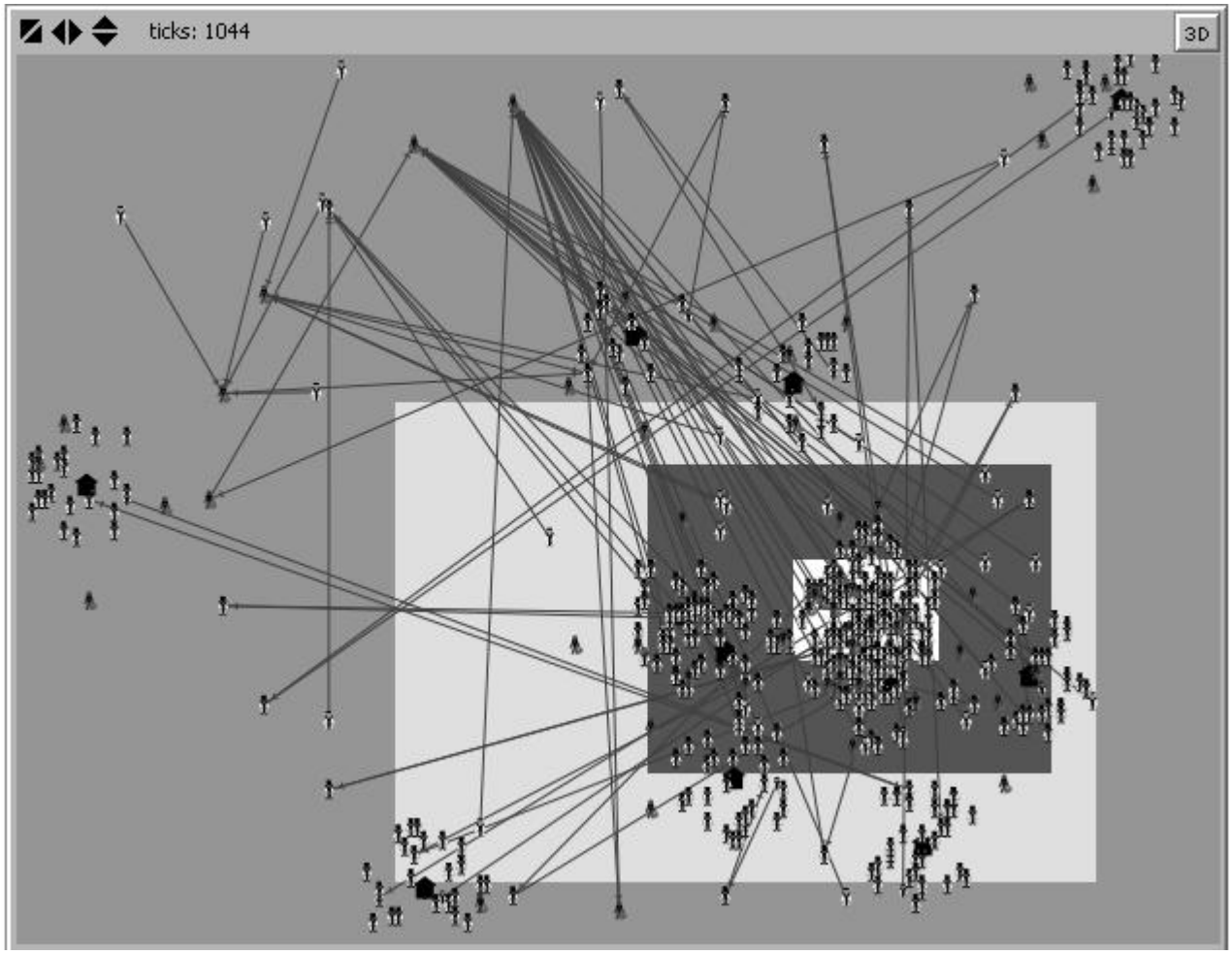
As one may notice, this structure offers a “blood taking” service and shows no queues since it is private. Looking at its distance in terms of patients to the family doctor circled in blue it seems that the proximity is no longer evaluated by the family doctor in its decision making process. The professional n°2850 is closer to the patients than the professional n°2865. It presents no queues and takes blood sample as well. Anyway, it is completely ignored.
The professional n° 2865 shows the following features:



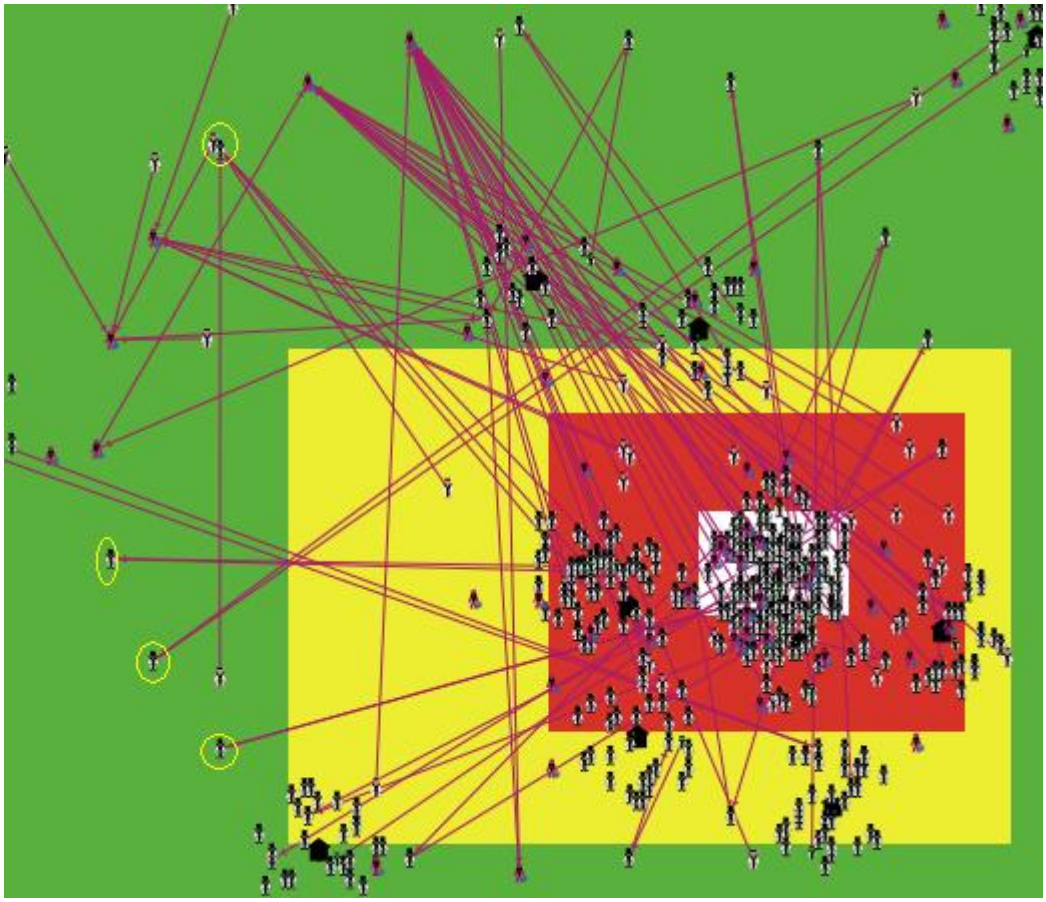
It provides both the “blood taking” center and the blood analysis laboratory (codes “101” and “102” respectively).
It seems quite strange that the professional n° 2850 is completely ignored, but this example may suggest two possible answers to the question. First of all, it can be a matter of quality of the services. Although we have assigned a low probability to such type of preference, family doctor formula is deeply affected by quality weights when they are significantly high (as in the case explained so far where the professional n° 2865 has a reputation of 94 against the value of “17” of the professional n° 2850). Secondly, the contemporaneous supply of the two services related to the “blood tests” by a single structure. Indeed, the fact of providing both the two functions in the same

structure may be reasonable, considering the real world: it can be more efficient to provide jointly these services instead of interacting with some other structures.
Looking at the way we have modeled the decision formula evaluated by family doctors, it seems reasonable to accept the first answer, although the second one may be considered valid too. The fact that the decision making process is governed by a computation of a precise value, it is obvious that low percentages for huge quantities determine significant results in the formula, driving the final decision towards a precise direction.
To conclude with the example examined so far, we can highlight that the professional located in the city center of Turin captures the entire area managed by the family doctor circled in blue. This is emphasizes by the unidirectional link connecting the two agents which shows an extremely high number of visits:





