

Fuzzy Inference Applied to Spatial Load Forecasting

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Abstract – Forecasting the future electric demand and its geographical distribution is a prerequisite to generate expansion-planning scenarios. The load growth pattern is related with the urban structure and its land-use. The model for simulating urban structures must be explicitly dynamic and must contain mechanisms for linking its macrostructure to micro behaviours. The paper presents a methodology, which uses a fuzzy inference model over a GIS support, to capture the behaviour of influence factors on the load growth pattern and map the potential for development. The load growth dynamic is simulated based on extended cellular automata in which the potential for development and demand for location in each stage drive the system into the following stage developments. By providing a series of simulation scenarios, the study unveils potential load growth maps to be used in expansion planning studies.

Keywords – Spatial Load Forecasting, Geographic Information Systems, Fuzzy Inference, Cellular Automata, Distribution Planning.

I. INTRODUCTION

The treatment of the distribution planning problem is finally reached maturity, after many years where researchers failed to recognize that there was more in it than just optimization techniques. In fact, the distribution planning problem is first of all a problem of massive data treatment in two dimensions - space and time; then, it is clearly a problem of generation of scenarios; and only in third place it is a problem of decision, where optimization techniques may play a part, perhaps not too important. Having worked intensively and with success on this part of the problem [1], and having also important work done with Geographical Information Systems (GIS) [2], we feel to be in the right position to appreciate the importance of the other steps to be taken.

The key factor in distribution planning is the load forecast - but due to its geographical dimension, one cannot adopt simple prediction models as in generation or transmission systems: one must make use of spatial load forecasting methods.

Land-use spatial load forecast simulation methods have been used to model the process of the load growth in order to predict load evolution in a spatial and temporal basis [3]. This methodology is particularly suited to high spatial resolution for long range forecasting and multi-scenario planning [4]. Several models have been used to simulate load growth and improve the performance of distribution load forecasting [5, 6]. The Geographical Information System (GIS) technology [7] and its spatial analysis capabilities [8] provides an excellent platform to implement spatial load forecasting techniques.

Spatial load forecasting (SLF) based on land-use is a modeling technique that consists on identifying and mapping areas with similar growth pattern for each customer-class. Land-use pattern recognition techniques are used to identify and model some of the causes of load growth. A land-use class has a pattern template of influences. Each template models the influences of several geographical factors on the land-use pattern development and is represented by spatial shape rules defining influence factor coefficients. Examples of those functions are, for instance, the positive influence of a radial distance to an urban center or the negative influence of the distance to a waste treatment center.

In recent years some works have enhanced the land-use methods applied to urban redevelopment, using fuzzy logic, GIS, multi-objective programming [9, 10, 11].

In urban planning, a large work is being done to model land-use conversion. This is done under the assumption that a simulation approach under the self-organization paradigm is appropriate for addressing the process of land development [12, 13, 14]. To simulate the dynamics of the process, a recent work adopts cellular automata (CA) - this approach emphasizes the way in which locally-made decisions give rise to global patterns.

In this paper we will follow the land-use approach for (SLF), expanding the traditional modeling on dynamic simulation used in urban planning. The model presented has two innovations: the first is the use of a Fuzzy Inference model to capture the geographical pattern of influence factors, and the second is the dynamic simulation modeling of new consumers based on cellular automata (CA).

The fuzzy inference module automatically models the influence of several geographical factors, i.e. distance to roads, distance to urban center, number of houses in the neighborhood, number of shops in the vicinity. To accomplish our objectives we split the problem into three levels, all implemented on a GIS platform.

- First, we identify the most important geographical influence factors, we normalize the maps and we define the membership functions for the input variables (i.e. distance to roads, distance to urban center, number of houses around, number of shops around each point).
- Second, we generate automatically the rules for the fuzzy system and we adjust the fuzzy system parameters based on historical data and on the experience of the planning experts. The output of the fuzzy system is the potential for development.
- Third, using the database of fuzzy rules and new thematic covers representing influence factors, we compute the new maps of potential for development.

The map of potential for development represents a continuous and static map indicating the actual preference for development and load growth. Applying the fuzzy rules

on other regions or other time scenario the model allows the estimation of the load in each map location based on the similarity with other time-space experience or/and based on planners expertise for future planning rules.

The load growth or land-use development change is a discontinuous and dynamic problem. The development is discontinuous because the load increase has minimum values, generally characterized by an integer number of consumers. The development is dynamic because the development for a following time stage is highly dependent of the state in previous stages.

We found that a CA model could demonstrate an ability to act under these two characteristics (discontinuous and dynamic), computing the map of development (growth of number of consumers) in short term stages. In each time step t the CA recalculate the potential growth $P(t)$; this calculation is based on three factors, which determine potential growth [15].

- The vacant space, which is related with the saturation level, characterized by an S curve (sigmoid function).
- The interaction and feedback, which is related with the potential values on a location and in the neighborhood (calculated based on the potential in the previous iteration).
- The innovation effect, which is modeled as random noise.

