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APPLYING CONTROL THEORIES AND ABM TO IMPROVE RESILIENCE-BASED DESIGN OF SYSTEMS

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ABSTRACT

Applying optimal control theories and agent base modeling to improve resilience assessment of systems is a new field which has not been explored yet. A resilience decision support system should include some critical elements: (i) Assess risk, (ii) identify choices (Identify choices for reducing vulnerability that focus on joint solutions across social, economic, and ecological systems; provide decision support, including Web-based guidance and scenarios to assess options) and (iii) take actions (Help communities develop and implement solutions). The field of structural control provides loops which are able to approach the problem in a more rational way and provide practical solutions to the resilience design strategies. The paper describes the concept and provides some promising applications of the proposed interdisciplinary approach.

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Applying control theories and ABM to improve resilience-based design of systems

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Applying optimal control theories and agent base modeling to improve resilience assessment of systems is a new field which has not been explored yet. A resilience decision support system should include some critical elements: (i) Assess risk, (ii) identify choices (Identify choices for reducing vulnerability that focus on joint solutions across social, economic, and ecological systems; provide decision support, including Web-based guidance and scenarios to assess options) and (iii) take actions (Help communities develop and implement solutions). The field of structural control provides loops which are able to approach the problem in a more rational way and provide practical solutions to the resilience design strategies. The paper describes the concept and provides some promising applications of the proposed interdisciplinary approach.

Introduction

This paper is introducing the concept of *resilient control system* design. The goal of this design process is to maximize the functionality of the critical infrastructures and systems when they are subjected to adverse operating conditions. In literature, resilient control design consists in modeling uncertainties using H_2 and H_∞ [1, 2] design methods. However, in this paper we are not focusing on the resilience of the control system, but on the resilience of the system (e.g. infrastructure) to be obtained using optimal control theory. According to the authors, several concept of optimal control theory can be used in Resilience-based design of infrastructures [3].
In the next paragraphs are shown some applications of concepts borrowed from structural control theory and signal processing in the new field of Resilience-Based design. Applications of agent base modeling as a promising tool to evaluate resilience is also explored.

Optimal control theory to resilience systems

Resilience of natural and critical infrastructural systems is becoming very important due to the harmful effects of anthropogenic actions as well as natural disasters (e.g. earthquakes). Such systems should survive the most severe accidents such as component degradation and failures, natural disasters, human errors, malicious attacks and environmental changes. Being embodied in a multi-disciplinary environment, a suitable mathematical measure of resilience is essential to quantify sustainability and to communicate successfully amongst various fields. Since natural

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and infrastructural systems are constantly evolving by being dynamic systems, time dependent decisions to achieve resilience are more effective. Optimal control theory, commonly used in engineering applications, can be applied to derive such time varying decision profiles. The natural system that has been used to show the application of optimal control theory to derive time dependent decisions is the three species predator-prey model [4]. The model is given by the following set of differential equations

$$\begin{aligned}
\frac{dx_1}{dt} &= x_1\left[r\left(1-\frac{x_1}{K}\right)-\frac{a_2x_2}{b_2+x_1}\right]\\
\frac{dx_2}{dt} &= x_2\left[e_2\frac{a_2x_1}{b_2+x_1}-\frac{a_3x_3}{b_3+x_2}-d_2\right]\\
\frac{dx_3}{dt} &= x_3\left[e_3\frac{a_3x_2}{b_3+x_2}-d_3\right]
\end{aligned} \tag{1}$$

where, x_1 (prey), x_2 (predator) and x_3 (superpredator) are the population variables of three different species in the food chain, in the ascending order of the position in the chain. r and K are the prey growth rate and the prey carrying capacity, respectively, and a_i, b_i, e_i and d_i, i = 2; 3, are the maximum predation rate, half saturation constant, efficiency, and death rate of the predator (i = 2) and the super-predator (i = 3). Various control strategies can be used to manipulate the food chain. This includes top-down control (control by manipulating the super-predator mortality) and bottom-up control (control by manipulating the prey carrying capacity). In optimal control there is a time dependent performance index which is

$$J(t_0)=\int_{t_0}^{T}F\left(x(t),u(t),t\right)dt \tag{2}$$

where F is a function to be optimized over the time interval of $[t_0, T]$. The optimal control law is given by the solution of the Hamiltonian problem which is described elsewhere [5]. The presented problem can be solved for various cases where human intervention to maintain resilience is essential. The results [5] showed that using bottom-up control with variance minimization objectives ensure system stability and achieves the desired population dynamics in most cases. The example shows that when the decisions are viewed as options available to be exercised the importance of optimal control theory in resilience is evident.