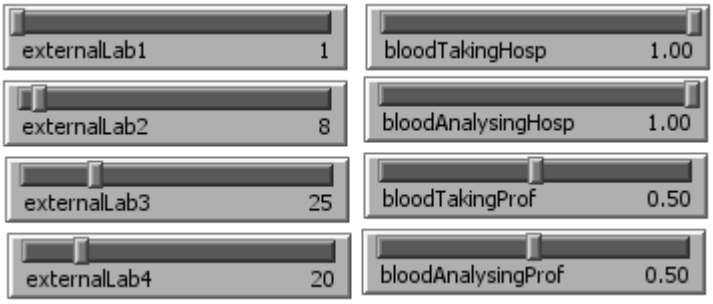
To conclude with this experiment, we present the network structure derived from the simulation. In this case one may notice that private structures determine the fundamental nodes of the network in that they exhibit no waiting lists (they almost cover the left side of the network circle which is characterized by nodes with higher betweenness values). The private clinics located in the city center of Turin capture the majority of patients living in the near boundary of Turin and other patients located in the third belt. In other words, also in this case the two main structures, in terms of network measures, in the “blood test” network are private. However, it has to be noted that certain hospitals have a principal function yet.



The specialists circled in yellow represent significant values in terms of betweenness measures and belongs to various geographical areas (Rivoli, Ivrea and some hospitals in the city centers as the Molinette). Also the other specialists in the network structure exhibit links that present large number of passages, but they have little or none importance in terms of betweenness because they work isolated in the affiliated hospitals rather than cooperating with other structures.

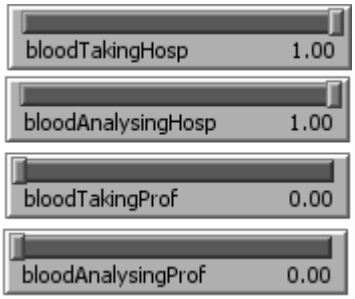
Experiment n° 4

Since we have added sliders concerning the probabilities of having “blood taking” centers and “ blood analysis” laboratories in both the hospitals and the private structures, it is useful to consider different scenarios that these controls may generate. Furthermore, one may vary the amount of external structures for each belt since, looking at the previous experiments, there are few private clinics that have huge impacts on the network structure. In other words, this set of experiments focuses on the supply side of the two types of services connected with “the blood circuit” of the district. In doing so, two sets of sliders will be taken into account: the probability set regarding the provision of the two types of services and the set of slider managing the total amount of private structures for each belt. In particular, for all the previously described experiments, we have adopted the following probabilities set and the following private structures distribution in the district territory:

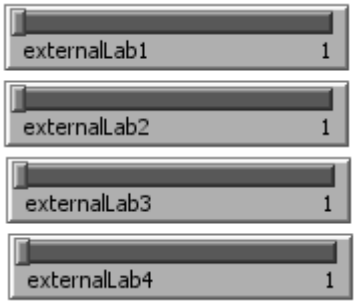


The world scenario generated so far has been characterized by few private centers in the city center of Turin, and a relatively stronger presence of these agents in the external areas of the world, meaning that the private structures tend to appear in those area with less hospitals. However, as we have noticed, the empirical evidence of the previous experiments has pointed out a concentration in few structures. This phenomenon may be associated to the set of sliders which assigns probabilities of providing codes “101” and “102” types of services in the private clinics. Indeed, looking at the sliders above, we have modeled a world where only half of the professionals provide “blood tests” centers and “blood analysis” laboratories. On the other hand, as in the real healthcare system under investigation, all the public hospitals provide internally these two services. Surely, also the amount of private structures spread all over the territory may impact the resulting network associated to the “blood circuit”. Hence, modifying these sets of sliders regarding the supply of the two services may reveal some interesting phenomena.

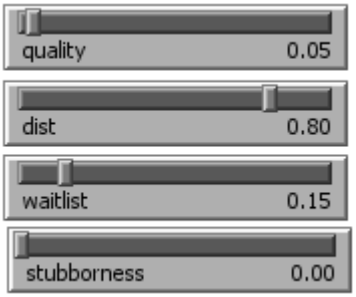
We start from a world characterization in which only hospitals take blood samples and analyze them internally. We want to evaluate a situation in which private structures do not enter in the blood circuit.



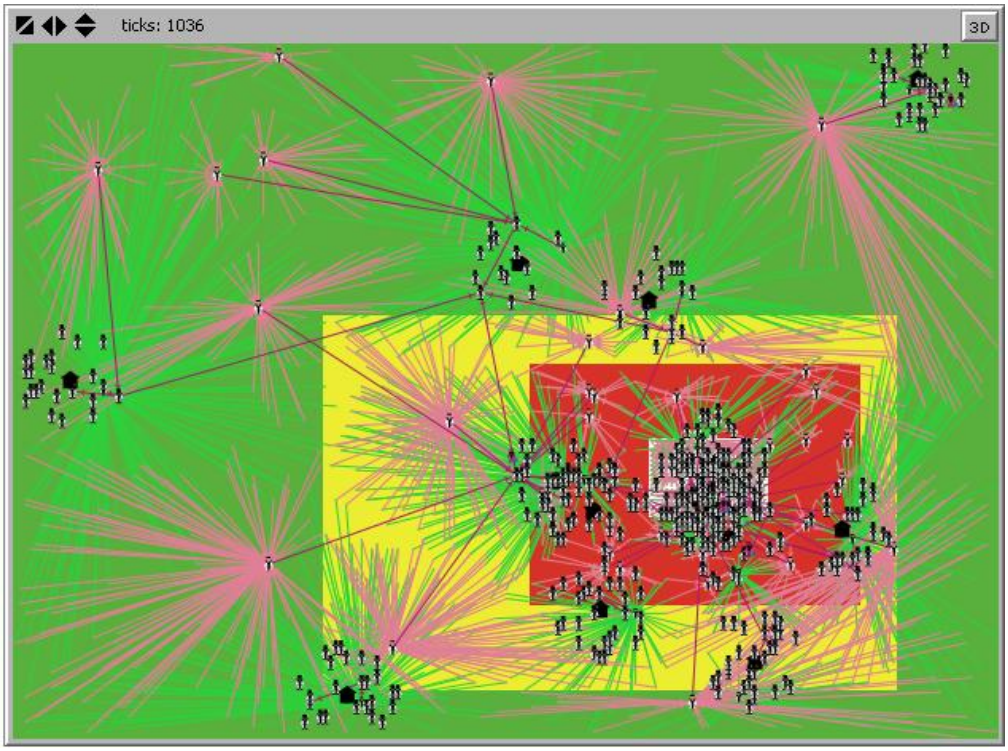
We have to highlight the fact that the procedure associated to the creation of professionals assigns them at least one treatment although the sliders above are set equal to zero. Then, since the amount of private structures cannot be zero, we may have a private structure providing one of the two types of treatments under analysis. Anyway, we have imposed the minimum amount of private structures for each belt:



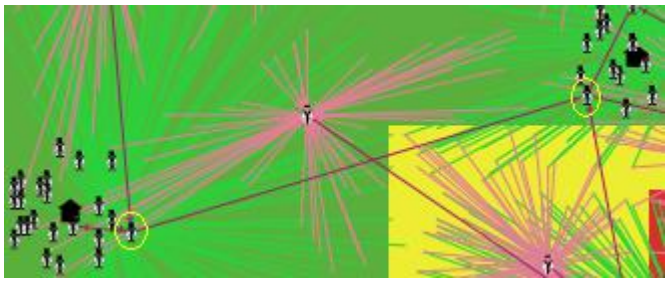
In order to take away from the "blood circuit" the effect of some private structures we have assigned low weights to patients preferences concerning quality of the services and waiting times.



