Impact of Structuring Elements on Agents' Behavior in Social Simulations

Marcelo Pita, and Fernando B. de Lima Neto, *Senior Member, IEEE*

***Abstract*—Agent-based social simulations have been widely used to help social scientists on the understanding of several social phenomena. Traditional approaches to agents most often tackle well the behavioral and the temporal aspects of the carried out simulations. However, a frequent limitation in social simulations is the lack of simultaneous support for spatial specifications of social structures. That is, the incorporation of placement and neighboring of real world conceptual structuring elements such as houses, hospitals, roads, and workplaces. Moreover, the incorporation of mechanisms that affords assessing means on the action selection of all social agents is deemed also to be seminal. In this paper we use the Plausible Agents matriX (PAX) framework to investigate the influence of these social structuring elements on the intelligent agents' behaviors, considering some disease dissemination scenarios. Results obtained show how influential is spatiality (*i.e.* consideration of the abovementioned structuring elements) on the overall epidemics understanding and sought control. These findings are instrumental for the development of more effective tools to support decision makers, namely the ones who work with health care and other public policies.**

I. INTRODUCTION

THERE are frequent limitations for rigorous investigations in Social Sciences due to difficulties of applying the Cartesian scientific method to social phenomena. For instance, controlled real environments for social phenomena experimentation is obviously limited and hard to obtain.

Some mathematical models were put forward as attempts of capturing the essence of human social behavior. However, these analytical models are based on not always true premises. The works of John von Neumann and Oscar Morgenstern that resulted in the Game Theory [1], for example, assume perfect rationality when players adopt strategies. For real human players this assumption is evidently false, because human intelligence is something more complex than the optimization of a gain (or performance) function.

The search for suitable scientific tools, aiming to carry rigorous investigations in Social Sciences, directed many social scientists to experiment the use of computational modeling and simulation. This differs greatly – but not essentially – of the traditional deductive inference models for generating confirmations of hypothesis or answers to research questions.

Simulations of social phenomena are known as *social simulations* [2]. When the simulations are modeled and instantiated from agent architectures, they are commonly referred as *agent-based social simulations* (ABSS) [3]. The major motivation to use agent-based models is the possibility of modeling and controlling different granularity levels, namely, the social global level and also the individual level. This advantage enables the researcher to produce highly heterogeneous and sophisticated kinds of virtual societies.

Regarding the use of computer models instead of analytical ones, perhaps the major benefit is that the former are more flexible. A computer model can represent real phenomena as good as a set of equation, with the advantage of providing abstractions when necessary, can be easily re-configured and re-run [4]. As a matter of fact, computer simulations can even incorporate analytical models. About ABSS, Epstein and Axtell have shown strong arguments encouraging the use of agent-based models instead of analytical ones [5].

ABSS also support the study and prediction of many human like behaviors such altruism, egoism, perseverance, as well as social-like phenomena such as reputation formation, leadership action, group gathering, culture transmission, spread of various features across population (*e.g.* diseases) and many others. This research field evolved greatly since Neumann's self-replicating machines and cellular automata [6]. Most recent works deal with cognitive social simulations [7] [8].

Along the evolution of the ABSS field, many simulation environments, toolkits, frameworks and models were proposed, *e.g.* Sugarscape [4], SARS [9] and the Vidya platform [10]. For this paper in particular, previous works and some learnt lessons using the Vidya platform are of great value.

In the past the authors managed to use Vidya to simulate egoistic and altruistic behaviors of agents [11], as well as disease dissemination on virtual societies [12]. The latter work revealed interesting and realistic social dynamics, such as social exclusion of the sick and group re-gathering after

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The authors are with Department of Computing and Systems, Polytechnic School of Pernambuco - University of Pernambuco, Recife 50720-001, Brazil.

Fernando Buarque de Lima Neto (SM'07), the corresponding author, can be reached by phone: +55 (0)81 3184-7555 extension 7542; fax: +55 (0)81 3184-7555 extension 7536; and e-mail: fbln@dsc.upe.br.

the simulated epidemic is over. Besides the exciting results obtained then, some limitations were also encountered. These are to be addressed here, that is the absence of structuring social elements.

In many ABSS tools (including Vidya), we have identified the lack of flexibility to include structuring elements such as houses, roads, hospitals and workplaces. This means that across the simulation (search) space, of those tools, events are equi-probable to happen. However, this is ratter unrealistic, thus we strongly advocate that this flexibility must be considered in order to the production of plausible high level social simulations that include organizations, individuals and symbols.

