CELLULAR DISCRETE-EVENT MODELS FOR SOCIAL SYSTEMS

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ABSTRACT

Understanding and predicting how people behave collectively is becoming crucial in many fields including marketing, military, psychology, anthropology, economics or epidemiology. Social simulation provides a useful tool to address this problem. Although numerous research works have been published, only a few have formally described the models used to represent the human behavior and the interaction between the individuals. The aim of this work is, from a practical point of view, to show how social simulation problems can be formally described under the Cell-DEVS formalism and to probe their functionality by showing results from them, implemented through the CD++ simulator.

Keywords: Social Simulation, DEVS, Cell-DEVS, CD++

1 INTRODUCTION

Individuals modify their opinions, attitudes, beliefs, or behavior through social interactions (Flache et al. 2017). The modeling of such individual behavior and of different social interactions has applications in a variety of fields, ranging from marketing, military, psychology, human-machine interface, economics, epidemiology, etc. The main problem is that even in simple cases it is difficult to understand the aggregate behavior of groups of people whenever they interact over any significant period. This is due to the nonlinear interaction effects between individuals and the interplay between individual behavior and social dynamics and structures (Squazzoni, Jager, and Edmonds 2014). Likewise, the interaction between individuals may give rise to interesting self-organization phenomena and emergent properties, which cannot be understood from the behaviors of the single elements or by adding them up (Helbing 2012) .

The results obtained from social simulation are important to analyze, predict and even modify the social phenomena resulting from individual behavior and group interactions. Actions can be performed to lead the social behavior towards a desired one, like public policies or rules changes inside organizations.

There are several ways to construct models to perform social simulations, in most cases through the literature on this field, the models proposed are solutions ad-hoc for a specific problem with no formal definition, and this approach makes the models hard to understand, reuse and compare with new ones. Having a formal model allows to deal with this problem. On one hand it allows to define unequivocally the model's details and on the other hand allows the reuse of the models, the main ideas can be extracted from previous approaches easily and new models can be compared and build from existing ones. In order to do this, we used the Cell-DEVS formalism, an extension of the DEVS formalism. The models presented here were formally defined as Cell-DEVS models and later implemented using the CD++ simulator, an uncomplicated way to implement and visualize Cell-DEVS models.

We introduce an experimental approach, in which the problems under consideration were formally described and assessed under different scenarios. Our aim is to show the use of the Cell-DEVS formalism can be used to model social problems in a simple but formal way (departing from existing informal ad-hoc methods traditionally used in social simulation), probing the versatility of the formalism to represent diverse social simulations.

The results presented show the diversity of social phenomena that can be modeled with a method like Cell-DEVS, a formal method that makes the definition of the models easier to evaluate and reuse, and its usefulness to model and simulate diverse and complex social phenomena and understanding emerging social behavior.

2 BACKGROUND AND RELATED WORK

Since the 60's there have been a lot of efforts to model and simulate social sciences (Gilbert and Troitzsch 2005). For instance, (Squazzoni et al. 2014) presents a survey on how simulation can be applied to various areas of social sciences. The models proposed in the field are diverse as social simulation itself, but according to (Garson 2008) they can be categorized in four classes: network models, spatial models, systems dynamics models and agent based models.

- Network models can be classified those using queuing theory and discrete event modeling (Gilbert and Troitzsch 2005) and those using neural networks and methods derived from artificial intelligence and cognitive science (Sabuncuoglu and Touhami 2002).
- Spatial models show how social influence is directly related to physical factors and physical distance (Liu et al. 1995). The capacity to combine spatial models with agent-based models has led to a variety of simulations that model dynamic processes in graphical (spatial) formats, in which change over time in the simulation is driven by agents (Heppenstall et al. 2011).
- Systems dynamics models involve systems of equations for modeling. These models were widely used during the 1960's and 1970`s (Forrester 1970; Meadows et al. 1972) and they are still being used; for example, (Karami et al. 2017) proposed a model to measure social impact. The main disadvantage of this kind of models is the complexity to build them a huge amount of knowledge is required both mathematical and of the problem itself. Similarly, the models proposed in this category are specialized to solve to a particular problem and cannot be generalized.
- Agent based models are commonly used for social simulation (Davidsson 2001; Lane 2018). In (Wilensky and Rand 2015), the authors reported that thousands of agent-based models have been published in the past decades. Agent simulation languages and systems, such as SWARM (Iba 2013), RePast (North et al. 2013), Ascape (Inchiosa and Parker 2002), NetLogo (Wilensky and Rand 2015), and Mason (Cioffi-Revilla and Rouleau 2010) have stimulated the use of agents models in many research fields, including social simulation. The main advantage of these models is the capacity to be built from simple rules in a bottom-up way. The models resulting from this approach are simple to understand. Therefore, the models in this category have become a most common way to simulate social phenomena.

