Forest Fire Modelling using Rule-Based Fuzzy Cognitive Maps and Voronoi Based Cellular Automata

João Paulo Carvalho   Marco Carola   José A. B. Tomé

INESC-ID - Instituto de Engenharia de Sistemas e Computadores

IST – Instituto Superior Técnico

R. Alves Redol, 9, 1000-029 LISBOA, PORTUGAL

Phone: +351.213100238   Fax: +351.213145843

E-mail: joao.carvalho@inesc-id.pt   marco.carola@gmail.com   jose.tome@inesc-id.pt

***Abstract* — This paper focus on the modelling and simulation of forest fire propagation using Dynamic Cognitive Map Cellular Automata, where Rule Based Fuzzy Cognitive Maps are used to represent the evolution of burning areas in Voronoi region based cells.**

I. Introduction

Forest Fire propagation is a complex spatial and temporal dynamic process that depends on a large number of uncertain and imprecise factors such as wind, slope, type of vegetation (also known as fuel), temperature, humidity, etc. Many approaches to forest fire propagation modeling have been previously proposed with varying degrees of success and limitations. A great range of techniques have been used in those approaches, from pure "crisp" mathematical models (usually based on the Rothermel equations), to cellular automata and models based on computational intelligence techniques (neural nets, fuzzy sets, etc.), but none can claim to be an ideal solution to the problem due to several reasons:

- Pure crisp models cannot deal with the variety of real world terrain and the uncertainty of fire propagation factors, and most dynamic models do not integrate well with GIS due to fundamental incompatibilities in conceptual representation of space and time [1][2][3];
- Cellular automata models have improved through time (especially with the use of Voronoi region based cells [4][5]) but are still limited in what concerns modeling fire behavior in each individual cell and, therefore, fire propagation[6][7][8];
- Individual computational intelligence techniques present potentially interesting but, up to date, limited solutions with limited applicability and results [6][9].

In order to model and simulate forest fire propagation we propose the use of Rule Based Fuzzy Cognitive Maps and Voronoi based fuzzy Cellular Automata. This Fuzzy Set theory based approach tries to consolidate and take advantage of previous approaches strong points:

- The spatial propagation nature of forest fire is modeled using cellular automata principles;
- Cells are based on Voronoi region tessellations obtained from Fuzzy Geographical Information Systems (Fuzzy GIS), which allow a much more proper real world modeling;
- Forest fire cell dynamic behavior is modeled using meta-states and Rule Based Fuzzy Cognitive Maps (RB-FCM) [10][11][12][13], which are a tool to model and simulate complex and uncertain system dynamics. In the proposed approach each meta-state contains a RB-FCM that is simulated when its meta-state is active, and transition between meta-states occurs when the active RB-FCM reaches certain conditions;
- Factors such as Fuel computation are based on fuzzy adaptations of crisp equations with a strong theorical background.

In this paper we describe the details of the proposed RB-FCM Voronoi Cellular Automata approach to Forest Fire modelling and simulation, and present a simulation based on real world geographic data.

II. Irregular Cellular Automata

A. The Voronoi Spatial Model and Voronoi Based Cellular Automata

Regular Cellular Automata (CA) have cells with identical shape and size. Since geographic features in nature are usually not distributed uniformly, regular spatial tessellation obviously limits modelling and simulation potential of regular CA. In order to overcome this limitation, several authors have extended the CA model to irregular cells. The most successful

* This work was supported in part by the FCT - Portuguese Foundation for Science and Technology under project POSI/SRI/47188/2002

approaches use the Voronoi spatial model [4][5][14].

The Voronoi spatial model is a tessellation of space that is constructed by decomposing the entire space into a set of Voronoi regions around each spatial object. By definition, points in the Voronoi region of a spatial object are closest to the spatial object than to any other spatial object. The generation of Voronoi regions can be considered as 'expanding' spatial objects at a unique rate until these areas meet each other. The mathematical expression of the Voronoi region is defined as [14]:

$$V(p_i) = \{p \mid d(p, p_i) \le d(p, p_j), j \ne i, j = 1...n\} \quad (4)$$

In this equation, the Voronoi region of spatial object p_i, $V(p_i)$, is the region defined by the set of locations p in space where the distance from p to the spatial object p_i, $d(p, p_i)$, is less than or equal to the distance from p to any other spatial object p_j.