Transfer function analogies

It is possible to find analogous quantities in resilient systems and structural control when considering transfer functions. To see the analogies more clearly let's introduce the resilience index which is defined as [6, 7, 8]:

$$R_i=\int_{0}^{T_c}\left(\frac{Q_i(t)}{T_c}\right)dt \tag{1}$$

where R_i is the value of resilience of the i^{th} system, $Q_i(t)$ is the functionality of the i^{th} system at time t, T_c is the control period. This index should be considered as a response parameter and not as an intrinsic property of the system. If the system it is assumed linear-time invariant (LTI), then the concept of transfer function $H(\omega)$ which is usually adopted in the analysis of systems such as single-input single-output filters can be adopted. This concept is borrowed from the fields of control theory and signal processing, but it can be applied in the resilience field under certain assumptions. In this case, the relation between the input and the output can be written as

$$R(\omega, I) = \frac{H(\omega)}{I} \tag{2}$$

where w are the parameters identifying the system; I is the intensity of the event. Please note that I is at the denominator, because the resilience term reduces as the intensity of the input increases. Therefore, the new parameter which is independent from the intensity I of the input, called "*Resilience Transfer Function*" is defined as

$$H(\omega) = R(\omega, I) \cdot I \tag{3}$$

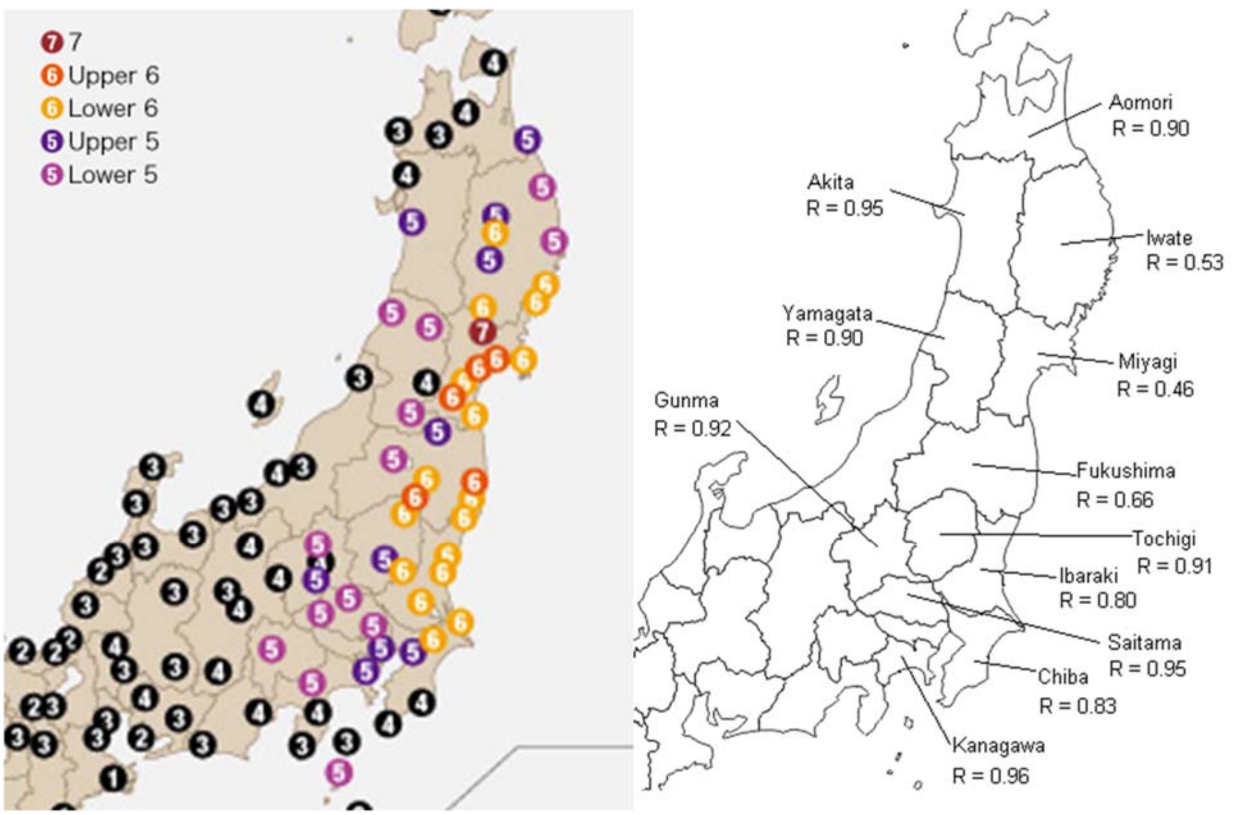


Figure 1 (a) Shindo intensity measures of Tohoku earthquake; (b) Resilience index evaluated under Tohoku earthquake

The reason for the introduction of this new parameter should be justified with an example, considering the restoration curves from the March 11th 2011 Tohoku Earthquake in Japan. In fact, by evaluating the resilience indices for the different prefectures and infrastructures it can be observed that the resilience index is higher in the prefectures that are far from the epicenter [9, 10] as shown in