Nevertheless, the literature only includes a few formalized models, and in most cases, this is proposed in a simple algorithmic way. This makes it difficult to reason about the problem at hand, and hard (or almost impossible) to reuse the software or partial the ideas from existing models to create new ones. The advantage of having a formal description is that those problems can be resolved easily, as the formalism gives a mathematical notation to reason about the models, as we will show later with the models described with Cell-DEVS, and extension to the DEVS formalism (Discrete Event System Specification) for modeling Discrete Event Systems (Zeigler, Praehofer, and Kim 2000). The hierarchical and modular structure of DEVS allows defining multiple models that are coupled through their inputs and outputs. In the same way, the resulting model can also be coupled with other models defining multiple layers in the hierarchical structure. In DEVS, atomic models define the behavior of the system, and coupled models describe the structure of the system. The hierarchical and modular structure of DEVS allows model reuse and reduces development and testing times. The model definition, implementation, and simulation are separated. One main advantage in this model is that the abstract simulation mechanism is independent of the model itself.

The DEVS formalism supports an open approach to formalism extension, allowing the researcher to explore new extended or specialized formalism (Zeigler and Vahie 1993). These extensions help the development of models for various applications in many different domains such as biology, engineering, and sociology. (G. A. Wainer 2009) proposed the Cell-DEVS formalism to describe cell spaces as discrete-event models where each cell is represented by a DEVS basic model component to combine the advantages of cell and DEVS methodologies in a systematic way. Using a modular interface, each DEVS basic model can communicate with its neighboring cells in the cell space, as well as other models outside of the cell space. Cell-DEVS is a combination of cell and DEVS that allows the implementation of cellular models with timing delays. A Cell-DEVS model is defined as a lattice of cells holding a state variable and a computing apparatus to update the cell state. This is done using the present cell state and a set of inputs coming from cells in the neighborhood. Cell-DEVS improves the execution performance of cellular models by using a discrete-event approach. It also enhances the cell's timing definition by making it more expressive. Each cell is defined as an atomic model using timing delays. It can be later integrated to a coupled model by putting together a number of cells interconnected by a neighborhood relationship.

To implement the Cell-DEVS models, the CD++ tool provides a language and an API to build both DEVS and Cell-DEVS models. The architecture and the implementation of the CD++ simulator allow simple definition and reuse of components (G. Wainer 2002; G. A. Wainer 2009). In CD++, the local transition function is defined as a set of rules. They are implemented following the CD++ high-level language with the form:

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rule: POSTCONDITION DELAY { PRECONDITION }
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This expression indicates that when the PRECONDITION is satisfied, the state of the cell will change to the designated POSTCONDITION, whose computed value will be transmitted to other components after consuming the DELAY. If the precondition is false, the next rule in the list is evaluated until a rule is satisfied or there are no more rules,

As mentioned earlier, few researches have modeled social simulation problems formally. For instance, in (Seck et al. 2007) the authors describe a formal model to study human behavior in military forces. DEVS has been used for building evacuation (Wang et al. 2017), the impact of human interaction, for instance, (Behl, Wainer, and Ruiz-Martin 2018) focuses on how human interactions can influence human behavior and (Bouanan, Zacharewicz, and Vallespir 2016) proposes a model to social interaction and influence during a product launch.

In the following sections we show a practical application about how different problems in social simulation can be modelled by the Cell-DEVS methodology.

3 CELL-DEVS MODELS OF SOCIAL INTERACTION

In order to show how social simulation problems can be formally described with Cell-DEVS, we introduce two different case studies. The two problems are significant different in scope, size and goals. The first of them focus on the employees' behavior in a complex workplace. The second one presents the case study of the urban population grow of a region in China. The idea is to show a variety of representations of models and their definition as Cell-DEVS specifications and their implementation in the CD++ tool.