ABSS environments may be classified according to three requirements for which they shall provide support, regarding relationships among entities of the simulation: (*i*) behavioral, (*ii*) temporal and (*iii*) spatial relations [13]. Traditional approaches to ABSS most often tackles well the behavioral and the temporal aspects of carried out simulations. However, a frequent limitation in artificial environments is the lack of simultaneous support for spatial specifications of social structures.

Considering (i) and (ii), in this paper, we are interested in analyzing the impacts of spatial relations (including placement and neighborhood of simulation elements) on simulated agents' behaviors and, consequently, on the overall simulation results. This not so easy task is suitably addressed by the new PAX (Plausible Agents matriX) framework, which is still under development, but sufficiently mature to afford full specifications of social structuring elements and basic simulation infrastructure. Hence, this paper can also be seen as a proof of concept of using the PAX framework, which is a more comprehensive tool for ABSS.

As case study, we investigated the influence of using a connecting road (*i.e.* a social structuring element) that links communities to far away hospitals. This feature minimized transportation costs for its users when compared with inhabitants that do not use it. Simulated scenarios included epidemic spread (and control) in the presence and absence of the road connecting communities to a hospital. Several other conditions were also simulated and influenced directly on the intelligent agents' behaviors.

Results show that the social structuring element investigated, here the simple concept of a road (but could be any other cocept, *e.g.* vaccination or radio broadcast), had a seminal importance in he epidemic dynamics and control.

This paper is organized as follows: section 2 gives an overview on the main concepts related to agent-based social simulations; section 3 explains the PAX environment; section 4 discusses the experimental setup and the carried out simulations; and section 5 concludes the paper and gives some prospective views.

II. AGENT-BASED SOCIAL SIMULATIONS

Computer simulations in social sciences besides to be a young field, have produced very interesting tools that aims to approximate computational models to real social phenomena, complying also with some scientific demands. Among them, we highlight the following [14]: (*i*) *prediction* of future social outcomes; (*ii*) *test-bed* of social hypothesis; (*iii*) *discoveries* of new relationships and principles.

The principles of social simulations came from the studies of John von Neumann and Oscar Morgenstern on Game Theory [1]. Later, the Neumann's model of self-replicating machines motivated him to work with Stanislaw Ulam in the construction of the first cellular automata model [6], giving the first steps in the direction of ABSS. Each cell in a cellular automaton can be seen as a very simple agent, because it "perceives" its neighborhood, perform very simple computations on this "perception" considering a small set of rules and, finally, "act" (*i.e.* change its state and maybe the environment).

Based on the model of self-replicating cellular automata, John Conway builds the Game of Life, demonstrating graphically that very simple local rules can generate complex global patterns. This way to view complex systems has influenced recent studies, including "the new kind of science" of Stephen Wolfram [4].

The Conway's Game of Life influenced a new generation of social simulations, like the Boids algorithm developed by Craig Reynolds to simulate flocking birds [14]. The Boids is widely used in high definition computer graphics animations to simulate swarm behavior. The agent-based approach, following Reynolds's works, became more evident with the creation of the research field of Artificial Life (ALife).

Joshua Epstein and Robert Axtell pioneered in ABSS through their works in simulating social, economic and biologic phenomena, using explicit agent-based models [1]. Later, Epstein and Axtell created the first general purpose ABSS model, the Sugarscape [4]. Recently, Ron Sun has proposed the adoption of more realistic cognitive agents' architectures [8], influencing a new generation of highly plausible cognitive social simulations.

This work is strongly motivated by previous instigating results (of the same authors) obtained using the Vidya multi-agent systems platform. Actually, Vidya was initially introduced as a god-game based on intelligent agents whose actions were devised through evolutionary computation [10]. Later, the Vidya platform was used to simulate human-like behavior [11], as well as simulate the spread of diseases over populations in unstructured virtual worlds [12].

The authors believe that the possibility of incorporating structures, like roads, houses, hospitals, and workplaces, as well as structural levels such as health, transportation and communication systems is a natural step on the construction of more realistic bread of ABSS. No need to stress that all that helps increasing the realism of produced social simulations of highly organized societies.

The next section explains the PAX framework, which among other functionalities allows a easy specification of structuring elements and structural levels.

III. The PAX Framework

PAX is an ABSS framework, developed with the Java programming language (JDK 6). The framework architecture was conceived to give support to context specific agent-based social simulations in the following aspects:

1. *Specification of environments* – environments are specified their comprising structures and structural levels;
2. *Specification of entities or objects* – objects are specified by spatial characteristics (positional coordinates) and the specific structure where they are located;
3. *Specification of objects' interaction interfaces* – an object interaction interface supply the set of actions that others objects can produce on it, considering restrictions based on its state;
4. *Specification of agents* – agents follow the BDI (Beliefs-Desires-Intentions) model [15] [16], and abstract the perception and planning phases, needing to be implemented together with specific context intelligent components.