Fig. 2a. However, higher values of resilience in region far from the epicenter (Fig. 2a) such as Kanagawa do not necessarily mean that the prefectures would have been resilient to earthquakes that would occur closer. If the resilience index is normalized with respect to the earthquake input such as the local level of ground shaking (Fig. 1a) for the different prefectures then results, appear independent of the earthquake input (Fig. 1). The results of the normalized function called "*resilience transfer function*" are given in Fig. 2b. It appears now that the three prefectures (Akita, Aomori and Iwate) located in the North side of the region affected by the earthquake have lower values of *resilience transfer function*. Even if now the new index is independent from the level of ground shaking, the proposed Equation (3) shows some discrepancies especially for the prefectures facing the Pacific coast (Miyagi, Iwate, Fukushima, Ibaraki, Aomori) where the tsunami caused relevant damage (lower values of the resilience index), as well as areas far from the epicenter (Chiba, Kanagawa). For example, Chiba suffered more damage than Tochigi even if Chiba is more distant from the epicenter of the earthquake than Tochigi. So one of the limitation of Equation (3) is that is not able to take in account side earthquake effects (e.g. tsunami, fire etc.) which are independent from the level of earthquake shaking. Therefore, Equation (3) could be improved by including in the term *I* an index which could measure the intensity of the tsunami waves in the different prefectures.

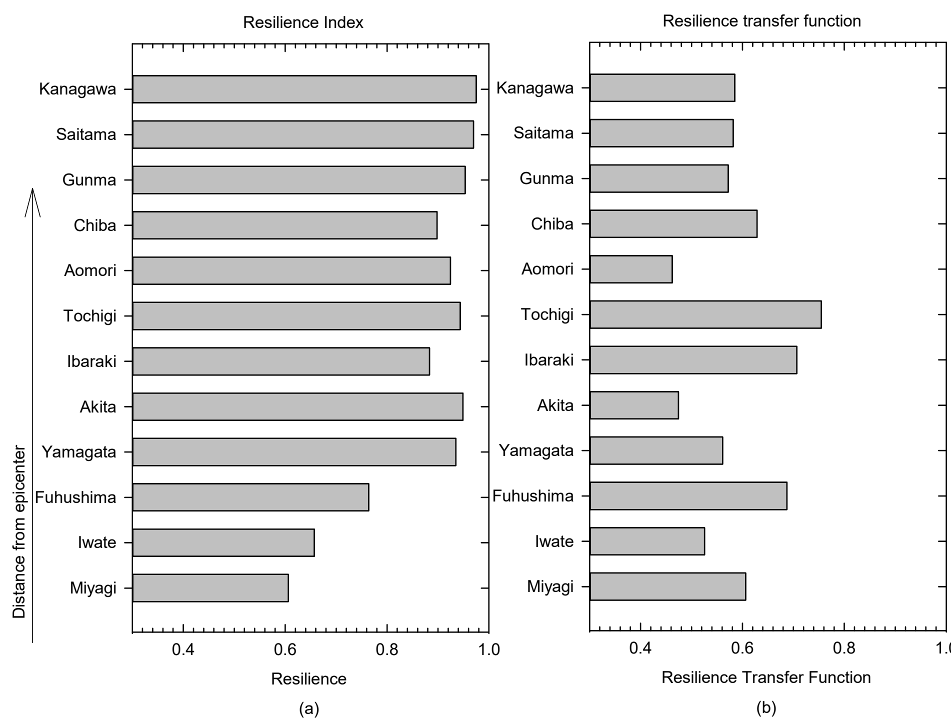


Figure 2 Comparison of (a) Resilience index vs. (b) Resilience transfer function

Agent base modeling in Resilience-based design

We live in an increasingly complex world and the systems that need to be analyzed are becoming more complex. Some systems are approaching the design limits such as the transportation network, while infrastructures both physical (e.g. electricity, natural gas, water,