II. SPATIAL LOAD FORECASTING STRUCTURE

The fuzzy system, the cellular automata, the end use model and the scenario generator compose the main model structure. The fuzzy inference model uses historical data about the influence factors (input variables), and analogue histories of development, to extract or generate fuzzy rules to be used by the fuzzy system. The planner is allowed to formulate rules that are not automatically recognized from historical data.

The set of fuzzy rules can be applied on other space-time scenario characterized by a new set of geographical data. The fuzzy system, implemented on the GIS, computes a new scenario map of potential for development. This map of potential is recalculated in each stage for each consumer class.

A global trend module is necessary to compute the growth in the number of consumers in each time stage and for each consumer class. The result is applied to the cellular automata, which dynamically and discontinuously spread the consumers over the map of potential. The cellular automata compute simultaneously for all consumer classes taking in account saturation levels.

The process can be repeated along several stages, recalculating the potential for each consumer class and allowing the interaction with the user or with other planning events or new infrastructures.

The scenario generator module controls the scenario orientation for each time stage. The objective of this module is the generation of a tree of scenarios for load growth, which can be done in two different ways:

- a) In each stage the user can redefine the geographic thematic coverage that represent the influence factors used as input (e.g. new road; new urban plan

guidelines); the new geographic element can have several hypothesis leading to the ramification of the scenario tree.

- b) The second hypothesis of interaction is on the global trending module; different socio-economic scenarios can be formulated leading to several growth curves for each class of consumers. The scenario generator formulates the several hypotheses in a tree of scenarios for load growth.

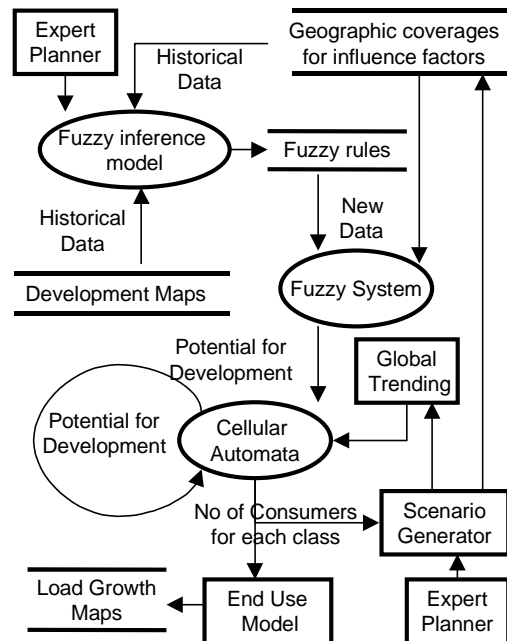


Figure 1 – OMT functional model of the methodology steps

Finally the result - maps with the number of consumers of each class - is transferred to an end-use model that computes the load growth. The end-use model is not within the scope of this paper; its objective is to model the demand of each consumption type as function of typical load curves and other variables relevant for consumption values. In this respect, in our team we have also considerable experience, namely with Neural Network models [16].

III. FUZZY INFERENCE MODEL

To capture the regression (function approximation) between geographic influence factors and preference (development) we have developed a geographical fuzzy inference model. Some conventional SLF methods use simple linear or polynomial regressions, without geographical partitioning [3]. In some cases the user specifies the weights parameters. More advanced methods use geostatistics to compute these relations. Examples of these methods are geographical weight regression and expansion methods [17].

The fuzzy systems deal with qualitative information allowing the implementation of linguistic descriptions for influence factors (close to the road; far from urban center; many houses; few industries). Other advantage of a fuzzy approach is its capacity for generalization, allowing information aggregation and extrapolation to other space-time scenarios with less descriptive information.