The PAX framework also contains classes (regarding to the object-oriented paradigm) that help on the instantiation of specific contexts of simulations, as well as classes for simulation parameterizations and statistics.

The experiments presented in this paper were completely implemented with the PAX (Plausible Agents matriX) framework. Although it is still in development, its main functionalities are already operational. The following sub-sections detail PAX further.

A. Environments

PAX environments are made of structures and structural levels. Figure 1 illustrates a simple environment with the following structures: 27 houses, 3 factories, 2 roads and 1 hospital. They are all part of four structural levels: housing, occupation, transportation and health care.

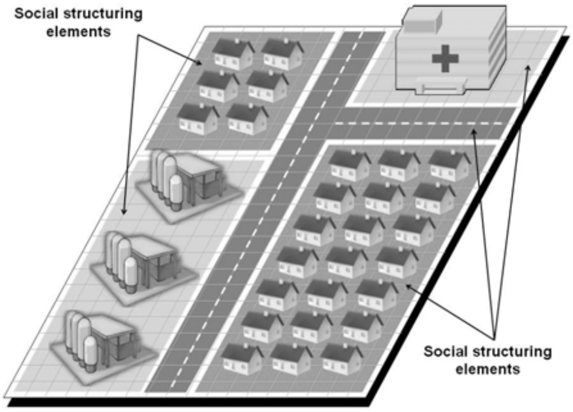

Fig. 1. Simple environment with its structures (houses, hospital, factories and roads) and structural levels (housing, occupation, transportation and health care).

The PAX framework supplies classes for instantiation of context specific structures and structural specific levels, at the same time maintenance effort is low and as transparent as possible. Each structure is an object with spatial coordinates (placement), dimensions (*i.e.* width and length) and may contain others substructures. This is an important feature, as a hospital may incorporate wards with different levels of sanitation, for example. Each structure also contains a set of adjacent structures, to which it is linked; agents can migrate across structures through these links.

In PAX, structures abstract high level cultural symbols that can be incorporated into the agents' intelligent processing. Hence, the presence or absence of social structures can influence the adoption of different agents' behaviors. For this reason, structures may function as instruments to promoting global order in open societies.

The idea of using (abstract) structural levels[1] came with the need of simultaneous specification of parameters to a group of structures that perform similar functions in the environment or collaborate among themselves, That is, structures that have to reach common objectives; *e.g.* hospitals and drugstores, although different, are both in the health care structural level. This concept makes possible, for example, the experimenter to enable or disable the operation of all structures of the same structural level at the same time.

The user of the PAX framework (*e.g.* a social scientist*)* may build simulation structures by only implementing some abstract methods that are context-specific, particularizing the environment to a target simulation purpose.

The PAX framework can be used not only to support agent-based social simulations, but also new AI algorithms that aims to solve computational problems through agent-based modeling. Structures can be seen, in this perspective, as *a priori* knowledge that guides agents to find the solution in the specific problem. This aspect affords PAX with great extensibility, regarding learning abilities.

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[1] They are abstract because they do not represent any real world entity.

B. *Objects*

PAX objects are anything conceivable to be included in one environment. Then, an object has also spatial coordinates (2-dimensional), a meta-location (*i.e.* the structures it is located, or no structure) and an object interaction interface.

This is the basic class of all simulations. It is used when the developer want to create context specific objects. These objects need to have some of its abstract methods implemented to become operational and effectively influence the simulation results.

Objects are also automatically perceived by agents, given some implementer defined restrictions such as distance for example, and may be considered or not by their intelligent engine. Of course, the experimenter should only create new objects that aggregate value to the sought simulation.

C. *Objects Interaction Interfaces*

As objects interact with each other, the set of rules that guide their interactions are implemented by objects interaction interfaces. The PAX object interaction interface may also include restrictions over actions that an object can perform onto another.

For example, considers the object syringe-of-vaccine; it has two possible states: (*i*) full and (*ii*) empty. Suppose that agents can interact with it by performing the following possible actions: (*a*) buy vaccine, (*b*) take vaccine, (c) dispose the syringe-of-vaccine and (d) re-use the syringe-of-vaccine. Thus, the interaction interface for the syringe-of-vaccine object captures its interaction protocol and only allows, for example, the agent to perform the following actions: *a* and *b* if syringe-of-vaccine is in state *i,* and action *c* if syringe-of-vaccine is in state *ii.* The action *d* can be set to never be allowed regardless of state. Interesting enough, PAX makes it possible the unthinkable re-use of syringes in given environments. Notice that this flexibility may completely invert the semantic value of a syringe-of-vaccine, but make it highly plausible for simulation of social problems.