3.1 Employee Behavior Model

Employees are a fundamental part of every organization, and their behavior can have a significant impact on the success of the organization. Studying the employees' behavior, it is important to lead them from a negative behavior to a positive one (Somers 2001). It is not easy to study and see the employees' behavior from general mathematical models. However, the cellular models have been used to simulate the employees' behavior, because each one of the employees affects and its affected by its neighbors and this process is self-reproducing.

Based on the model proposed by (Jiao, Sun and Sun 2007) we show an extension built as Cell-DEVS. The model considers three possible behaviors by the employees: Positive Behavior (PB), the behavior that the organization wants to encourage, Negative Behavior (NB), the behavior the organization wants to eliminate and Zero Behavior (ZB) a behavior not encouraged or forbidden. Employees in the organization are looked as the cell space, and each employee is a cell. Distance between cells is not the distance in physics, but in psychology and behavior. Each cell is influenced by its neighbors, and at the same time influences others, which cause the evolution and the update of the employee behavior. The closer the distance is, the more influence, and vice versa.

In the cell space, every cell at the *i, j* position, can be represented using three states values representing behavior at time *t*, namely $S_{i,j}^{t} = \{-1,0,1\}$ where 1 is the PB, 0 is the ZB and -1 is the NB. Similarly, two characteristics related to the employees' behavior are modelled: influence and insistence. Influence represents the extent on which the employee affects their neighbors. Insistence is the extent of the employee's holding their own behavior. High-Insistence employees are rarely affected by their neighbors. In this way each cell has two characteristics: influence $INF_{i,j} = \{1,2,3\}$ and insistence $INS_{i,j} = \{1,2,3\}$, and each characteristic has three degrees.

Employee behavior is affected by their neighbors. Different neighbor behavior makes different influence on the cell. The cumulate influences of PB, NB, and ZB neighbors on one given cell are separately called Positive, Negative, and Zero Environmental Disturbances Degree, formulated by:

$$ped_{i,j}^{t} = \sum_{i=i+2}^{i+2} \sum_{j=j-2}^{j+2} \frac{INF_{i',j'}}{\sqrt{(i'-i)^2+(j'-j)^2}}, S_{i',j'}^{t} = 1 \tag{1}$$

$$ned_{i,j}^{t} = \sum_{i=i+2}^{i+2} \sum_{j=j-2}^{j+2} \frac{INF_{i',j'}}{\sqrt{(i'-i)^2+(j'-j)^2}}, S_{i',j'}^{t} = -1 \tag{2}$$

$$zed_{i,j}^{t} = \sum_{i=i+2}^{i+2} \sum_{j=j-2}^{j+2} \frac{INF_{i',j'}}{\sqrt{(i'-i)^2+(j'-j)^2}}, S_{i',j'}^{t} = 0 \tag{3}$$

Where i' and j' are indices for the neighborhood of each cell, i and j represent the cell of interest. Similarly, the following local rules are defined:

(a) When $S_{i.j}^{t}$=1, if $ped + INS_{i,j} = \max\{ped + INS_{i,j}, ned, zed\}, then\ S_{i,j}^{i+1} = 1$; else, if $ned > zed$, then $S_{i,j}^{t+1} = -1$; if $zed > ned$, then $S_{i,j}^{t+1} = 0$; if $zed = ned$, then $P\{S_{i,j}^{t+1} = 0\} = 0.5$, $P\{S_{i,j}^{t+1} = -1\} = 0.5$.

(b) When $S_{i.j}^{t}$ = -1, if $ned + INS_{i,j} = \max\{ned + INS_{i,j}, ped, zed\}, then\ S_{i,j}^{i+1} = -1$;

else, if $ped > zed$, then $S_{i,j}^{t+1} = 1$; if $zed > ped$, then $S_{i,j}^{t+1} = 0$; if $ped = zed$, then $P\{S_{i,j}^{t+1} = 0\} = 0.5$, $P\{S_{i,j}^{t+1} = -1\} = 0.5$.