Voronoi region boundaries are convex polygons. Points along a common boundary between Voronoi regions are equidistant to the corresponding spatial objects. Objects which share a common boundary are neighbours to each other in the Voronoi spatial model.

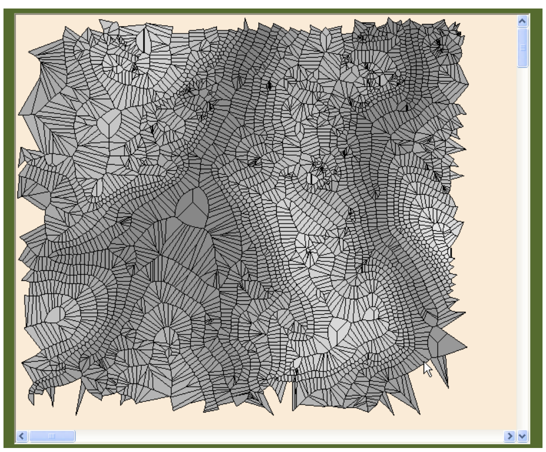

Fig. 1- Voronoi regions: on hilly terrain, the Voronoi space model allows a better modelling of terrain Slope, which, after Wind, is the most influent factor in fire propagation direction and velocity

A Delaunay triangulation in which each edge of the triangle implies the neighbouring relations of two objects is a dual representation of the Voronoi spatial model that is useful in many calculations. An edge of the Delaunay triangle must be associated with each pair of neighbours in the Voronoi spatial model.

One immediate consequence of using Voronoi Regions as cells is that the number of neighbours is no longer constant, which means that CA cell state transition rules must be flexible to cope with this change.

On a Voronoi Based Cellular Automata (VB-CA), each cell is associated to a given relevant spatial object or feature of a relevant spatial object. Examples of features that can be used to create a space tessellation when modelling a forest include *Altitude*, *Type of Vegetation*, *Humidity*, *Degree of Imunity*, *Income*, etc. The tessellation would mean, taking *Altitude* as an example, that each point in each Voronoi region would have a more similar altitude to the centre of its region than to the centre of any of its neighbours.

B. *Fuzzy Cellular Automata*

Fuzzy Cellular Automata (FCA) differ from CA by using a set of fuzzy variables to define its state, and by using a Fuzzy "*IF…Then*" Rule Base (FRB) as the set of transition rules. The FRB infers the next automata state, based on current fuzzy state and current fuzzy inputs (fuzzy antecedents).

The use of Rule Based Fuzzy Systems to model cell state and cell state transition has the obvious and known advantages of both allowing an easy way to model expert knowledge, and a proper way to model expert and data uncertainty and imprecision. It also allows an easier and more proper integration with Fuzzy GIS, which are being increasingly acknowledged as a solution to GIS modelling of real world specificities, like, for example, how to classify areas located in the transition zone between a rural and an urban area [15].

However, Rule Based Fuzzy Systems with Feedback suffer from the problem of an uncontrolled spread in uncertainty representation due to the intrinsic characteristics of classical fuzzy inference, that not even type-2 uncertainty representation can address [16]. This fact seriously hinders Fuzzy CA implementations, especially in what concerns cell state transitions. The best available solution to overcome this problem is to use Rule Based Fuzzy Cognitive Maps [10].

III. RULE BASED FUZZY COGNITIVE MAPS

Rule Based Fuzzy Cognitive Maps (RB-FCM) were introduced in [11][12][13] and were developed as a tool to model and simulate real world qualitative system dynamics while avoiding the limitations of FCMs [10][17], but maintaining their versatility in what concerns ease of change in the model, due to the fact that rule bases are not subject to combinatorial rule explosion due to the use of a new fuzzy operation – the Fuzzy Carry Accumulation [18].