When the PAX experimenter is designing an object and needs to include restrictions on its behavior during interactions with others objects, he also has to implement an interaction interface for the other object. Of course, the interaction interfaces only allow or restrict behaviors, so they do not implement any intelligent processes that work on the selection of plans; this is a private task of agents.

D. *Agents*

PAX agents are special types of objects designed to be intelligent. Notice that the framework does not supplies any intelligent component for agents' behaviors. The surround architecture is based on the BDI model, thus the framework supplies routines that abstract the perception phase (*i.e.* perception generate facts, that are part of the agents' beliefs) and represent plans of actions mapped out from intentions.

The experimenter, when implementing a specific kind of intelligent agent, have to build the intelligent component that will map perceptions to plans of actions (*i.e.* implement the mechanisms that generate agents' desires). The BDI model was used because of its ability to incorporate high level of cognition to PAX agents [16].

IV. CASE STUDY, EXPERIMENTAL SETUP AND RESULTS

This section explains the case studied, which was implemented using the PAX framework. Results of simulations for several social scenarios are presented and commented.

A. *Case Study: Spread of Disease over Population*

The case study was the simulation of an environment made of 4 agents' communities that are suffering with a known epidemic. Each community contains 200 habitants (*i.e.* a total of 800 agents), of which 10% of them (*i.e.* 20 inhabitants in each community) are initialized as sick. Here we are not simulating a real world disease. We are solely analyzing the transmission dynamics and if PAX is able to provide the necessary features for the simulation.

Each agent has a sickness label, indicating if it is sick or healthy, and a contamination level, indicating how sick the agent is. The contamination levels of agents initialized as sick are randomly determined with a uniform distribution in the interval [0.0; 1.0]. The higher the contamination level of an agent is, the higher the risk of contamination of others agents is in the same location. Thus, the transmission is probabilistic.

In the simulated environment there are 2 hospitals shared by all communities. The first of these hospitals (Hospital-1) is the nearest, as show Figure 2. We arbitrarily attributed costs for an agent to transit from its community to a hospital and vice-versa. *Ad hoc* we have attributed the cost 1.0 to "Community→Hospital-1", "Hospital-1→Community", "Hospital-1→Hospital-2" and "Hospital-2→Hospital-1". Also *ad hoc* we have attributed the cost 2.0 to "Community→ Hospital-2" and "Hospital-2→Community". Another kind of structure that represented a road was built to link all communities to the Hospital-2. This alternative route could be made available or not at the experimenter will. So agents could also follow the alternative route: "Community→ Road→Hospital-2" and "Hospital-2→Road →Community". Actually this was one of the features that we investigated, which is the impact of attributing different cost values to alternative transportation ways.

Figure 2 illustrates the communities and hospitals with graphical indications of their crowdness.

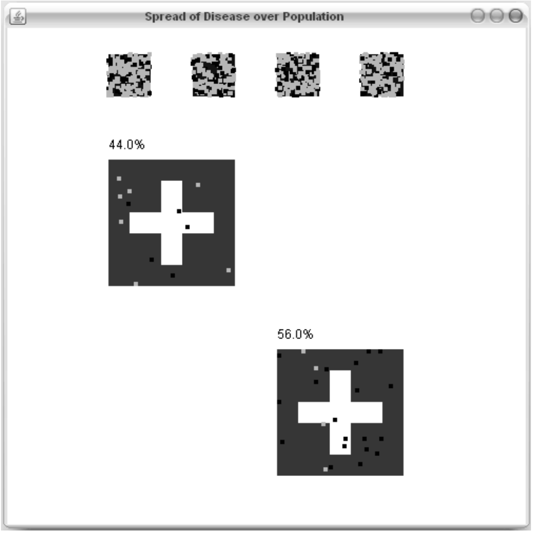

Fig. 2. Screenshot of a simple graphical interface developed using the PAX framework to visualize the simulation progress, showing the 4 agent communities (top) and 2 hospitals at different distances. The dots are agents (colors not seen here indicate levels of contamination).

The developed structuring elements, that is, the “community”, “hospital” and “road” structures, belong to the “housing”, “health care” and “transportation” structural levels, respectively. This conception allows global parameterization of structures, as explained in section III.

Regarding to the disease dynamics, sick agents can disseminate the disease to others that are inside the same structure. In the same community, the presence sick agents enhances the probability of healthy agents be infected. Concerning to hospitals, we investigated the possibility of them contributing to be disease dissemination areas as well, instead of simply disease treatment locations. Thus, we simulated scenarios where agents can disseminate disease even in hospitals (*i.e.* scenarios with nosocomial infection) and others where disease cannot be disseminated in hospitals.