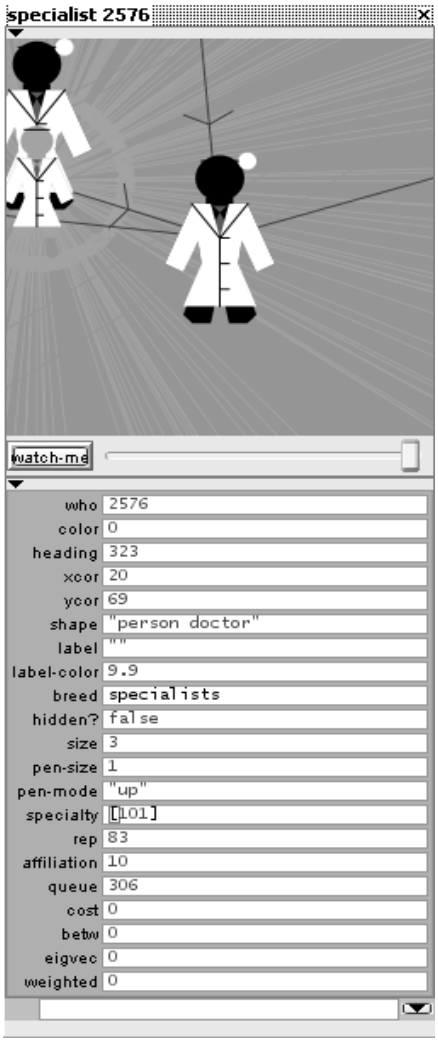
Cutting the private supply means analyzing the public provision scheme of public hospitals with respect to the "blood circuit".The world scenario figures as follows after the entire cycle of simulation:

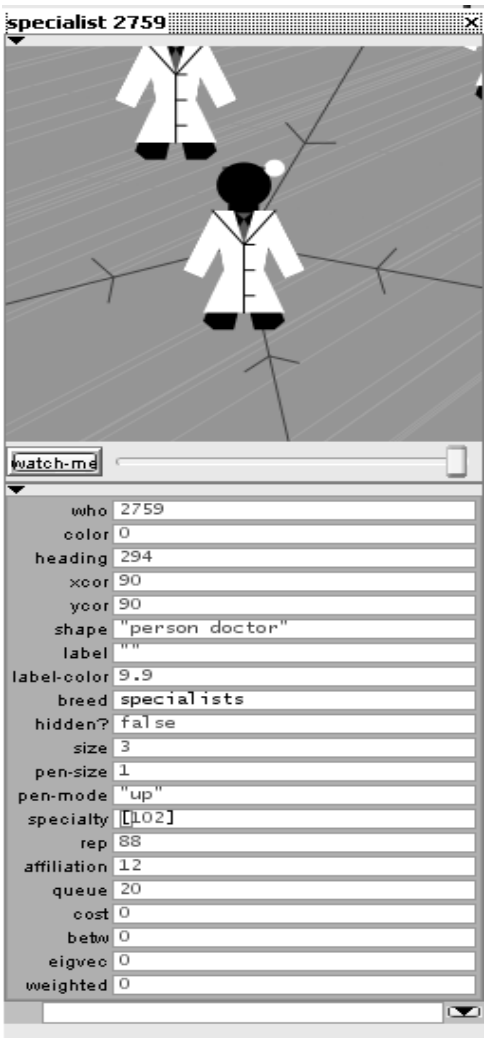


The private structures (professionals agents) seem to be totally absent in the world scenario, so the supply comes from the public structures. We have a representation closer to the real healthcare system with respect to the “blood tests” point of view, in which patients select the nearest structures (hospitals) and each of them tends to provide services internally. However, the figure suggests that the more we approach to the city center, the more we note concentrations around few significant “blood tests” centers. Indeed, the distance for patients inhabiting the area close to Turin and the city center has little importance in that the public supply is relevant in these densely populated areas. Patients in the city centers are focused on quality and waiting times more than patients living in rural areas. Then, we may identify few crucial “blood test points” that we will analyze looking at the network structure. However, it can be identified some example of cooperation between public hospitals. The example reported below represents a collaboration between the hospital of Susa and the one located in Lanzo.

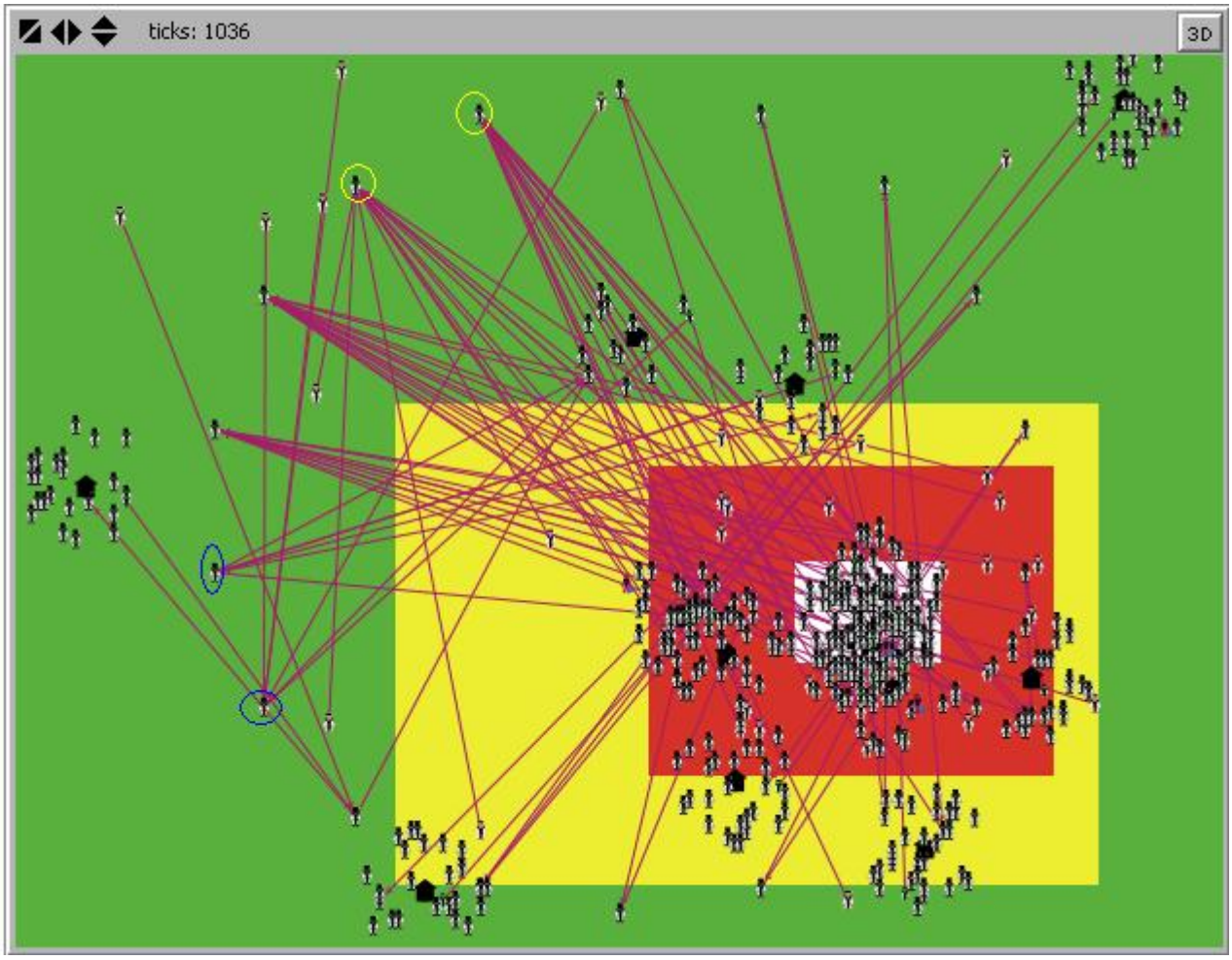


The two specialists circled in yellow figure as follows:





The simulation has generated a connection between the hospital of Susa, providing a “blood taking” center, and the hospital of Lanzo, analyzing the blood samples in its laboratory. The two medical divisions circled in yellow shows high “reputation” values and so family doctors, in computing their decision formula, decide to send their patients to these two distant structures. In other words, despite the huge weigh assigned to the distance patient preference, the preference with respect to the quality of a service has some significant effect in the final network. It seems that, in every experiment, the variable “quality” represents a fundamental driver of the system under analysis. This may be associated to our formula computed by family doctors. Surely, such rule represents a strong assumption that has to be implemented and improved by means of detailed data and model characterization of the system under analysis.
The network structure figures as follows:



As we expected before, there are only public specialists involved in the “blood circuit”. In particular, the left-hand side of the circle (representing those nodes with high betweenness centrality values) presents specialists belonging mainly to hospitals located in the city center or in the first red belt. This proves some kind of centralization towards big hospitals with high reputation located in the city center. The main nodes, circled in yellow, in terms of betweenness centrality (the ones which connect more agents) are the “blood tests” centers located in the Mauriziano and Rivoli hospitals. However, there are also two “blood tests” centers circled in blue belonging to the hospitals of San Carlo Canavese and Lanzo. However, the hospitals in the city center as the Molinette and the Mauriziano have strong impacts on the network structure. The variable “reputation” identifying the quality of the services works as major driver for the family doctor

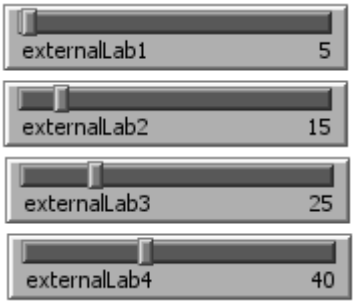
decisions. Indeed, all the nodes located on the left-hand side of the network structure exhibit high qualities of their services. The examples below refer to the “blood tests” centers of the Mauriziano, the hospital of Rivoli and the one in San Carlo Canavese:

who	2452
color	0
heading	340
xcor	72.7686906838315
ycor	131.08002035108402
shape	"person doctor"
label	""
label-color	9.9
breed	specialists
hidden?	false
size	3
pen-size	1
pen-mode	"up"
specialty	[101]
rep	86
affiliation	1
queue	9
cost	0
betw	55
eigvec	false
weighted	1

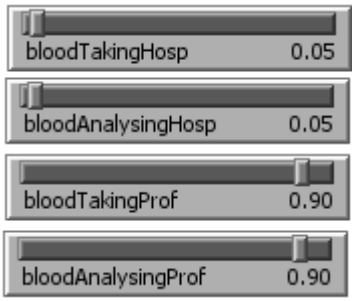
who	2729
color	0
heading	320
xcor	53.21880537037493
ycor	119.79288880273356
shape	"person doctor"
label	""
label-color	9.9
breed	specialists
hidden?	false
size	3
pen-size	1
pen-mode	"up"
specialty	[101]
rep	88
affiliation	9
queue	29
cost	0
betw	33
eigvec	false
weighted	1

who	2751
color	0
heading	240
xcor	38.708348754011496
ycor	37.49999999999997
shape	"person doctor"
label	""
label-color	9.9
breed	specialists
hidden?	false
size	3
pen-size	1
pen-mode	"up"
specialty	[101]
rep	14
affiliation	12
queue	122
cost	0
betw	5
eigvec	false
weighted	1

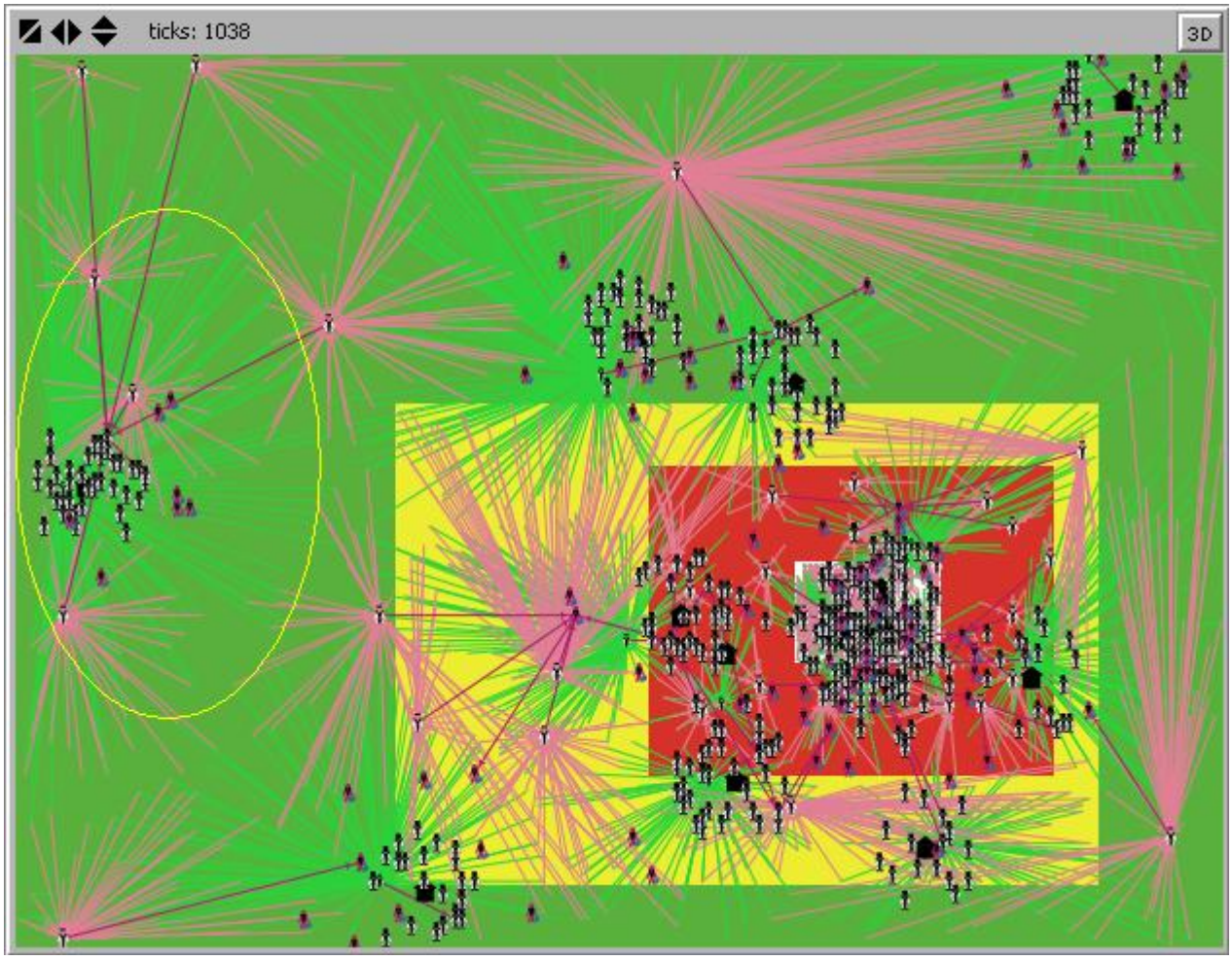
We can also investigate the opposite case in which mainly private structures tend to provide “blood taking” tests and blood analyses. In other words, we may simulate a world scenario in which the supply of services connected with the “blood circuit” is mainly private. In doing so, we have to imagine a stronger presence of professionals spread on the district territory:



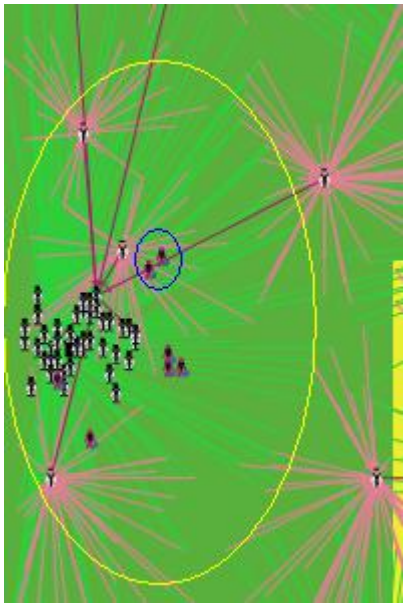
The amount of private structures increases moving away from the city of Turin (having many private structures in the city center is irrelevant since the territory is smaller with respect to the rest of the territory). In addition to this, we have to establish the probabilities connected with the provision of the services under analysis (codes “101” and “102”).



We expect the opposite situation referring to the previous simulation: the “blood circuit” entirely managed by private structures. The increased private supply may generate large cooperation between laboratories and “blood taking” centers.
Looking at the scenario at the end of the simulation, it is immediately evident to the observer the interesting isolation of the links identifying blood tests (colored in magenta). This result significantly differs from the other experiments investigated so far. The empirical evidence mines completely our expectations: the emergent scenario seems to be characterized by isolated networks identified around the public hospitals. The interaction among health and care providers is limited to each hospital neighborhood and, more surprisingly, the increased amount of private structures seem to be totally irrelevant in that the links converge mainly to one professional for each neighborhood.
Another feature, that is worth looking into, addresses the presence of some specialists in the isolated networks. Each “isle” seems to be characterized by recurring cooperation schemes: one or few professionals connected with some specialist.