RB-FCM can be represented as fuzzy directed graphs with feedback, and are composed of fuzzy nodes (Concepts), and fuzzy links (Relations). Concepts are fuzzy variables described by linguistic terms, and Relations are defined with fuzzy rule bases.

RB-FCM are essentially iterative fuzzy rule based systems with fuzzy mechanisms to deal with feedback, timing mechanisms and new ways to deal with uncertainty propagation, and have several kinds of Concept relations (Causal, Inference, Alternatives, Probabilistic, Opposition, Conjunction, etc.) to cope with the complexity and diversity of the dynamic systems they can model.

There are two main classes of Concepts in RB-FCM: Levels, that represent the absolute values of system entities (e.g., Fire is Intense); and Variations , that represent the change in value of a system entity in a given amount of time (e.g., Fire_Intensity increased very much).

IV. Dynamic Cognitive Map Based Cellular automata

Dynamic Cognitive Map Based Cellular Automata (DCM-CA) try to take advantage of CA strengths on modelling the dynamics of spatial propagation and of Dynamic Cognitive Map strengths to model and simulate system dynamics. On a DCM-CA, cell dynamics (i.e. states and state transitions) are modelled and simulated using Dynamic Cognitive Maps (like FCM or RB-FCM). Cells should also, for obvious reasons, be based on Voronoi Regions. The integration of Voronoi Based CA with Dynamic Cognitive Maps is possible due to the fact that either FCM and RB-FCM have the capability to include or remove new inputs without the need of major changes in existing knowledge (rule bases in RB-FCM), or major loss in usability or performance. On a "classic" rule based fuzzy system, this approach would not be possible, since the simple fact of having a different number of neighbour cells would imply major changes in the cell rule base (and one does not need to mention the problem of rule number explosion as new antecedents are added to a rule base).

Conventional RB-FCM-CA uses a single RB-FCM to model cell behavior. Cell state is defined by the values of the RB-FCM Level Concepts. However, real world temporal and spatial propagation processes can be very complex. In some systems one might need to use more than one RB-FCM per cell to model cell behavior.

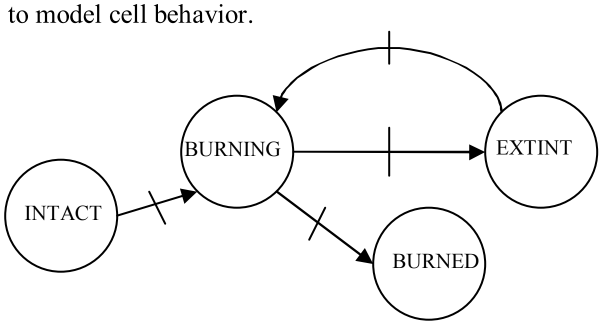

Fig. 2- RB-FCM-CA Cell Meta-states: Each meta-state contains a RB-FCM that is simulated when its meta-state is active. Transition between meta-states occurs when the active RB-FCM reaches certain conditions

A possible approach to model these systems is to define several cell meta-states, where each meta-state is a RB-FCM. Transition between meta-states occurs when, during simulation, the RB-FCM reaches certain conditions. Meta-states can be represented using state diagrams (Fig. 2).

V. Modelling and Simulation of Forest Fire Propagation

A. *Forest Fire Modelling*

Forest fire propagation is a complex spatial and temporal dynamic process that depends on a large number of uncertain and imprecise factors such as wind, slope, type of vegetation (also known as fuel), temperature, humidity, etc., being the first two the most important by a large margin.

Since slope is the most important non-variable factor in forest fire propagation [19], our model creates an altitude based Voronoi tessellation. The Voronoi regions are computed based on the orography of the area being modelled, which is obtained from a GIS database.

Each Voronoi region is associated with a cell in a CA. Besides *Height*, each cell has attributes for *Fuel*, *Local Slope*, *Dominant Wind Azimuth*, *Temperature* and *Moisture*. These attributes are present in common GIS, and can be Crisp or Fuzzy, according to the GIS nature. Temperature, wind and/or moisture can have real time values as long as sensors to measure and transmit real time data exist. Each cell is also associated with a parameter named *Ignition Factor*, which is computed based on the other cell attributes.