Notice that in the beginning of all simulations agents do not know the best options of actions to perform. As the simulation progresses, they learn through reinforcement learning to tune-up their behavior to their particular needs and according to their current state. Agents may be in any of the possible states:

1. At a Community and healthy;
2. At a Community and sick;
3. At Hospital-1 and healthy;
4. At Hospital-1 and sick;
5. At Hospital-2 and healthy;
6. At Hospital-2 and sick.

For each state above there are a set of possible actions that can be performed by an agent. The possible actions for the agent are the following:

I. No action;
II. Go to Hospital-1;
III. Go to Hospital-2;
IV. Go to Hospital-2 via Road (if available);
V. Go to Community;
VI. Go to Community via Road (if available);

The combination of states and actions result in a transition graph, illustrated in Figure 3. Notice that inhabitants may not migrate from one community to another in some particular simulations.

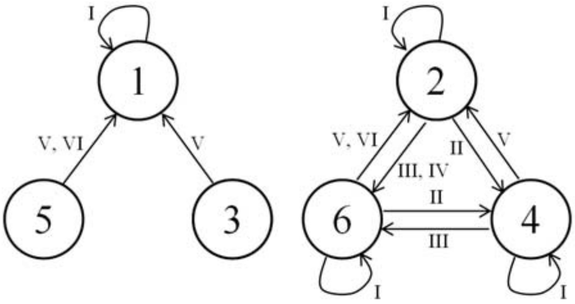

Fig. 3. Agent’s transitions graph. Learning here can be understood as weighting each transition by reinforcement through agent’s experience.

The agent’s learning mechanism consists of weighting each transition by reinforcement originated from agent’s experience (interaction) with the environment. The weights of transitions represent probabilities of selecting the actions they codify, so the action selection is not deterministic, but probabilistic.

B. *Experimental Setup*

The main objective of the carried out experiments was to verify the impacts of inserting a new social structuring element (the road) on the agents’ behaviors (*i.e.* the actions they select), considering different associated costs. The experiments also investigated the impacts of nosocomial infections (*i.e.* disease transmission inside hospitals). Therefore, the simulation has 3 parameters: (*1*) the presence or absence of the road; (*2*) the cost to use the road; (3) presence or absence of nosocomial infection.

The road, when “on”, links communities to Hospital-2, reducing the cost when compared to the main route (*i.e.* no road). Notice that the main route to Hospital-2 costs 2.0. We used 4 possible road costs: 1.0, 0.5, 0.25 and 0.1. Notice that all these costs are less than the main route cost.

We combined all possible configurations of the above parameters. Each configuration was executed 5 times, and final results are average over the 5 executions (in all cases standard deviation was so low, so there are no outliers).

All simulations last 2000 iterations (meaning 2000 agents’ actions) and approximately 3 minutes running in a regular desktop (Pentium IV 2.8 GHz, 512 MB of RAM). This number of iterations was deemed to be sufficient to distinguish different tendencies for each configuration. Simulations were inspected every 200 iterations (*i.e.* 10 times).

C. Simulation Results

The first experiments aimed to verify the agents' behavior without a road that links all communities to Hospital-2.

Figure 4 shows the percentage of sick individuals over time in the scenario without road, and, with and without the possibility of nosocomial infection.

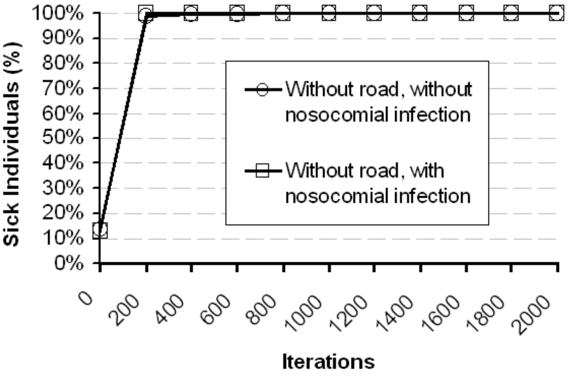

Fig. 4. Percentage of sick individuals, without road. Notice that curves for the two scenarios (with and without nosocomial infection) are similar, indicating that in both cases sick agents give preference to stay at their communities, instead of going to hospitals.

The similar curves may suggest that hospital attendance was drastically reduced even in the first iterations of the simulation. That is sick agents give preference to stay at their communities without treatment. This hypothesis is confirmed in Figure 5 and Figure 6 (i.e. number of appointments) and is justified by the high cost of transportation to either hospital.