(c) When $S_{i.j}^{t}$ = 0, if $zed + INS_{i,j} = \max\{zed + INS_{i,j}, ped, ned\}, then\ S_{i,j}^{i+1} = 0$; ;

else, if $ped > zed$, then $S_{i,j}^{t+1} = 1$; if $ned > ped$, then $S_{i,j}^{t+1} = -1$; if $ped = ned$, then $P\{S_{i,j}^{t+1} = 1\} = 0.5$, $P\{S_{i,j}^{t+1} = -1\} = 0.5$.

The organization want to encourage good behavior and to forbid unruly behavior. In order to so do, the following rules were proposed. To encourage the PB of employees Formula 4 is used and to punish the NB of employees Formula 5 is used.

$$ped_{i,j}^{t} = \sum_{i=i+2}^{i+2} \sum_{j=j-2}^{j+2} \frac{\alpha INF_{i',j'}}{\sqrt{(i'-i)^2 + (j'-j)^2}}, S_{i',j'}^{t} = 1 \tag{4}$$

$$ned_{i,j}^{t} = \sum_{i=i+2}^{i+2} \sum_{j=j-2}^{j+2} \frac{\beta INF_{i',j'}}{\sqrt{(i'-i)^2 + (j'-j)^2}}, S_{i',j'}^{t} = -1 \tag{5}$$

Where $\alpha \in R$, $\alpha > 1$, $\beta \in R$, $0 < \beta < 1$.

These rules can be formally modeled as Cell-DEVS equations, using a 3D model in which each rule is associated to a different plane in the model, as seen in Figure 1. Plane 0 defines the employee behavior, plane 1 the influence plane, and plane 2 the insistence plane.

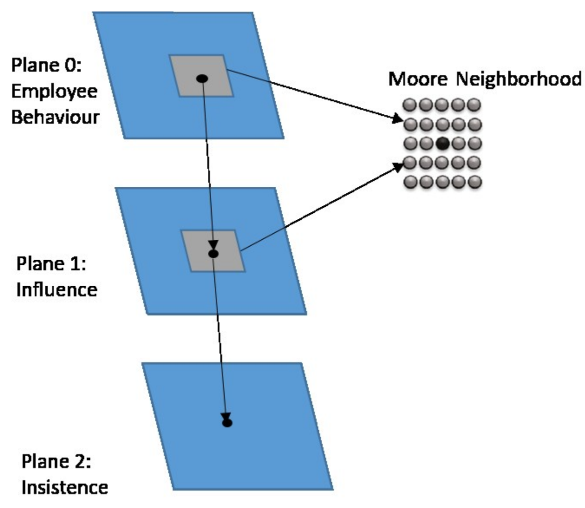

Figure 1: Neighborhood of cells in plane 0.

Each cell in plane 0 represents an employee that can have 3 states: -1, 0 and +1, corresponding to PB, ZB and NB. Each cell in Plane 0 uses an extended Moore's neighborhood with 25 cells at the same plane, plus a Moore's neighborhood with 25 cells in plane 1, and its corresponding cell in plane 2, as shown in Figure 1. Each cell in the influence plane (plane 1) can have values 1, 2 or 3, representing the degree of influence the employee has on its neighbors. A value of 1 means that the employee has little influence, 2 means it has medium influence and 3 means it has major influence. Each cell in the insistence plane (plane 2) can have values 1, 2 or 3 and this value represents the degree of insistence the employee has (the capacity of being affected by other employees' behavior). A value of 1 means the employee is little affected by other, a value 2 means is moderately affected by others, and a value of 3 means they are highly affected by others.

The rules of the Employee behavior model are defined such that only the cells in plane 0 which represents the actual behavior of each employee changes. The influence and insistence values for each employee (plane 1 and plane 2 respectively) are always the same. However, note that the influence and insistence of a cell is used to determine the employee behavior of that cell (in plane 0). In addition, the model is defined such that if cell (0,0,0) represents an employee, the corresponding cell in plane 1 cell (0,0,1) is that employee's influence value and similarly the corresponding cell in plane 2 which is cell (0,0,2) is that employee's insistence value.

A cell space of 225 cells (15 x 15) was used to experiment with this model. As this number of cells corresponds to a small medium enterprise (SME). The initial values of the cells in Plane 0 were specified such that although the state of the cells is set random, there is a 1:1:1 proportion of PB, NB and ZB states. The insistence and influence planes were defined with the cell values 1,2 and 3 distributed uniformly. The model was written using the CD++ tool and loaded on the Cell-DEVS Simulation Viewer to produce the visual representation shown in Figure 2. The cells with value 0 have the black color, the cells with value 1 have the red color, the cells painted with value 2 have the red color, the cells with value 3 have the purple color and the cells with value 4 have green color.