The localization of the family doctors is an essential element driving the patients towards the various “isles”. It is interesting to notice that the healthcare “isle” of Susa (circled in yellow in the figure above) is characterized only by specialists, despite the huge number of professionals in the area.



The example of the “isle” of Susa merits attention in that not only there are no professionals involved in the network, but the professionals circled in blue both provide services of codes “101” or “102” and exhibit significantly high values of reputation (quality of the services). It is quite far from being obvious thinking about this phenomenon. Comparing the features of the professionals and the main specialist of the network we confirm the empirical evidence:

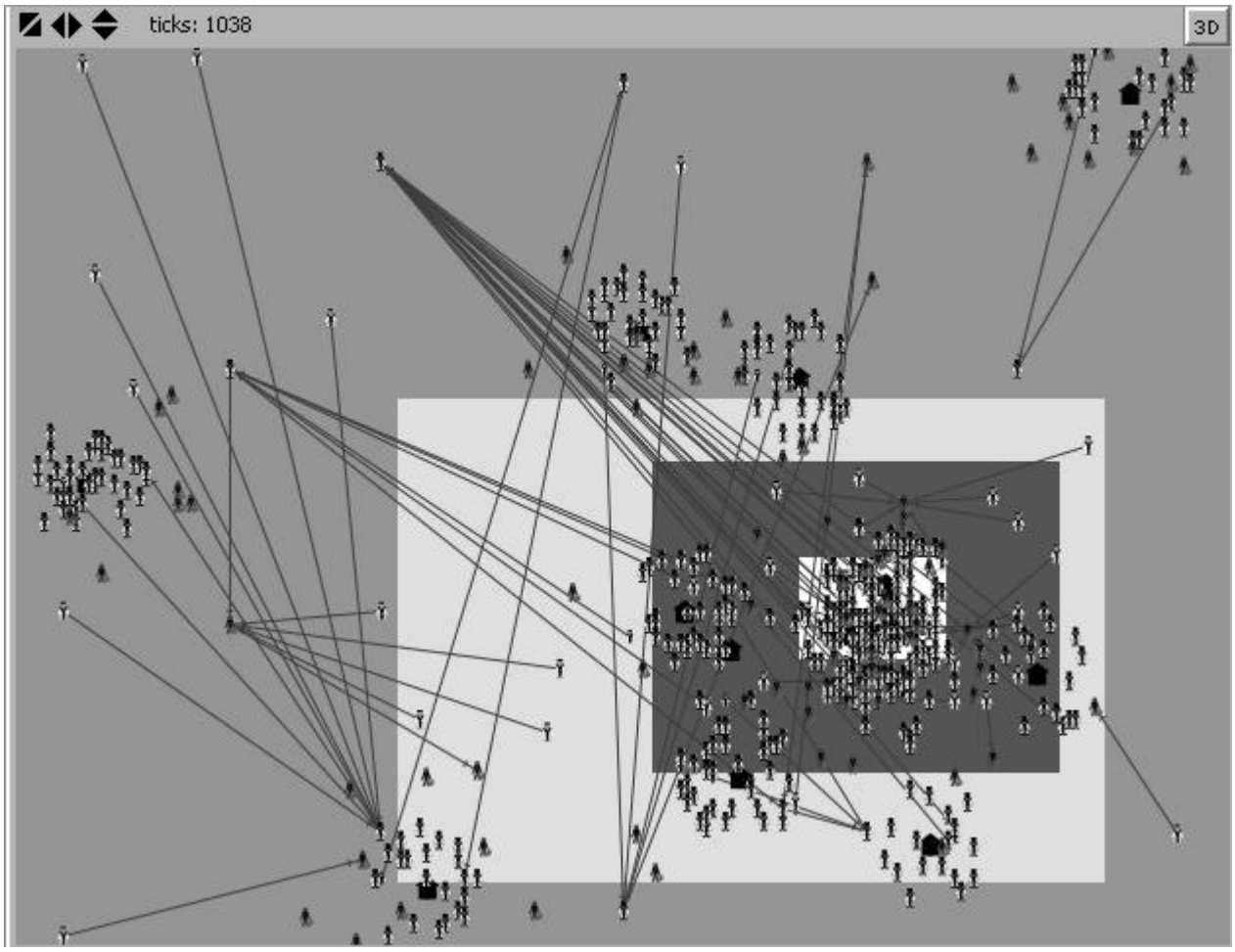
who	2707
color	0
heading	323
xcor	14
ycor	80
shape	"person doctor"
label	""
label-color	9.9
breed	specialists
hidden?	false
size	3
pen-size	1
pen-mode	"up"
specialty	[101]
rep	55
affiliation	10
queue	150
cost	0
betw	0
eigvec	0
weighted	0

who	2866
color	125
heading	206
xcor	22
ycor	84
shape	"person business"
label	""
label-color	9.9
breed	professionals
hidden?	false
size	3
pen-size	1
pen-mode	"up"
specialty	[101 102 105 113 116]
cost	28
queue	0
rep	43
betw	0
eigvec	0
weighted	0

who	2897
color	125
heading	259
xcor	24
ycor	86
shape	"person business"
label	""
label-color	9.9
breed	professionals
hidden?	false
size	3
pen-size	1
pen-mode	"up"
specialty	[303 311 314 318 101 102]
cost	97
queue	0
rep	90
betw	0
eigvec	0
weighted	0

If the professional n° 2866 does not exhibit the same quality level of the services as the specialist, the professional n°2897 presents an extremely high level of quality assigned to its services. Moreover, both the private clinics provide a blood taking center and a blood analyses laboratory. Hence, neither the smaller probabilities related to patients preferences of quality nor the ones of waiting lists seem to impact in the final decision of family doctors. This example may provide an exception to the strength of the patients preferences in the final result of the simulation.

The network structure is very weak looking at the quantity of links, stressing the isolation of the subjects involved:

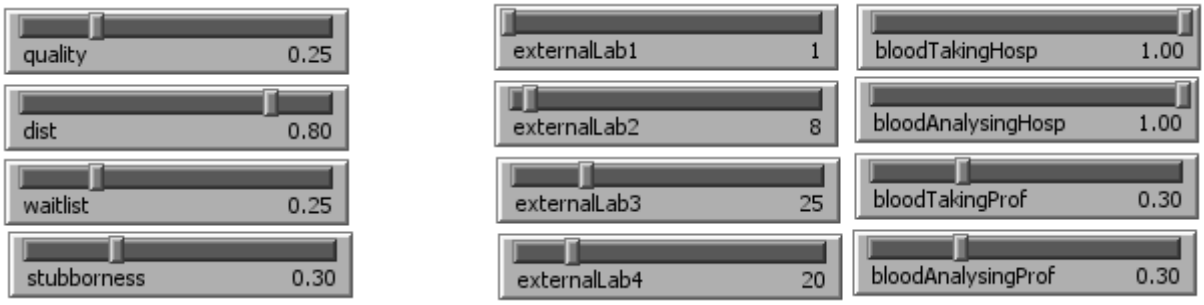


The fundamental node in the network is a blood taking center located in the Molinette hospital. The only professional with a significant role in the network structure is the professional located in the yellow belt (the only professional on the left-hand side of the circle). Otherwise the network is highly disconnected. It has to be highlighted that the specialist of the Molinette hospital shows a relatively low quality level of its service.