Due to forest fire propagation complexity, four different cell Meta-states were defined: *INTACT*, *BURNING*, *EXTINCT*, and *BURNED*. Fig. 2 represents a state diagram for transitions between the four Meta-states. Three of the Meta-states are associated to RB-FCMs: *INTACT*, *EXTINT* and *BURNING* (the first two sharing the same RB-FCM). State *BURNED* is a non-dynamic final state, and therefore does not need to be modeled by an RB-FCM.

B. *State Transition and Fire Propagation in CA Models*

CA Forest Fire propagation models usually use quite simple methods to simulate propagation between cells. In most approaches, e.g. [20][21], whenever a cell starts burning, it is calculated a time interval during which the cell will be in the *BURNING* (active) state. The time interval is computed based on cell characteristics, and can be more or less accurate depending on the model. When the time interval ends, the cell goes into state *BURNED*, and neighbour cells are ignited and enter the *BURNING* state.

Even assuming a perfectly accurate model to calculate burning time, this propagation model has many flaws and is unable to model fire propagation properly even though wind is used to model fire propagation direction and combustion. In fact, the model basically ignores wind effect in what regards fire propagation:

- In strong winds it is perfectly plausible that fire propagates to neighbour cells faster than complete combustion occurs;
- Under wind absence and an unfavourable slope it is perfectly plausible that fire can extinguish before propagating to other cells.

Other flaw in these propagation models is that the possibility of fire re-ignition is never considered.

One can say that these models are not hindered by the approaches used to model the dynamic process of fire combustion, but because of cellular automata limitations to cope with real-world complex systems.

In the proposed RB-FCM-CA approach, state transition and cell propagation are handled independently and take into consideration a number of parameters much closer to reality.

C. *State Transition and Fire Propagation in RBFCM-CA*

Initial state for all cells in the RB-FCM-CA is *INTACT*. In order for a target cell to ignite, one or more Voronoi neighbor cells must be in state *BURNING*, and geographic conditions must be favoring fire propagation to target cell. Fig. 4 shows the RB-FCM associated to meta-state *INTACT*.

The RB-FCM uses a variable number of inputs depending on the number of burning neighbors.

Fire Propagation Velocity from each burning neighbor ("source") is calculated using a chain of FIR (Fuzzy Inference Relations [11][12]) that includes fuzzy concepts such as Radiation and Convection, which use as inputs the most important factors related with fire propagation [19]:

- A measure relating wind strength, wind direction and orientation of source/current cell axis (given by the edge of the Delaunay triangle associated to both cells);
- Slope between current cell and source cell;
- Source local temperature;
- Source combustion intensity.

The above inputs can be either crisp or fuzzy according to the GIS system being used. Crisp inputs are fuzzified using relevant linguistic terms defined by experts. Fig. 3 represents linguistic terms for variable Slope. All FIR rule bases were also defined by experts. Currently, 133 rules are being used to infer Propagation Velocity.

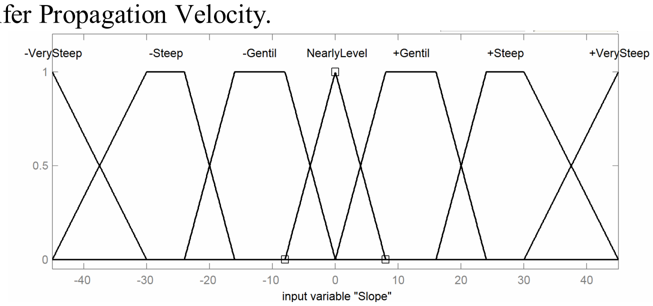

Fig. 3 –Linguistic terms for input Slope

The fire Propagation Rate from each source is calculated based on the inferred Propagation Velocity and on data from the involved Voronoi regions, using the following arithmetic equation:

$$\Pr opRate = \frac{4 \cdot (\Delta T * V \Pr op) \cdot AreaO \cdot Front}{Dist \cdot (AreaO + AreaD) \cdot \left(\sqrt{AreaD} + \sqrt{AreaO}\right)}, \qquad (5)$$

where ΔT is the iteration interval, VProp is the Fire Propagation Velocity from source cell, AreaO is the area of the source Voronoi region, AreaD is the area of the current Voronoi region, Dist is the distance between the centre of both cell Voronoi regions, and Front is the size of the frontier between both cells.