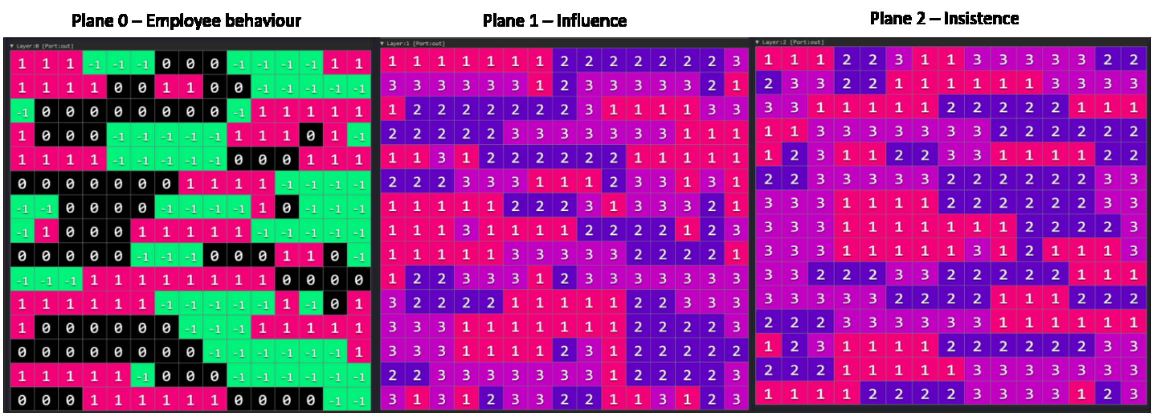

Figure 2: Initial values of the cell space.

We show the results of three different experiments that show the model execution under different assumptions. In the first, one no encouragement policy factor or punishment policy factors were considered. The state of the cell space at the end of the simulation period is shown in Figure 3. Note that the Influence and Insistence planes remain constant but the Employee behavior plane changes to mostly positive behavior (PB) cells, some zero behavior (ZB) cells and no negative behavior (NB) cells.

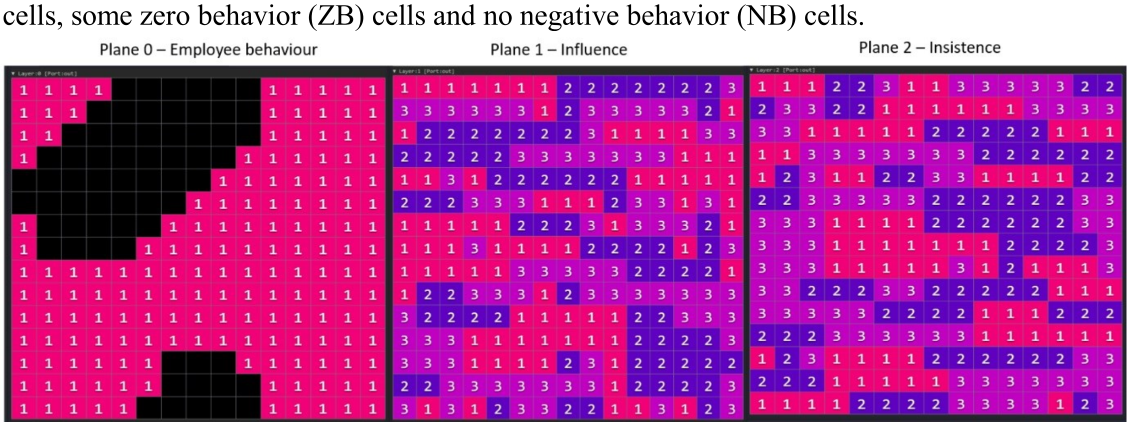

Figure 3: Final cell values after experiment 1.

The second experiment was performed simulated using *ped* as defined in Equation (4) with $\alpha = 1.1$, while *ned* and *zed* are as defined in Equations (2) and (3) respectively. The resulting cell state space is shown in Figure 4 below. The highlighted area shows the new positive behaviors cells.