Experiment n° 5

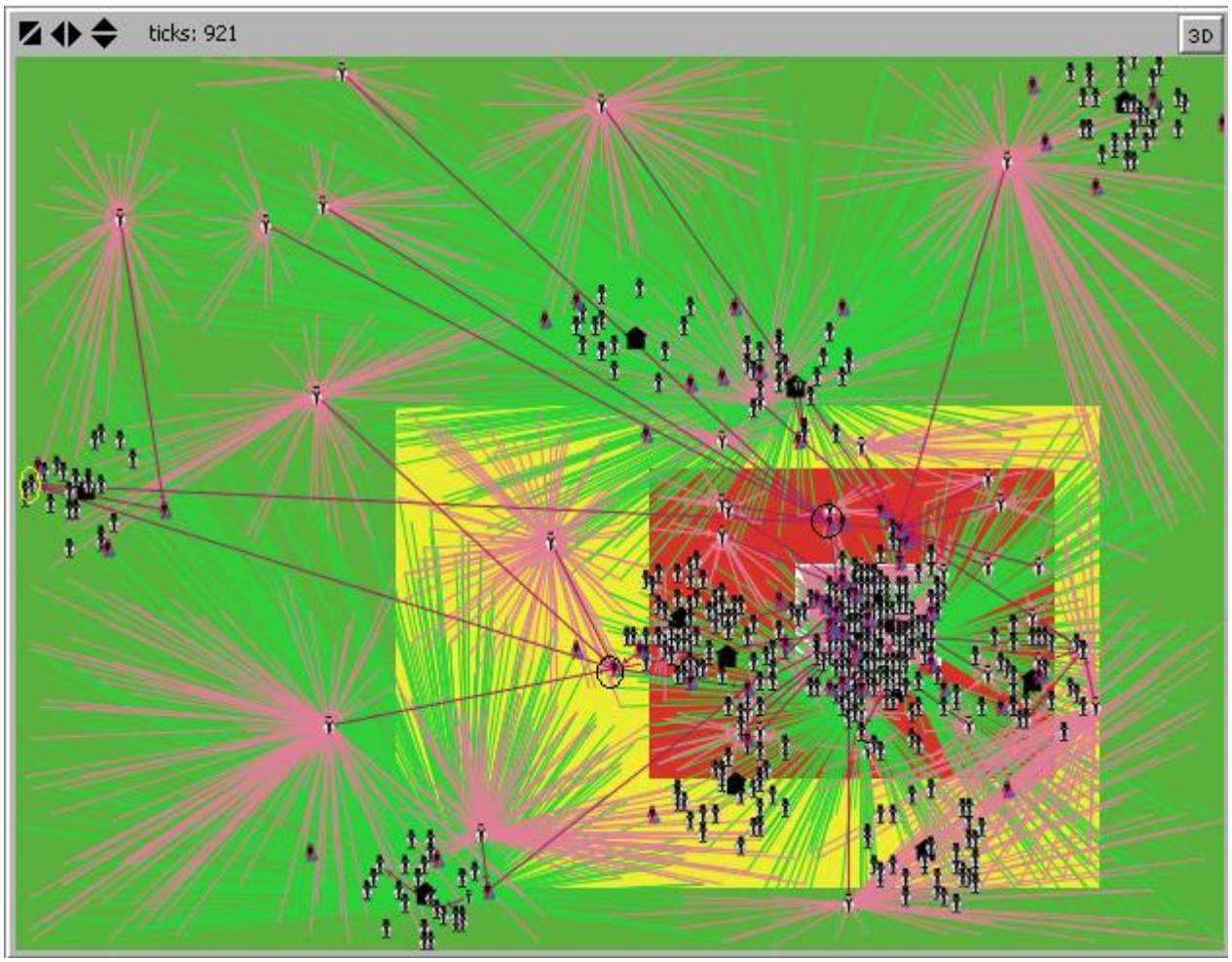
The real healthcare system of the Turin district is characterized by the presence of an emergency department for each public hospital. Indeed, in all the experiments previously explained, we have proceeded under this characterization. However, it has been already stressed the fact that emergency departments tend to "capture" patients affected by diseases with high degrees of emergency. Those patients, then, are usually treated inside the correspondent hospital associated to the emergency department that has received them. Hence, emergency departments may be seen as a potential element of isolation for the hospitals. Anyway, we may imagine a different scenario in which not all the hospitals contain an emergency department.

The slider managing the probability associated to the presence of ERs in hospitals is set with a low value. For the other settings regarding patients preferences and the supply of services connected to the "blood circuit" we have proceeded as follows:



The family doctor decision formula has a significant role in the simulation (relatively low stubbornness) while, from the supply point of view, each hospital provides code "101" and "102" treatments while only the 30% of private structures deals with these services. So, these settings try to emulate the real system under investigation which has to be evaluated under the important assumption according to which only few hospitals provide emergency department services (treatments with code "300"). Going back to the procedural characterization of our program, patients affected by diseases with high degrees of emergency (a treatment with code "300" in the first position of the recipe) have to be sent to the nearest emergency department. It may be the case that few ERs will determine huge congestions around the hospitals in which they operate.

The scenario resulting after a cycle of simulation, with the same random seed as in the first experiment, shows on the one hand some aggregations correspondent to the "isles" identified by the hospitals. On the other hand, it is possible to observe some cooperation among different structures, in particular moving towards the city center. Family doctor decision formula tends to select those crucial centers already presented in preceding experiments. The world scenario figure is shown in the following page.



This simulated scenario presents only six hospitals having an emergency department: Regina Margherita, CTO, Valdese, Pinerolo, San Carlo Canavese and Moncalieri. Looking at the green links, we can notice the concentration of emergencies into those structures.
The presence of "healthcare isles" is less relevant in this experiment. The set of probabilities assigned to private structures seems to support some kind of cooperation across private centers and specialists. Moreover, if this cooperation usually occurs from the external belts to the city center, the scenario presented above suggests also the opposite situation: from professionals located near the city center to external specialists. A good example is the hospital of Susa with its blood analysis laboratory circled in yellow, which receives patients from the yellow and even the red belt (the two professionals circled in black). The in-coming links of this laboratory show huge number of passages:

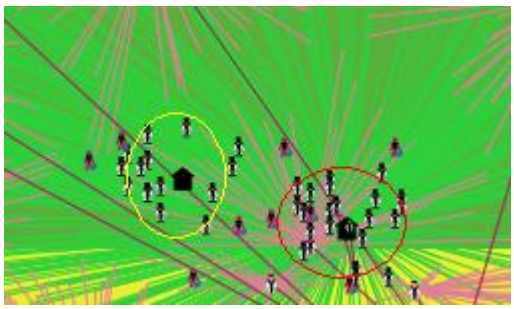
end1	(professional 2850)
end2	(specialist 2795)
color	125
label	""
label-color	9.9
hidden?	false
breed	tests
thickness	0
shape	"default"
tie-mode	"none"
visits	235

end1	(professional 2846)
end2	(specialist 2795)
color	125
label	""
label-color	9.9
hidden?	false
breed	tests
thickness	0
shape	"default"
tie-mode	"none"
visits	183

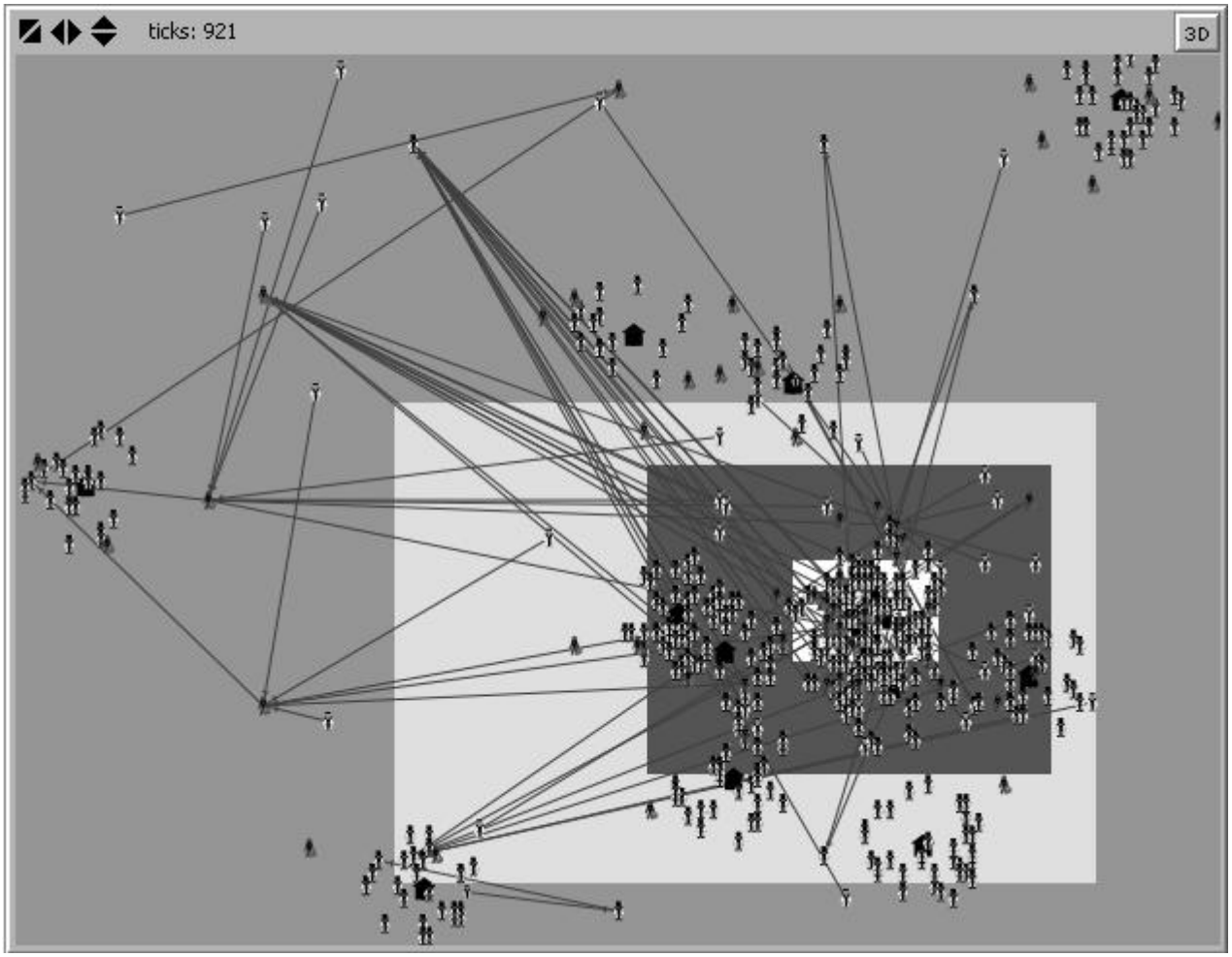
The specialist circled in yellow shows an extremely low quality level associated to its service (look at the variable “rep”):