telecommunication etc.) and not physical (economic, business etc.) are more and more interdependent. The huge amount of data on these systems is now organized in databases at finer levels of granularity, so now micro-simulations are possible. In this complex world, agent-base simulation is a new field that allows to effectively capturing a very rich set of complex behaviors and interactions; therefore, it is highly suited to modeling complex phenomena in the field of social science, economy etc. and complex physical systems such as infrastructures.
Agent-based modeling (ABM) is a type of modeling in which the focus is on representing *agents* which are discrete entities with their own *goals* and *behaviors*, which can be programmed accordingly, as well as the mechanisms the agents can interact. In agent-based models, as in real complex systems, a set of inductively generated *local rules* and *behaviors* of agents give rise to emergent phenomena at a group or system-wide level. ABM has its historical roots in *complex adaptive systems* (CAS) which are systems that have the ability to self-organize and dynamically reorganize their components in ways better suited to survive and excel in their environments. These systems are built from the ground-up in contrast to the top-down systems view taken by System Dynamics.

Definition of Agent

There is no universal agreement on the definition of the term "agent". According to Mellouli et al. (2003) [11] agents are components with an adaptive behavior; components that can in some sense learn from their environments and change their behaviors in response. Agents should contain both base-level rules for behavior as well as a higher-level set of "rules to change the rules." The base level rules provide responses to the environment while the "rules to change the rules" provide adaptation. Beside the definitions, in ABM the agent is modeled using *attributes*, *rules of behavior*, *memory*, *sophistication* and *resources*.

Agent's behavior through integrated human decision making model based on BDI framework

Human decision behaviors have been studied by researchers in various disciplines such as artificial intelligence, psychology, cognitive science, and decision science [12]. As a result of those efforts, several models have been developed to mimic human decision behaviors.
Among them integrated *Belief-Desire-Intention* (BDI) modeling framework is a powerful tool that can be used for human decision making and planning of physical infrastructures considering interdependencies. BDI is a model of the human reasoning process, where a person's mental state is characterized by three major components: *beliefs, desires,* and *intentions*. *Beliefs* are information that a human possesses about a situation, and beliefs may be incomplete or incorrect due to the nature of human perception. *Desires* are the states of affairs that a human would wish to see manifested. *Intentions* are desires that a human is committed to achieve. The key novelty of the model is its ability to represent both the human decision making and decision-planning functions in a unified framework. The agents (models of human) can be simulated using the BDI framework and implemented in any agent-based simulation software (AnyLogic, Promodel, NetLogo, etc.). Whenever an agent needs to make a decision, it performs planning via Probabilistic Depth-First Search (PDFS), which in turn accesses Decision Field Theory (DFT) and the Bayesian Belief Network (BBN) to obtain preferences and assess the environment, respectively. Once DFT obtains an assessment of the environment from the BBN, it calculates

the preference value of each option, which will be used to calculate the choice probability of each option. Then PDFS selects an option and makes a plan based on the calculated choice probability. Since the decision has been made based on the preference value of each option with the predicted human preference value provided by DFT, which has been successfully applied to many cognitive tasks, it can mimic the cognitive nature of human decision behavior.