Propagation Rate from each burning neighbor is accumulated using an inverse FCR (Fuzzy Causal Relation). One must note that FCR are accumulative and their inference mechanism is independent from the number of antecedent neighbors.

The absolute value of Ignition Factor will decrease as the Propagation Rate effect from all neighbor burning areas accumulates as time passes.

Transition to *BURNING* state will occur when Ignition Factor reaches zero. Fig. 5 shows the RB-FCM associated to meta-state *BURNING*.

In our approach, contrary to other CA approaches, cell characteristics are not kept constant while the cell is burning. Other approaches attribute a given crisp [3][7][8][20][21][22] or fuzzy [6][9] value to factors such as Temperature or Humidity, and these values will be unchanged while the cell burns. However, this not the most realistic approach, since the burning process will locally cause those values to change, and these changes can affect the burning process itself. Using a RB-FCM allows us to model those local changes and provide a more realistic model. Scenarios like fire extinguishing itself, or drastic variations in fire intensity are possible with this approach. Causal influences between concepts are modeled using Fuzzy Causal Relation Rule bases (FCRBs), and concept variations are defined by linguistic terms such as "Increase_much", "Decrease_Very_Few" or "Maintains".

One of the most important concepts in the *BURNING* RB-FCM, is Local Convection. Although this concept is represented, for simplicity reasons, as an external input, it depends on local cell wind (which can change during the burning process) and on cell slope. Sudden variations in wind intensity and direction (which sometimes are a consequence of the burning process) associated to the slope of the burning area, are one of the main causes to the above mentioned scenarios.

Transition from the *BURNING* meta-state to the *EXTINT* meta-state occurs whenever cell Combustion Intensity falls to zero before the entire cell is burned. As it was mentioned above, this situation can occur due to unfavorable conditions to fire propagation. This state is different from a state where the entire cell has burned due to the fact that nothing prevents it from start burning again. Therefore this state is modeled using the same RB-FCM of state *INTACT*. This possibility is ignored in all known CA Fire Propagation Models, like for instance [6][7], which represents an obvious flaw in those models.

Transition from the *BURNING* meta-state to the *BURNED* meta-state occurs obviously when the entire cell area is burned. This state is a non-dynamic final state, which is not associated to any RB-FCM.

VI. RESULTS AND CONCLUSIONS

A complete modelling and simulation software application was developed to test the proposed approach. The application creates Voronoi tessellations of the input geographic data, allows input of crisp and fuzzy relevant data, allows tuning of fuzzy variables' linguistic terms and membership functions and also tuning of all model rule bases.

Fig. 6 presents a screen shot of the application where a fire propagation simulation example is shown. The modelled area consists in 258Ha of hilly terrain. The simulation shows fire propagation 120 min after fire ignition under strong wind conditions. Each different shade represents fire propagation after 20 min.

Although the system has not been optimized or compared to real fires (due to lack of data), obtained results show that simulated fire propagation behaves as expected by experts, and that complex fire behaviour, like temporary fire extinction and consequent re-ignition can occur in several scenarios. Other CA based proposed systems are not able to exhibit this behaviour.

The proposed RB-FCM-CA based approach has the theoretical advantage of allowing a more proper and versatile modelling of forest fire propagation simulation. This is accomplished without the need to recur to complex mathematical knowledge while allowing modelling of uncertain and imprecise knowledge.