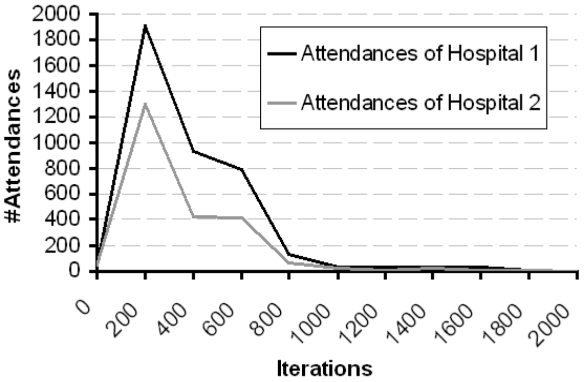

Fig. 5. Attendance figures of Hospital-1 and Hospital-2 over time, without road and *without* nosocomial infection.

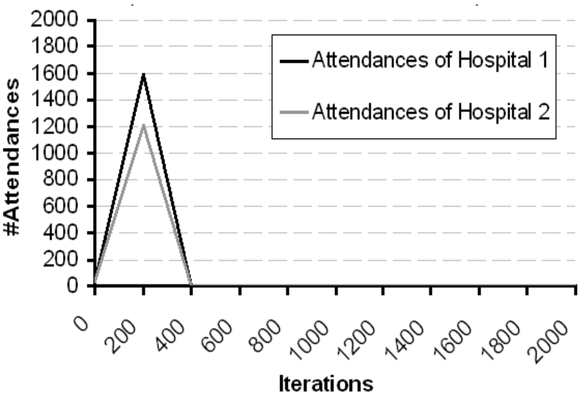

Fig. 6. Attendance figures of Hospital-1 and Hospital-2 over time, without road and *with* nosocomial infection.

Notice the clear difference between curves of Figure 5 and Figure 6, revealing that in scenarios of nosocomial infection, agents relinquish more rapidly hospital help. In both cases, the majority of the sick agents give preference to go to Hospital-1, instead of going to Hospital-2, again this is explained by cheaper transportation cost.

When we analyze the average contamination level of population over time (Figure 7), it is possible to identify a small difference in the curves that represent the scenarios with and without nosocomial infection. The curve for nosocomial infection has a faster growth, although it reaches a little higher plateau when the simulation stabilizes (approximately after 800 iterations).

When we include in the environment a road that links all communities to Hospital-2, we observed a totally different dynamics for different road costs. This could be seen as a metaphor for government positive action towards public health. Figure 8 and Figure 9 show the percentage of sick individuals when the road is present, with and without nosocomial infection, respectively.

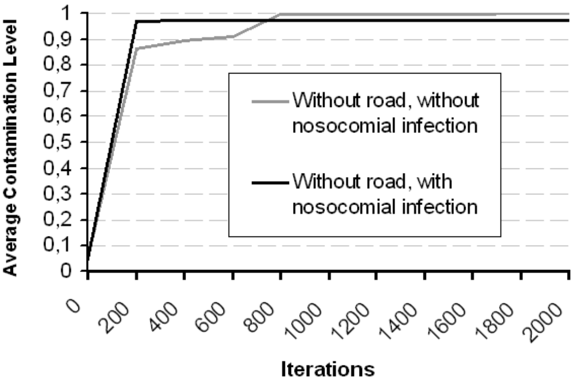

Fig. 7. Average contamination level of population without road, for scenarios without and with nosocomial infection.

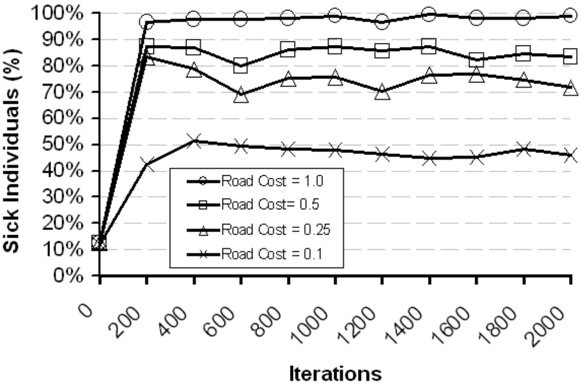

Fig. 8 Percentage of sick individuals, with road and *without* nosocomial infection.

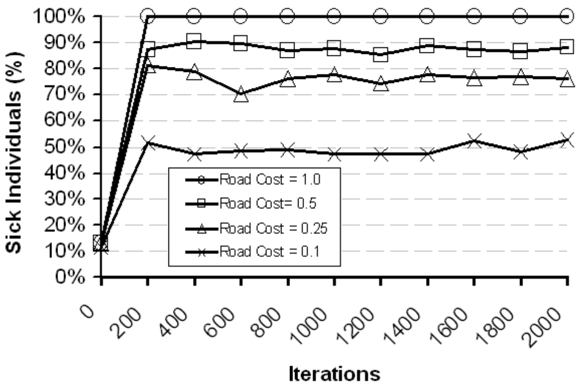

Fig. 9 Percentage of sick individuals, with road and *with* nosocomial infection.