who	2795
color	0
heading	323
xcor	2
ycor	73
shape	"person doctor"
label	""
label-color	9.9
breed	specialists
hidden?	false
size	3
pen-size	1
pen-mode	"up"
specialty	[102]
rep	16
affiliation	10
queue	26
cost	0
betw	0
eigvec	0
weighted	0

If the quality of the service provided by this specialist is so low, it is clear that the lack of private structures providing code “102” treatments (because of the introduced low probability values) must cause this compulsory cooperation among far structures, although it may seem strange that none of the hospitals in the city centers are preferred. A possible answer may be found in the ERs presence in the territory. This experiment proves the fact that emergency departments capture the patients in that they treat the nearest patients. However, with few ERs, patients must be sent to those few emergency departments that may be far away from them. So, the distance criterion, is computed making references to these emergency departments.
A good example of this alteration given by the lack of ERs may be represented by the hospital of Lanzo circled in yellow in the figure below:



It is completely ignored by patients (no magenta links passing through its specialists). Indeed, this hospital does not have any emergency department, which on the contrary is presented in the hospital of San Carlo Canavese circled in red, which captures patients providing them also services connected with blood tests. It is singular that the hospital of Lanzo, despite its provision of both code “101” and “102” services, is completely ignored also by family doctors.



Looking at the network structure, we verify what we have already noticed before: there are some professionals located close to the city center that cooperate with many other structures. Indeed, we find the two professionals described above which cooperate with the hospital of Susa and with other hospitals in the city center. So, their betweenness centrality measures exhibit high values. However, the quality of the services provided is always a crucial driver in the network identification, since the fundamental nodes of this network are made by doctors with high level of reputation. As before, the city center is dominated by those agents on the left-hand side of the circle.

CONCLUSIONS AND FUTURE WORKS

This final paragraph aims at resuming the main topics that have been covered in the course of this work:

The first section named "*Complexity, Simulation and Healthcare*" establishes a direct connection between complexity and the use of simulation as a potential tool useful to analyze complex systems. After having described in paragraphs from 1.1 to 1.7 what complexity is, the section proceeds by highlighting the role of simulation models, focusing on the core argument of our work: healthcare systems. The key arguments of the section may be resumed as follows:

- We have seen that a complex system is characterized by many "parts" interacting with each other in multiple ways.
- Complex systems theory focuses on the emergent properties generated by the elements which compose these systems.
- Each interaction among the elements of a complex system may correspond to a precise emergent "behavior" and the nature of the "complexity" comes from the multiple behaviors that may emerge from various types of interaction.
- Complex system theory embraces several disciplines in various fields of application: biology, engineering, political science, economics, medicine and so on.
- Nowadays, the application of complex systems theory is increasing in the analysis of healthcare systems. A healthcare system, indeed, presents all the characteristics that are needed to make it complex: it is characterized by several elements, interacting with each other and generating emergent properties.
- The juxtaposition of complexity in healthcare systems is analyzed in paragraph 1.8.
- Thus, the section goes on introducing simulation methodologies (from paragraphs 1.9 to 1.13) as powerful instruments of analysis in the healthcare field.
- The interest of healthcare system analyses is increasing mainly because of modern challenges each Country has to face in order to achieve economic and efficiency results. Reorganization and efficiency are the main drivers almost in every State and healthcare systems constitute, without doubt, one of the critical areas capturing the attention of policy makers.

The *second section* named *"Modeling Healthcare Systems: Agent-Based Strategy"* focuses the attention on a particular simulation methodology: agent-based modeling. The following topics are considered in the section:

- The section starts with the fundamental issue of the modeling activities and its purposes (paragraph 2.1).
- Then, agent-based simulation modeling is introduced, exposing the main features characterizing this technique (paragraphs 2.2-2.6). The core elements of agent-based literature are also presented making reference to the usage of ABM techniques in healthcare applications, identifying fundamental aspects (paragraphs 2.7-2.10).
- Hence, the connection between complexity, simulation models and healthcare characterizes the entire exposition. In particular, since a complex system is made by interactions among elements, agent-based models (ABM) represent set of agents interacting in a precise environment. From those interactions it is possible to investigate emergent phenomena of the system under analysis.

- Thus, the implementation of agent-based modeling techniques to the healthcare field is substantially relevant. By means of simulating computer software, it is possible to model set of agents with precise characteristics and behavioral rules, generating a scenario of the considered system. When the model is running, the user may identify emergent behaviors coming from agent interactions.
- The advantages derived from the agent-based modeling may be particularly meaningful when dealing with social systems. Indeed it is quite far from being an easy task to make experiments in social systems where agents present several features and differences as well as completely different behaviors. So, through ABMs, it is possible to simulate agents behaviors of a precise social system and then it is possible to adopt such instruments as experimental platforms, useful both to scientifically analyze systems and to develop policy decisions.
- Furthermore paragraphs 2.11-2.12 expose an additional characterization of agent-based models and some complementary simulation methodologies: microsimulation and system dynamics.
- The section proceeds and ends with an application of ABM techniques to a real healthcare unit, quite common in the literature, of an emergency department (paragraphs 2.13-2.16).
- Paragraph 2.17 resumes some notes about the agent-based simulation software adopted in this work: NetLogo.

The *third section* named *"Network Analysis: What Does It Bring to ABM?"* deals with the implementation of agent-based models with network analysis theory. Core arguments may be reported as follows:

- The section starts with the characterization of the fundamental issues in Network Analysis Theory, with particular emphasis on Social Networks (paragraphs 3.1-3.6). The presented theoretical background shows the typologies of networks, classifying them according to their structure forms.
- Moreover, several measures used in social network analysis are explained, providing some evaluation parameters for our model characterization.
- However, the crucial part of the section emphasizes the cross-fertilization that occurs when network analysis supports agent-based modeling (paragraphs 3.7-3.10). Interaction among agents means that they have different roles in the overall social network of a particular social system. Network analysis investigates structures of the resulting networks in social systems, providing results that complete and support agent-based simulation models. In other words, agent-based modeling provides the scenarios in which network analysis operates, identifying measures and roles of the different nodes in the emergent network.
- Then, a joint effort between network analysis and agent-based modeling provides advantages in the healthcare field (paragraph 3.11), in particular for those models concerning health and care providers and efficiency criteria.

The methodology, presented above and described in details in the literature review sections, provides the basis for the work presented in the previous pages. The *fourth section* named *"The Model"* presents all the features constituting the project we have developed. A quick summary is shown below:

- Our work is characterized by a model representing the healthcare system of the district of Turin, developed by means of agent-based modeling technique.
- Firstly, we have proceed by identifying the environment (paragraph 4.1), dividing the district into four areas and geo-localizing the hospitals.