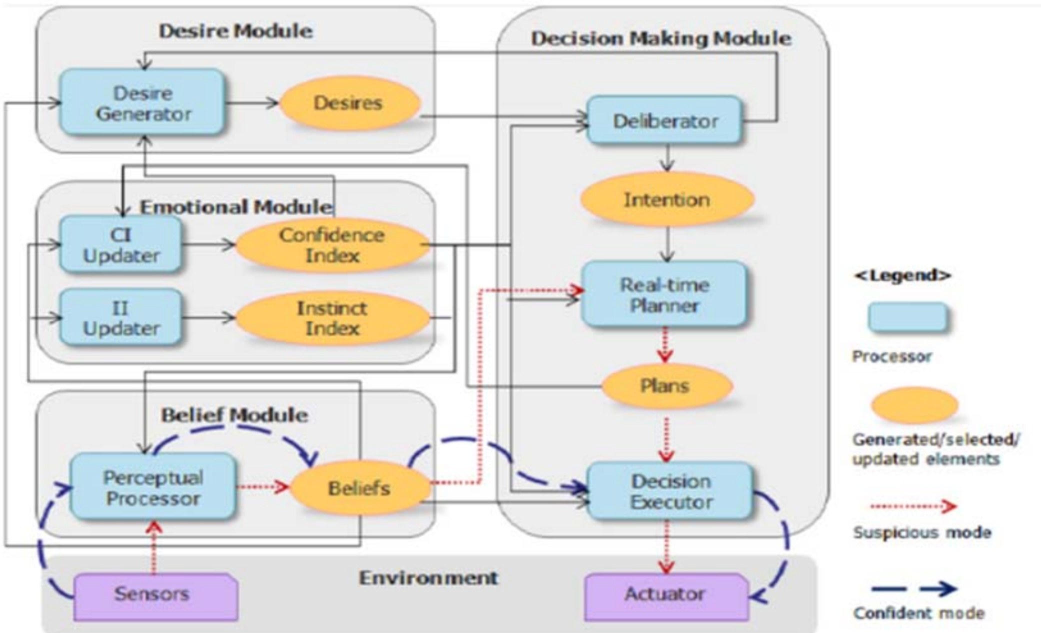


Figure 3 Components of the extended BDI framework (Adapted from [12])

This human decision behavior model can find several applications in the description of human behavior under natural and manmade disasters. For example different agents (models of humans) can be implemented based on: (1) familiarity with the area affected by the disaster (which will entail different evacuation planning), (2) risk-taking behavior, (3) confidence index (affecting the moving speed of an agent and leader/follower behavior), and (4) guidance by police or other officers. For example, the model can be very useful to describe the effect of human behavior on the performance of critical infrastructures under emergency. The infrastructures which will be more affected will be the one where the human decision plays a key role. One of the limits of this human behavior model is that the learning effect of agents is not considered in the model. Through the learning process, it can be represented how behavior of a novice agent become closer to those of commuter agents.

How to build ABM

Below is summarized a step-by-step procedure which can be used to build ABM, which requires:

1. Identify the purpose of the model;
2. Identify the agents types, get a theory of agent behavior and other objects (classes);
3. Identify the agent relationships and get a theory of agent interaction. Add the methods that control which agent interact, when they interact, and how they interact during the simulation;
4. Define the environment the agents will live in and interact with

5. Specify the methods by which agent attributes are updated in response to either agent-to-agent interactions or agent interactions with the environment;
6. Get the requisite agent-related data;
7. Validate the agent behavior models in addition to the model as a whole;
8. Conduct a series of what if experiments by systematically varying parameters and assumptions;
9. Run the model and analyze the output from the standpoint of linking the micro-scale behaviors of the agents to the macro scale behaviors of the system;
10. Understand the robustness of the model and its results by using sensitivity analysis and other techniques;

ABM in critical infrastructures analysis

Critical physical infrastructures (electric power, natural gas, transportation, petroleum, water, telecommunications, etc.) are becoming the focus of public attention as these systems approach their design limits and suffer regular breakdowns in normal operating conditions as well as during emergencies caused by extreme events. ABM can be applied in large scale decision support systems for critical infrastructures when real data are used and the systems that need to be analyzed become more complex in term of interdependencies. The idea is to model and simulate cross-infrastructure dependencies using communities of intelligent agents.
Critical infrastructures can be considered as Complex Adaptive Systems (CAS), so two approaches can be used to model them:

1. *Each system component of infrastructure is represented by an agent (micromodel)*
2. *Each infrastructure is represented by an agent (macromodel)*

ABM have also started to be used for modeling no physical infrastructures such as the economic markets giving a more realistic view of the systems, because traditionally this field made the problems analytically and computationally tractable assuming the notions of perfect markets, homogeneous agents, and long-run equilibrium [13, 13]. Although the majority of existing models are deterministic, the idea in the future is to incorporate probabilistic representations of infrastructure dependencies and failures.