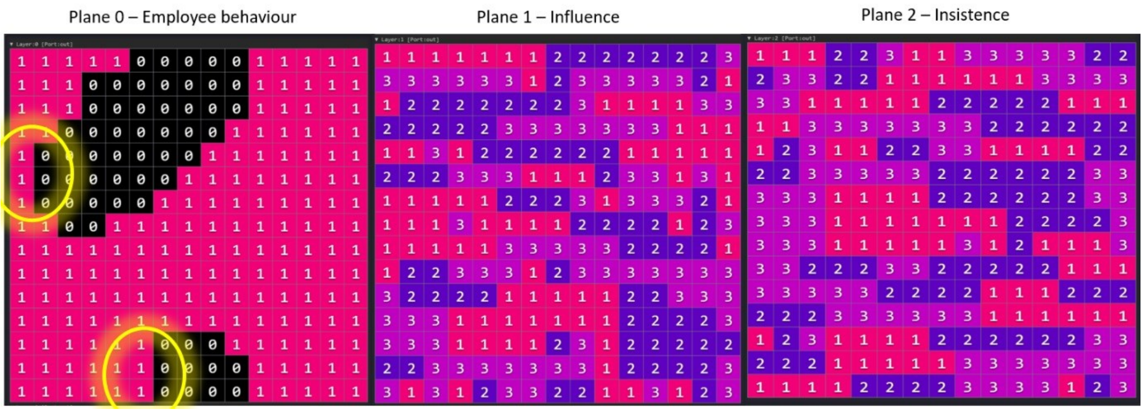

Figure 4: Final cell values after experiment 2.

Finally, an experiment was executed using *ped* as defined in Equation (4) with $\alpha = 1.1$ and *ned* as defined in Equation (5) with $\beta = 0.9$, while *zed* is used as defined in Equation (3). In this test, we check the effect of discouraging NB and encouraging PB simultaneously. For this case there was not an improvement in the positive behaviors cells if we compare it with experiment number 2.

3.2 Urban Growth Model

In recent years there have been numerous efforts on the application of social simulation for the prediction of urban growth. Individuals' decisions on where to live can create people's concentration in big cities as well as in unpopulated areas. Throughout the world there are diverging policies in the management and control of the environment, land use, scale and arrangement of settlements that leads to specific urban growth. The model in this section focuses on a case study for the Changjiang Delta Region in China. This area covers 75,900 km^2 of land with 10,200 km^2 of water bodies. There are 16 regional-level cities, 28 county-level cities and 1700 towns. The area is shown in Figure 5.

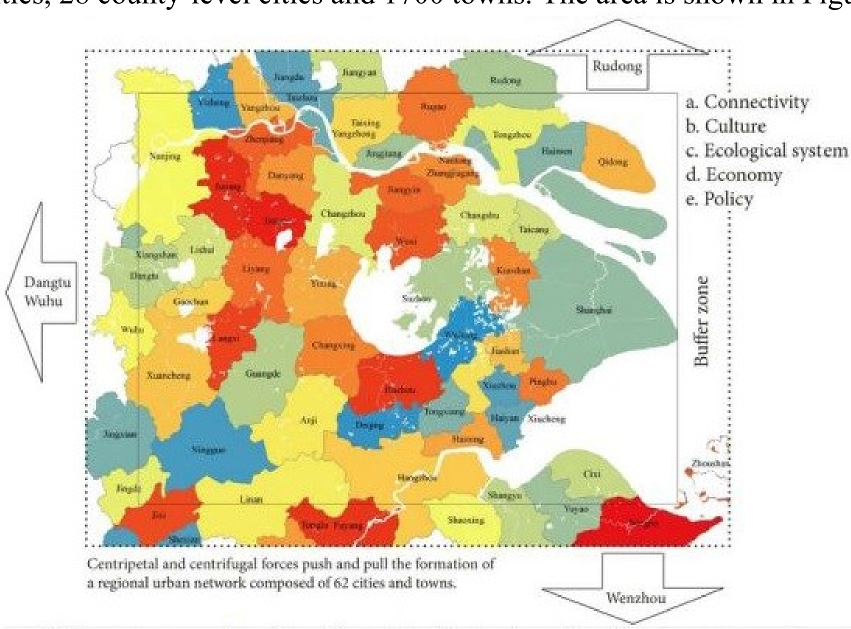

Figure 5: Study Area of the Changjiang Delta Region.