Results show that the possibility of nosocomial infection is less important to reduce the number of sick individuals than the transportation costs, although it accelerates all curves growth. It can also be noticed a small non-linearity on the relation between the road cost and the percentage of sick individuals of the population.

Figure 10 and Figure 11 show the average contamination level of the population with road, without and with nosocomial infection, respectively. Here we see that the cheaper is the road, the lesser the average contamination level of the population. For the road costs 1.0 and 0.5, the possibility of nosocomial infection accelerates the growth of the average contamination level. When transportation costs of the road to Hospital-2 are very low (0.25 and 0.1), the impacts of nosocomial infection are much reduced. Similarly to Figures 8 and 9, it can be noticed a non-linearity on the relation between the road cost and the average contamination level of population.

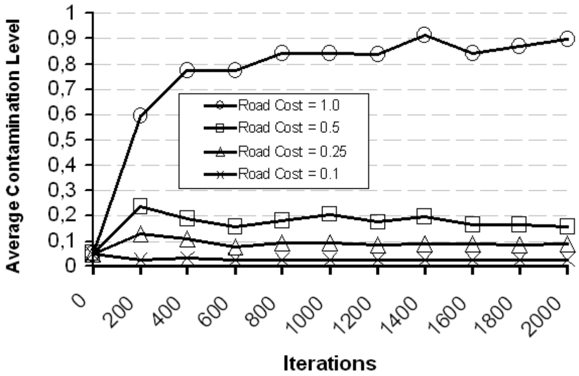

Fig. 10 Average contamination level of population over time, with road and *without* nosocomial infection.

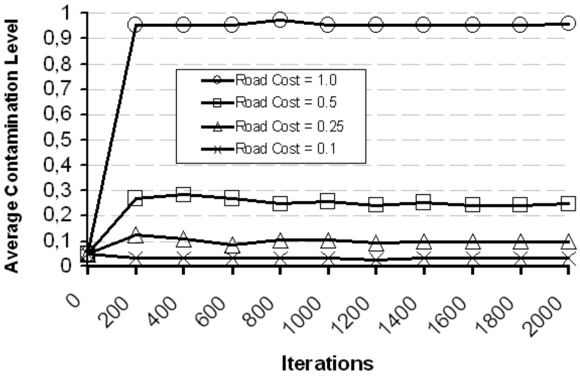

Fig. 11 Average contamination level of population over time, with road and *with* nosocomial infection.

Figure 12 and Figure 13 show the percentage of attendances of Hospital-2 in the presence of road, with and without nosocomial infection, respectively. Notice that the agents rapidly learn to choose the Hospital-2 as the best option (*i.e.* lower cost) and that the percentage of attendances of Hospital-2 is linearly related to the road cost.

According to the similarities of Figures 12 and 13, the possibility of nosocomial infection has little influence over the percentage of appointments in Hospital-1 and Hospital-2. This was the case because in our simulations there was no exchange of experiences between communities and agents.

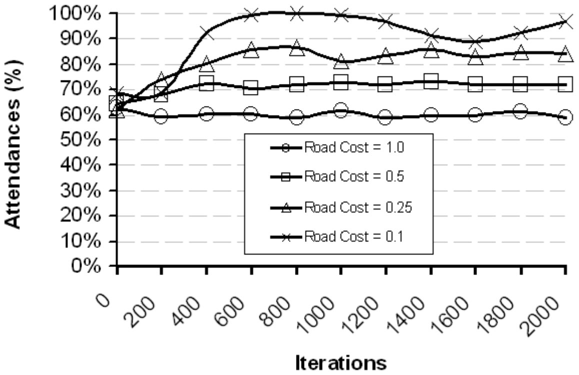

Fig. 12 Percentage of appointments in Hospital-2, with road (costs 1.0, 0.5, 0.25 and 0.1) and without nosocomial.

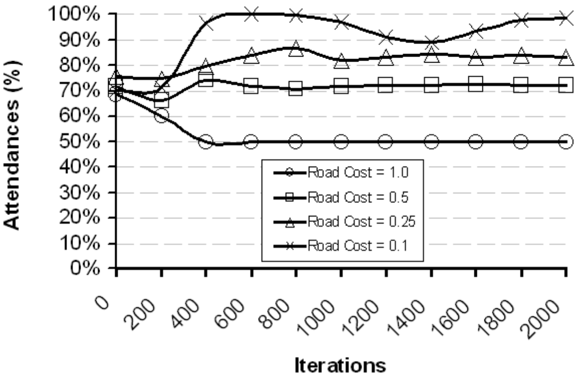

Fig. 13 Percentage of appointments in Hospital-2, with road (costs 1.0, 0.5, 0.25 and 0.1) and with nosocomial.