REFERENCES

[1] Burrough, P.A., McDonnell, R.A., "Principles of Geographical Information Systems", Oxford University Press, Oxford, 1998

[2] Hazelton,N., Leahy,F., Williamson,I., Integrating Dynamic Modeling and Geographic Information Systems", Journal of URISA, 4(2), 47-58, 1992

[3] Lopes AMG, Cruz MG, Viegas DX, "FireStation - An Integrated Software System for the Numerical Simulation of Fire Spread on Complex Topography", Environmental Modelling & Software 17(2002) 269-285, 2002

[4] Shi, W., Cheung Pang, M.Y., "Development of Voronoi-Based Cellular Automata—An Integrated Dynamic Model for Geographical Information Systems", Int. Journal of Geographical Information Science, vol. 14, no. 5, 455± 474, 2000

[5] Shiyuan1,Hu, Deren, Li, "Vector Cellular Automata Based Geographical Entity", Geoinformatics 2004, Proc. 12th Int. Conf. on Geoinformatics − Geospatial Information Research: Bridging the Pacific and Atlantic University of Gävle, Sweden, 2004

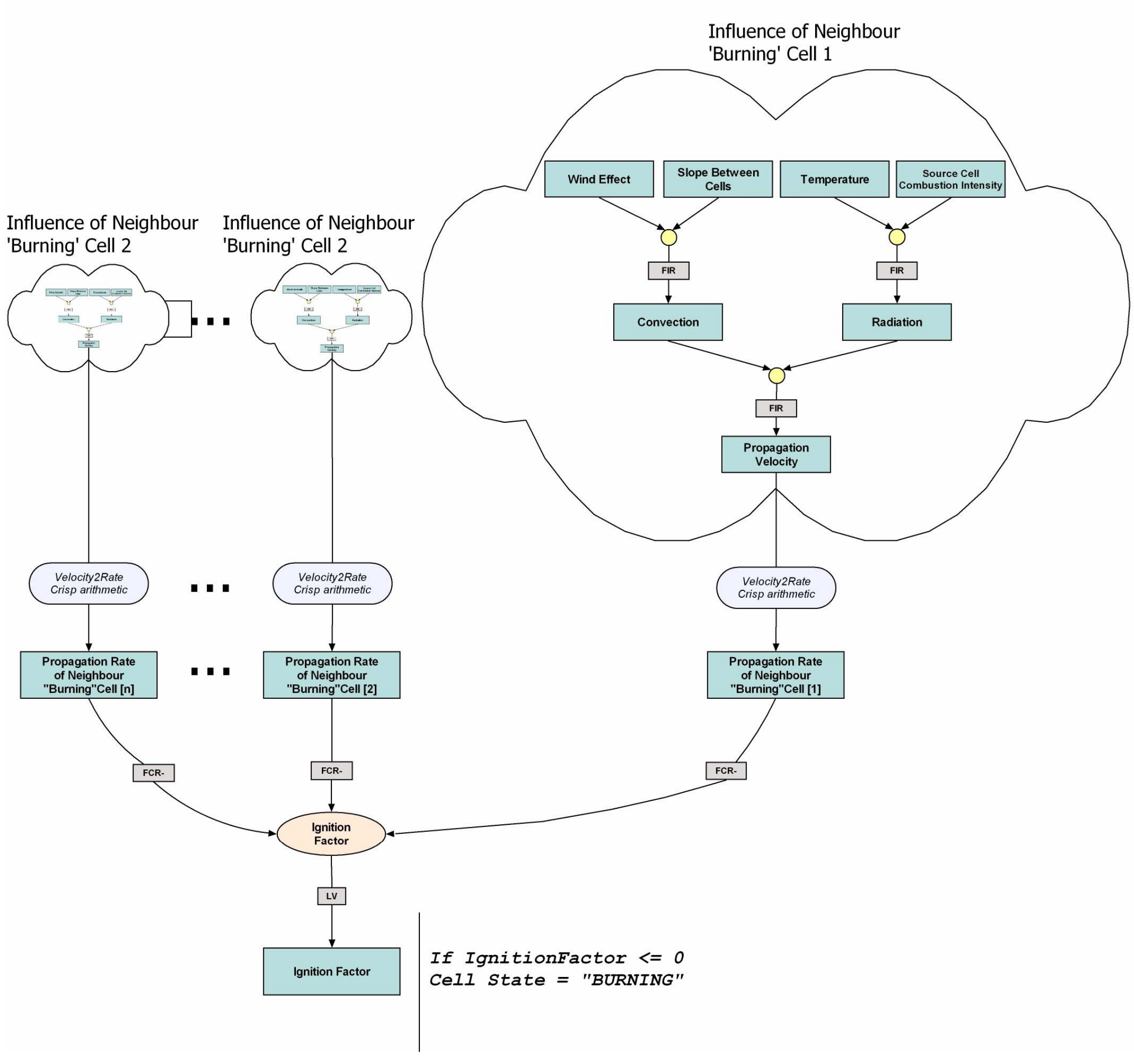

Fig. 4 -RB-FCM for cell Meta-states INTACT and EXTINT (Cell's Ignition Mechanism)

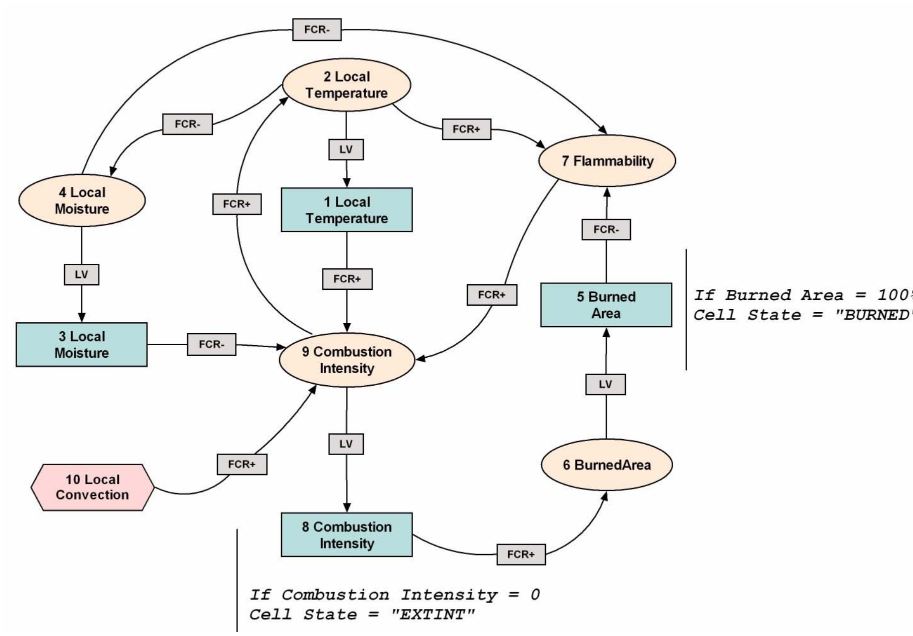

Fig. 5 - RB-FCM for cell Meta-state BURNING (Fire Evolution)

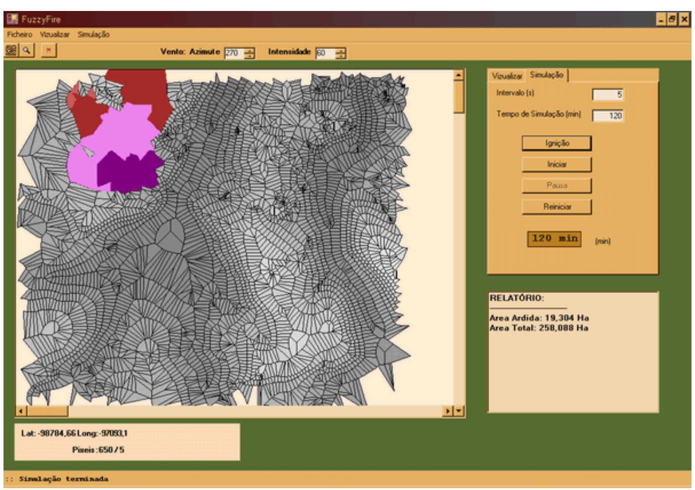

Fig. 6 – Example of simulation of Fire propagation

[6] Mraz M, Zimic N, Virant J., "Predicting Wind Driven Wild Land Fire Shape Using Fuzzy Logic in Cellular Automata", Proc. Of the ISAI/IFIS, 1996