- Then, we have modeled agents (paragraphs 4.2-4.7), assigning them precise features and behavioral rules (paragraphs 4.8-4.10). The agent set contains the following elements:

    - ✓ Specialists: head physicians managing a medical division of the hospital in which they operate.
    - ✓ Professionals: private structures.
    - ✓ ERs: emergency departments of the hospitals.
    - ✓ Family doctors: general practitioners .
    - ✓ Patients

- Particular attention is placed in the population of the district (patients), which corresponds to real proportions, and in the identification of the entire "healthcare lifetime" of each individual.
- Each patient presents some recipes identifying its medical events that happen through his life.
- The medical needs of patients correspond to three typologies of treatments that health and care providers in the district may offer: medical tests (in particular blood taking centers and blood analysis laboratories), specialist visits and emergencies.
- The purpose of the simulation is the evaluation of emergent networks (paragraph 4.11) characterizing the laboratories connected with the "blood circuit" in the district of Turin.
- The interaction between the demand side (patients) and the supply side (health and care providers) produces networks that can be differentiated on the basis of the services provided.
- The fundamental issue at the basis of our work is the "modeling approach". The attempt of the project is not centered on a precise real characterization of the healthcare system in the district of Turin, but it aims at providing an experimental platform of evaluation of different scenario settings (paragraph 4.12). Indeed, the user may directly change some features of the model in order to evaluate and compare various set of results.

Surely, our work may be improved on different aspects with further *future studies*:

- First of all, the data availability is the major issue that may provide further improvements to the model. Data collection in the healthcare field has to support modeling researches with detailed information and measures that drive models towards representations closer to real systems. In our context, the identification of treatments needs to be seriously characterized in terms of probabilities and typologies.
- Moreover, the decision formula adopted by family doctors in identifying health and care providers for their patients may seem too much stronger. Indeed, the assumptions concerning the quality of the services provided and on the waiting lists of the various structures (all randomly generated) have to be revisited in a softer way, trying to implement them with data concerning patients preferences.
- Then, it may be reasonable to isolate precise typologies of treatments in order to verify if there is some kind of emergent network charactering that particular supply side of the healthcare systems.
- Generally, our healthcare system is characterized by isolated systems corresponding to the public hospitals which usually satisfy patient needs internally, with little or no cooperation with other structures. Although this evidence comes directly from the real system, it may be interesting to evaluate changes in the procedural patterns followed by hospitals and family doctors . Such changes may result in better distributions of the patient flows or substantial improvements on the efficiency side.

- Another possible aspect of improvement in our model regards the geo-morphological representation of the district territory connected with the population density. We have ignored the mountain valleys which in turn constitute precise realities which have to be seriously considered from the healthcare point of view. Those areas in which the population density is inferior to the rest of the district have to be correctly covered, trying to identify solutions and schemes that can be modeled through an improved agent-based model.

BIBLIOGRAPHY

Amblard, F. and Quattrociocchi, W. (2013). Social Networks and Spatial Distribution, in Edmonds, B. and Meyer, R. (ed.) Simulating Social Complexity, pp. 401-430, Springer.

Barabási, A. L. and Albert, R. (1999). Emergence of scaling in random networks. SCIENCE vol 286, 15 October.

Barjis, J. (2011). Healthcare Simulation and its Potential Areas and Future Trends. SCS Mind & Society Magazine, no. 1, January.

Brailsford, S. (2007). Advances and Challenges in Healthcare Simulation Modeling: Tutorial. In Proceedings of the 39th Conference on Winter Simulation: 40 years! The Best Is Yet To Come. Edited by J. Tew, R. Barton, S. Henderson, B. Biller, M. Hsieh and J. Shortle. (Washington D.C., December 09-12, 2007).

Brailsford, S., Silverman, E., Rossiter, S., Bijak, J., Shaw, R., Viana, J., Noble, J., Efstathiou, S. and Vlachantoni, A. (2011). Complex Systems Modeling for Supply and Demand in Health and Social Care. In Proceedings of the 2011 Winter Simulation Conference, edited by S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu. (Phoenix, AZ, December 11-14, 2011).

Charfeddine, M. and Montreuil, B. (2008). Toward a Conceptual Agent-Based Framework for Modeling and Simulation of Distributed Healthcare Delivery Systems. Technical report, Interuniversity Research Centre on Enterprise Network, Logistics and Transportation (CIRRELT) – Canada.

Cioffi-Revilla, C. (2014). Introduction to Computational Social Science. Springer.

Dodder, R. and Dare, R. (2000). Complex Adaptive Systems and Complexity Theory: Inter-Related Knowledge Domains. Research Seminar in Engineering Systems. Retrieved from http://web.mit.edu/esd.83/www/notebook/ComplexityKD.PDF

Epstein , J.M. (2008). Why Model?. Journal of Artificial Societies and Social Simulation, 11(4): 12.

Epstein, J.M. and Axtell, R. (1996). Growing Artificial Societies: Social Science from the Bottom Up. Brookings Institute Press.

Escudero-Marin, P. and Pidd, M. (2011). Using ABMS to Simulate Emergency Departments. In Proceedings of the 2011 Winter Simulation Conference, edited by S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu. (Phoenix, AZ, December 11-14, 2011).

Fontana, M. and Terna, P. (2014). From Agent-Based Models to Network Analysis (and Return): the Policy Making Perspective. University of Torino, IT.

Gilbert, N. (2008). Agent-Based Models. University of Surrey, Guildford, UK. SAGE Publications, Inc.

Gilbert, N. and Terna, P. (2000). How to Build and Use Agent-Based Models in Social Science. Mind & Society no. 1(1): 57-72.

Glouberman, S. and Zimmerman, B. (2002). Complicated and Complex Systems: What Would Successful Reform of Medicare Look Like?. Commission on the Future of Health Care in Canada, Toronto.

Hamill, L. and Gilbert, N. (2009). Social Circles: A Simple Structure for Agent-Based Social Network Models. Journal of Artificial Societies and Social Simulation vol. 12, no. 23.

IBM. (2008). Healthcare 2015 and Care Delivery. Technical report.

Kanagarajah, A. Kay, Lindsay, P., Miller, A. and Parker, D. (2006). An Exploration into the Uses of Agent-Based Modeling to Improve Quality of Health Care. In Proceedings of the 6th International Conference on Complex Systems, at Boston, MA. Edited by A. Minai, D. Braha and Y. Bar-Yam, 10 p. The New England Complex Systems Institute.

Kenett, Y. Dror and Havlin, S. Introduction to Network Science. EPL journal. http://images.iop.org/journals_icons/Info/0295-5075/J%20EPL%20LF%200513%20Networks%20Intro-2.pdf.

Leykum, L., Kumar, P., Parchman, M., McDaniel, R. Reuben, Lanham, H. and Agar, M. (2012). Use of Agent-Based Model to Understand Clinical Systems. Journal of Artificial Societies and Social Simulation.

Macal, M. Charles and North, J. Michael. (2010). Toward Teaching Agent-Based Simulation. In Proceedings of the 2010 Winter Simulation Conference. Edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan (Baltimore, MD, 5-8 December, 2010).

Marzo F., Za, S. and Spagnoletti, P. (2014). Agent-Based Models to Simulate Social Support Networks. VeRSI-LUISS Guido Carli University, Roma, IT.

Waldrop, M. Mitchell. (1992). Complexity: the Emerging Science at the Edge of Order and Chaos. New York: Touchstone.

Wikipedia (2014). Wikipedia, The Free Encyclopedia. https://it.**wikipedia**.org

ACKNOWLEDGEMENTS

I would like to thank firstly my parents and my family for their extraordinary support across these years. In particular I want to dedicate this work to my uncle Bob who passed away recently.
I would like to extend special thanks and appreciation to prof. Pietro Terna for his patience and passion, guiding us towards the realization of this work. Without his effort, the work would not exist.
Many thanks to my special colleague and fellow countryman Alberto Baldovino for his support and help through these academic years. Without his insights, ideas and fun, I would have never been able to finish the studies. Thanks for your fun.
Thanks to prof. Sergio Margarita for his effort as an assistant supervisor.
I would like to thank all my friends that have made me happy during these years and, finally, thanks to Music and Cycling, they have made me a stronger guy, both mentally and physically.