Applications of Agent-based modeling

Applications of ABM are usually based on the local interaction among the agents which happen in local "neighborhoods" (Fig. 4). Various topologies connect Agents with Agents such as: (i) free continuous space; (ii) network which are general representations of agent interaction; (iii) Geographical Information Systems (GIS) tiling. The advantage of ABM models is that they are tying together micro-level behavior with macro level effects, however the main limitation is that a significant number of details may be required to properly represent systems and the resulting model may be stochastic. Below are shown some applications of ABM models to strategic buildings such as hospital which need to remain functional right after extreme event like earthquakes. For example in Fig. 5 is shown the model [15] of the Emergency Department (ED) of the Italian Mauriziano Hospital "Umberto I" which is a *discrete event simulation model* developed using the software PROMODEL. The purpose of the model is to improve the efficiency of the system by minimizing the waiting time [16] of the patients before receiving assistance. Patients are modeled as "entities" which are distinguished according to their codes (red, yellow, green and white) according to the type of injury using a procedure called "triage".

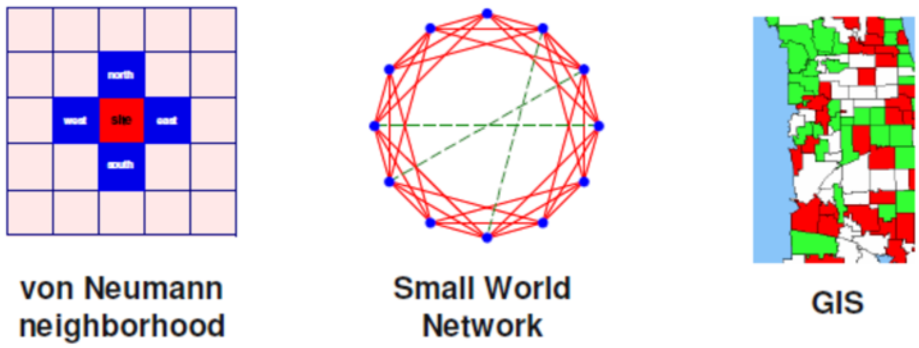


Figure 4 Simulated environment for local interaction among agents

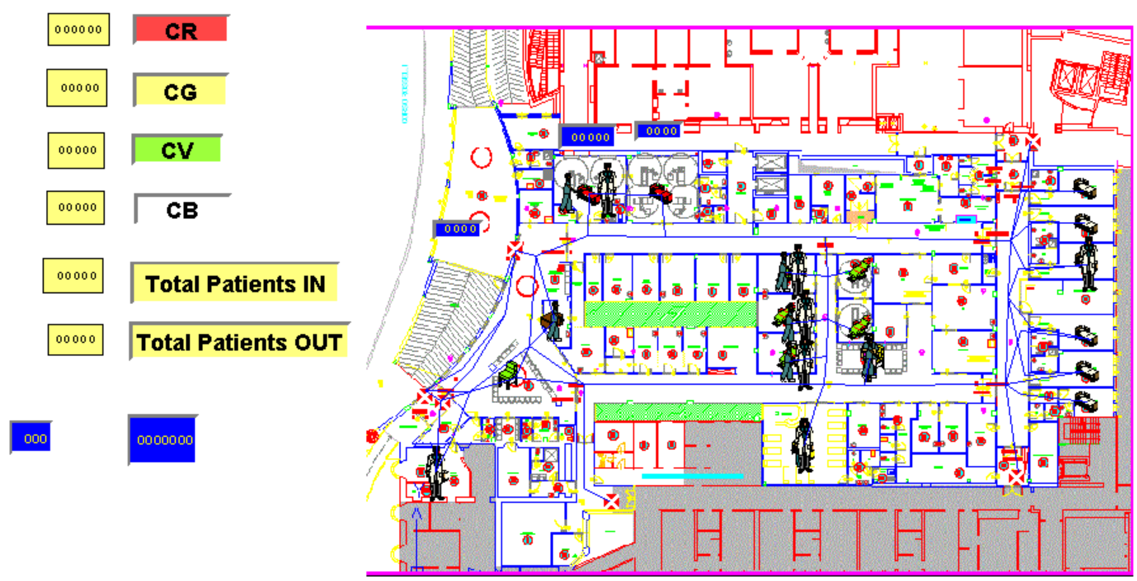
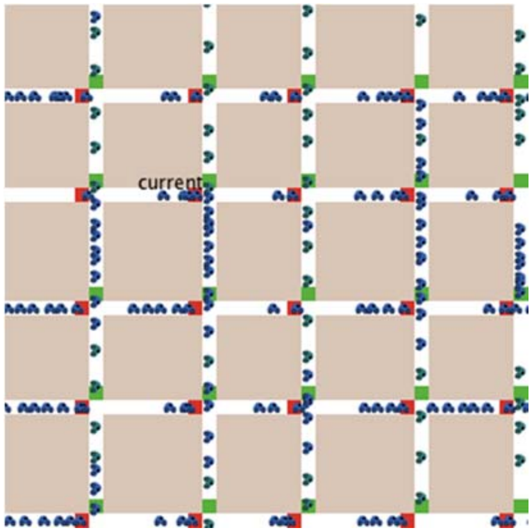