Figure 14 and Figure 15 show the some of the already presented information relative to average contamination level of population, this time allowing agents to share their findings and migrate to others communities. What one can observe is that knowledge spreads very quickly to the whole population. Notice the maximum value of the graphs scales (0.1), indicating a quick convergence to low values of contamination level when communication is enabled.

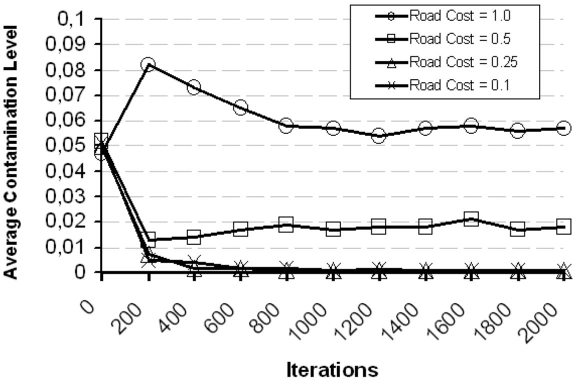

Fig. 14 Average contamination level of population. Scenario with road, without nosocomial infection and communication among agents enabled.

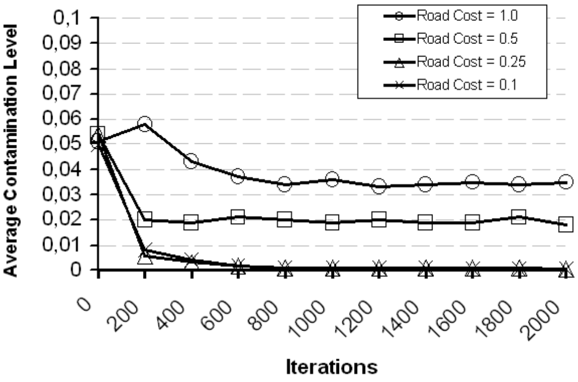

Fig. 15 Average contamination level of population. Scenario with road, with nosocomial infection and communication among agents enabled.

We observed that the results shown in Figures 14 and 15 are homogeneous in the population level (this is not evident in figures), because it was not incorporated any segregation mechanism in the agent level (*e.g.* reputation). Most certainly, the next step is the incorporation of such a segregation mechanism based on ascribed reputation among agents

V. CONCLUSIONS AND FUTURE WORK

In this paper the authors have investigated the impacts of structuring elements on agents' behaviors for social simulations. The case study selected was disease dissemination in an artificial population split into four communities with and without the existence of a structuring element (*i.e.* road) in the agent's world and some specific contextual variations (*i.e.* presence and absence of nosocomial infections). Learning is carried out be reinforcement drawn from interaction between agent and others world entities. The paper also introduces the PAX framework, which was used to carry out all simulations.

In our simulation model, which adopts structuring elements and structural levels, the meaning of the structures is intrinsically related to the simulation contexts. However this can be easily parameterized by an interested experimenter due to flexibility of PAX. In line with this, structuring elements and structural levels can be set to produce highly detailed simulations. They can also abstract *a priori* knowledge that can be used by agents to accelerate global and local learning.

Results demonstrated the high importance of structuring elements – in the simulated scenarios a road – in the whole agents' population dynamics. We see clearly that the introduction of such structuring element not only caused impacts on immediate behavior of agents, but in the overall performance, which in our case study is measured in terms of disease spreading and contamination level of agents.

Regarding to specific aspects of the simulated context, besides the simplicity of the modeled environment, it can be observed a very coherent emergent social behavior of agents, indicating that the model can be explored in simulating highly complex social scenarios in health contexts, benefited with the possibility of incorporating also highly complex structuring elements and other structural levels (*e.g.* broadcast of health information over a population through communication mechanisms).

Overall results revealed that PAX framework is a flexible means to perform social simulations and also indicated the importance (*i.e.* impact) produced by structuring element as a means to overcome undesired effects on stochastic phenomena on a population of agents. We argue that social scientists may profit greatly of using the platform just presented, as it is able of incorporating behavioral, temporal as well as spatial relations of among entities of the world.

The authors finally argue that the PAX framework and assumptions simulated here can be useful on public policies planning in health care and other governmental fields. For this, we are investigating new and plausible intelligent agents' models with elaborated communication skills, aiming to enhance their findings in reducing the error of simulations and real social phenomena.

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