[7] Karafyllidis I, Thanailakis A., "A Model for Predicting Forest Fire Spreading Using Cellular Automata", Ecological Modelling 99, 87-97, 1999

[8] Berjak SG, Hearne JW, "An Improved Cellular Automaton Model for Simulating Fire in a Spatially Heterogeneous Savanna System", Ecological Modelling, 148 (2002) 133-151, 2002

[9] Olivas JA., "Forest Fire Prediction and Management using Soft Computing", INDIN'03, Bannf, Canada, 2003.

[10] Carvalho,J.P., Tomé, J.A., "Rule Based Fuzzy Cognitive Maps and Fuzzy Cognitive Maps - A Comparative Study" , Proceedings of the 18th International Conference of the North American Fuzzy Information Processing Society, NAFIPS99, New York, 1999

[11] Carvalho, J.P., "Mapas Cognitivos Baseados em Regras Difusas: Modelação e Simulação da Dinâmica de Sistemas Qualitativos", PhD thesis, Instituto Superior Técnico, Universidade Técnica de Lisboa, Portugal , 2002

[12] Carvalho, J.P., Tomé, J.A., "Rule Based Fuzzy Cognitive Maps – Qualitative Systems Dynamics", Proceedings of the 19th International Conference of the North American Fuzzy Information Processing Society, NAFIPS2000, Atlanta, 2000

[13] Carvalho, J.P., Tomé,J.A.,"Rule Based Fuzzy Cognitive Maps - Expressing Time in Qualitative System Dynamics ", Proceedings of the 2001 FUZZ-IEEE, Melbourne, Australia, 2001

[14] Okabe, A., Boots, B., Sugihara, K., "Nearest Neighour Operations With Generalized Voronoi Diagrams", a review in International Journal of Geographical Information Systems, 8 (1), 43-71, 1994

[15] Roberts, D.W., Dowling, T.I., Walker, J., "FLAG – A Fuzzy Landscape Analysis GIS Method for Dryland Salinity Assessment", Technical Report, 8/97, CSIRO, Autralia, 1997

[16] Carvalho,J.P., Tomé, J.A., "Interpolated Linguistic Terms: Uncertainty Representation in Rule Based Fuzzy Systems", Proceedings of the 22nd International Conference of the North American Fuzzy Information Processing Society, NAFIPS2003, Chicago, 2003

[17] Kosko, B., "Fuzzy Cognitive Maps", International Journal of Man-Machine Studies, 1986

[18] Carvalho, J.P., Tomé,J.A., "Fuzzy Mechanisms For Causal Relations", Proceedings of the Eighth International Fuzzy Systems Association World Congress, IFSA'99, Taiwan, 1999

[19] Vakalis D, Sarimveis H. Kiranoudis C, Alexandridis A, Bafas G., "A GIS Based Operational System for Wildland Fire Crisis Management" I. Mathematical modelling and simulation., Appl Math Modeling 28 398-410, 2004

[20] Veach MS, Coddington P, Fox GC, "BURN: A Simulation of Forest Fire Propagation". Paper for a 1994 NPAC REU Program Project Proposal, Syracuse University, 1994.

[21] Vasconcelos MJP, Paúl JCU, Gonçalves A., "Geofogo – Testing a Forest Simulator System", In: Viegas DX, editor. Proceedings of the Third International Conference on Forest Fire Research, vol 2,718, University of Coimbra, Luso, Portugal, 1998

[22] Finney M.A., "FARSITE-Fire Area Simulator", Model Development and Evaluation.United States Department of Agriculture, forest Service, Rocky Mountain Research Station, Research Paper RMRS-RP-4 Revised