Several factors for city growth in the subsections of this area are considered, in particular: development corridors, corridors with big city growth, ecological system concerns, and disaster prevention with development corridors. All these factors impact in the development of the area. The complete information and the formulas used for this case study can be found in (Guan and Rowe 2016). In this case study we will focus on modelling the impact of big cities in the urban growth. In the mentioned work above, this is called "corridors with big cities". The formula for the city growth on a cell in this scenario is the following:

$$G_{\text{total}}^{t+1} = \sum G_{\text{spontaneous}(i,j)}^{t+1} + G_{\text{spread}(i,j)}^{t+1} + G_{\text{edge}(i,j)}^{t+1} + G_{\text{road}(i,j)}^{t+1} + G_{\text{corridor}(i,j)}^{t+1} + G_{\text{city}(i,j)}^{t+1} \qquad (6)$$

Where:

G_{total}^{t+1} is the total urban growth prediction, at year t+1; $G_{spontaneous(i,j)}^{t+1}$ is the spontaneous grow, the occurrence of random urbanization of land, at year t+1; $G_{spread(i,j)}^{t+1}$ is the spread the urban spreading of newly urbanized land cell, at year t+1; $G_{edge(i,j)}^{t+1}$ edge growth, the further expansion of newly spread cell, at year t+1; $G_{road(i,j)}^{t+1}$ is the road influence road at year t+1; $G_{corridor(i,j)}^{t+1}$ is the development corridor grow, at year t+1 and $G_{city(i,j)}^{t+1}$ is the big cities growth, at year t+1.

The formal model Cell-DEVS model to represent this problem is the following:

$$CDR = \langle X, Y, S, \theta, N, d, \delta_{\text{int}}, \delta_{ext}, \tau, \lambda, ta \rangle,$$

Where: $X = \{G_0\}$, $Y = \{G_{total}\}$, $S = \{G_{total}^t\}$, $\theta = \{G_{spon\text{taneous}}^t, G_{s\text{pread}}^t, G_{\text{edge}}^t, G_{road}^t, G_{\text{corridor,}}^t G_{\text{city}}^t,\}$, $N = \{[-1,-1],[0,-1],[1,-1],[-1,0],[1,0],[-1,1],[0,1],[1,1]\}$, $d =$ transport delay. δ_{int}, δ_{ext}, λ and ta are defined using the Cell-DEVS specifications. G_0 represents the initial cellular automata and τ is defined according to Formula 6.

A cell space of 900 cells (30 x 30) was used to experiment with this model, each cell has its own information about its growing potential defined in the θ set.

To show the model execution, we conducted an experiment with real values from the region, as shown in the first picture in Figure 6. Blue cells represent basic settlements, turquoise are roads, orange are development of the corridors and the pink ones are cities.

Figure 7 shows how the model evolves in time. To compare our model's results an overlap with the real map of the region, we over impose the simulation results and the area map in Figure 8. There is a similarity in the big urban centers locations as well as in the unpopulated areas.