Figure 5. Discrete event simulation model of the Emergency Department of the Mauriziano Hospital in Turin.

Therefore, after triage, patients can follow different path in the simulated environment according to the code. The waiting rooms, the fist-aid stations and the recovery rooms which represent all the rooms involved in the process are modeled as "locations". In the modeled ED, there are two waiting rooms, in which patients wait before being processed, seven first-aid stations, used by red codes, and seven recovery rooms, in which patients can stay before being discharged or transferred in another part of the hospital. The entire staff which works inside the ED is modeled as "resources". The Mauriziano Hospital staff includes seven doctors, nine nurses, four assistants and two health workers. The patients and staff follow paths which are described from the entry to the discharge by means of several processes that model all the actions performed in the ER. Another application is the traffic grid model [17] developed in NETLOGO. The model can control traffic lights, the speed limit and the number of cars, in a real-time traffic simulation. This model can be used also to test different agent with different behavior rules in a given simple environment. Other interesting applications that can be used to evaluate resilience of a given region are the Urban site- Economic Disparity [18].



(a)

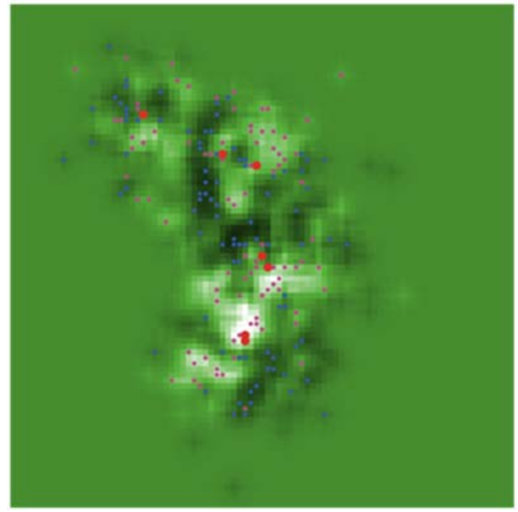

(b)

Figure 6. (a) Traffic grid model developed in NETLOGO; (b) Urban site- Economic Disparity in NETLOGO

This model explores residential land-usage patterns from an economic perspective, using the socio-economic status of the agents to determine their preferences for choosing a location to live. It models the growth of two populations, one rich and one poor, who settle based on three properties of the landscape: the perceived quality, the cost of living, and the proximity to services (large red dots) (Fig. 6b). The advantage of using these models is in predicting agent (e.g. infrastructures) behaviors and describing possible restoration paths after dynamic alteration of system equilibrium. These models will allow identifying causes and sources of uncertainties.

Conclusions

Agent-based simulation can be applied to evaluate of resilience of complex systems under extreme events. The simulations can find applicability in several fields such as in Economics (trade, financial markets, manufacturing, operations etc), but also in transportation network and in any type of infrastructure where agents are involved. In fact, as infrastructures are becoming more complex there is need for inserting agents, whose behaviors and decisions can affect the performance of the networks. Their use is essential in the infrastructures where agents can learn and engage in dynamic strategic behaviors and where agents can have dynamic relationships each other. In the long term, ABM will be used as a decision-making tool for various governmental agencies and private organizations working with emergency management. This requires an approach that brings together a broader spectrum of knowledge, skills, and expertise to study the policy impacts of critical infrastructure assessment, management, and planning.

Acknowledgments

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