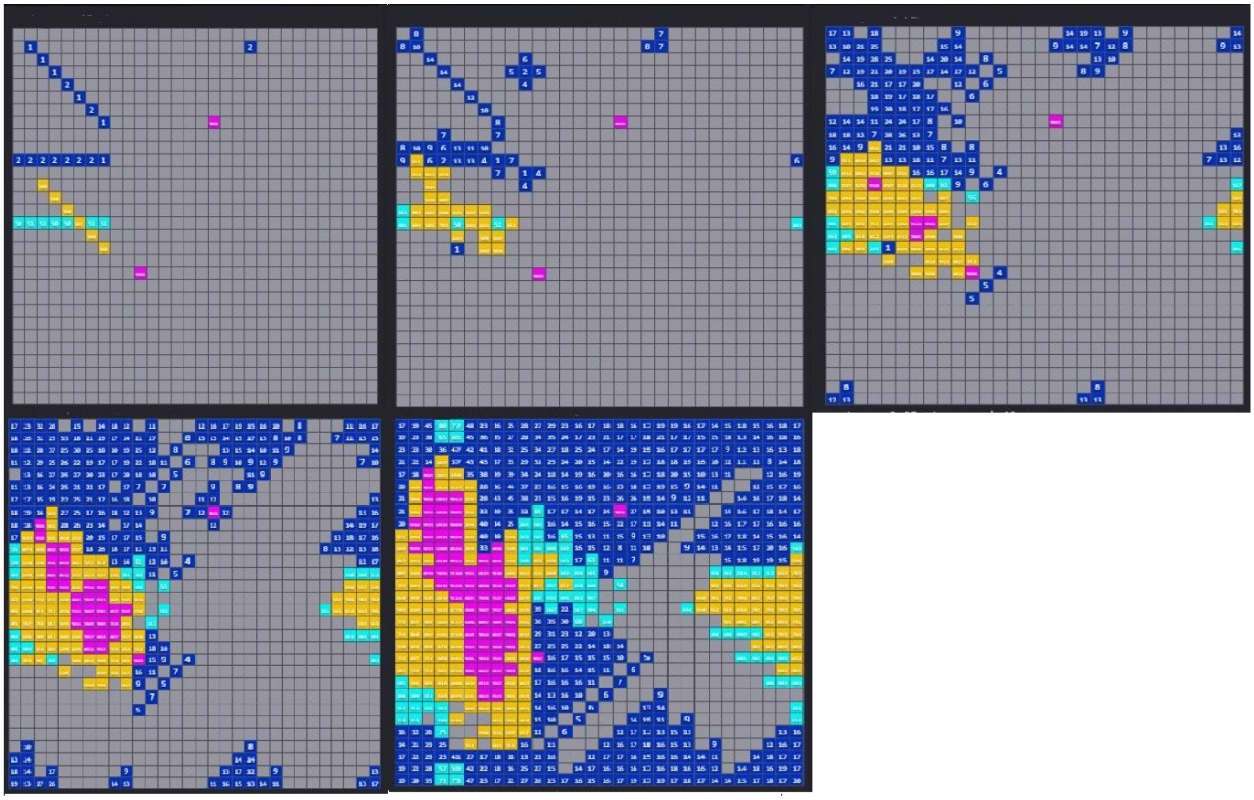

Figure 6: Model evolution.

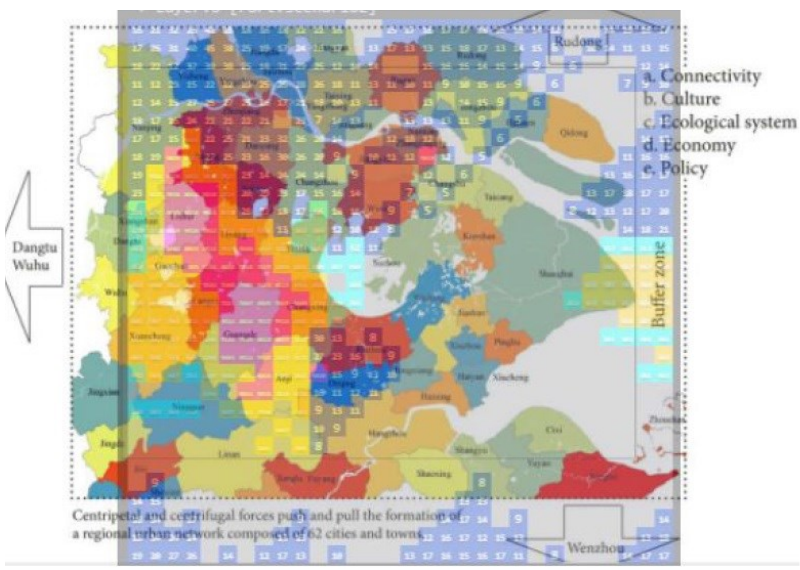

Figure 7: Comparison of our model's result with region.

4 CONCLUSIONS AND FUTURE WORK

We introduced the representation of social simulation analysis through the Cell-DEVS formalism and simulation results for these models were obtained by testing different scenarios with the CD++ tool. Through this study we show how Cell-DEVS is suitable for different social simulation problems. The models proposed give a starting point to model similar problems. As future work we propose to keep adding formally defined models in this topic and to make a comparative analysis with them. This way a characterization can be made to define some modelling patrons that can be applied to represent common features of interaction between individuals.

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