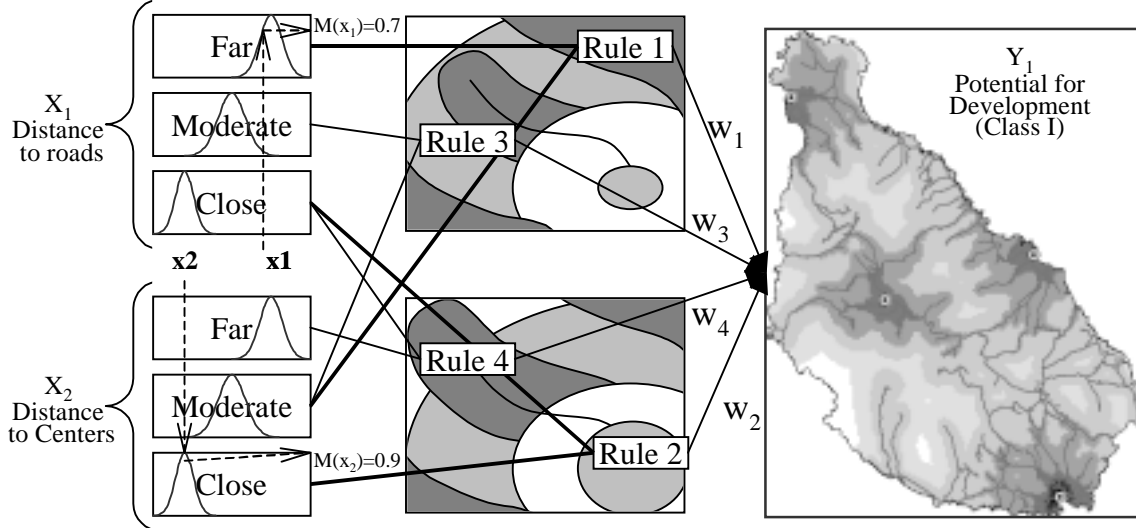


Figure 2 – Illustration of the fuzzy inference process - on each map location, MFs are activated by input values for several influence factors (e.g. distance to roads and distance to centers); several layers of rule zones are mapped; the weights of rules, stored on a database of rules inside GIS, are applied to each map of rules and a map of potential-to-development is generated for each consumer class (the presented map is the island of Santiago in Cape Verde); the darkest zones of the map represents the zones with higher potential-to-development (near centers and near roads).

Many variants and operations can be used in fuzzy-logic inference [18]. This section will describe briefly the technique we implemented on a GIS; for more detailed information on fuzzy logic see references [19, 20].

Fuzzy systems can model continuous input/output relationships; our objective is to model a function approximation (regression) between several geographic variables.

A basic component of a fuzzy system is a fuzzy rule. The rules are expressed using linguistic labels such as the rule:

IF (road is close) AND (urban center is close)
THEN (development growth index is 0.8).

Fuzzy membership functions (MFs) associate linguistic labels (e.g. close) with a particular area of inputs or outputs. In the example shown above the THEN-part of each rule does not consist of a membership variable but of the crisp value 0.8. This kind of systems is called zero-order Sugeno fuzzy system. In an n -th order Sugeno fuzzy system the THEN-part of each rule consists of a polynomial of degree n in the input variables. Different shapes of the MFs can be proposed such as triangular, trapezoidal, or Gaussian. For the following discussions we assume the Gaussian shape.

$$m_{iv}(x_v) = \exp\left(-\frac{(c_{iv} - x_v)^2}{2\sigma_{iv}^2}\right) \quad (1)$$

Where i denotes the index of the different MFs defined for variable v and x_v denotes the input for variable v . The parameters c_{iv} and σ_{iv} are the center and the "width". In order to minimize the number of layers used on the GIS implementation, for each input value only two membership functions have values higher than zero and their sum may be one. This can be achieved by using appropriated width and dividing each membership values $m_{iv}(x_v)$ by the sum of

all membership values, indexed as iv for label i in variable v , leading to normalized MFs.

$$M_{iv}(x_v) = \frac{m_{iv}(x_v)}{\sum_i m_{iv}(x_v)} \quad (2)$$

As input variables we can have three kinds of influence factors: distance factors (e.g. distance to roads, distance to urban centers); zone-count factors (number of houses on 5 km radius); local factors (e.g. terrain slope, urban planning directives). As output we have the map of development potential for each consumer class (number of additional consumers).

After the MFs definition we can formulate the rules j in term of linguistic values. Input variables are combined in expressions using fuzzy operators such as fuzzy AND (T-Norm) or fuzzy OR (T-conorm). In the case of Gaussian MF the fuzzy AND can be performed by the arithmetic product of membership values across the input variables x_v .

$$G_j(x_v) = \prod_v M_{iv}(x_v) \quad (3)$$

For each consumer class c the output value is calculated by the OR operation and can be generated by:

$$O_c(x_v) = \sum_j w_j G_j(x_v) \quad (4)$$

where w_j is the THEN-part (or output weight) of the fuzzy rule j . The output weights w_j can be set manually by domain experts. Alternatively a given training data set

$$D = (\xi^k, \zeta^k), \quad k = 1, \dots, M, \quad \xi^i \in \mathfrak{R}^n, \quad \zeta \in \mathfrak{R}^m \quad (5)$$

could be used to perform training, where M is the number of training points, n is the number of influence factors and m is the number of consumer classes. The goal of this training is to find the output weights that minimize the summed square error.

$$E = \frac{1}{2} \sum_{k=1}^M (O_k(\xi^k) - \zeta^k)^2 \quad (6)$$

If the IF-part of the fuzzy rules is fixed, the determination of weights w_j can be solved by the method of least squares based on standard matrix techniques

$$\begin{bmatrix} w_1 \\ \vdots \\ w_j \end{bmatrix} = \begin{bmatrix} \sum_k G_1(\xi^k)^2 & \dots & \sum_k G_1(\xi^k) \cdot G_j(\xi^k) \\ \vdots & \ddots & \vdots \\ \sum_k G_j(\xi^k) \cdot G_1(\xi^k) & \dots & \sum_k G_j(\xi^k)^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum_k G_1(\xi^k) \cdot \zeta^k \\ \vdots \\ \sum_k G_j(\xi^k) \cdot \zeta^k \end{bmatrix} \quad (7)$$

When implemented on GIS the rules are coded as map regions. To map the zones in maps of rules we used geographical reclassification functions. The number of rules activated in each geographical location is 2^v (the same number of maps is needed to store rule coding), where v is the number of input variables. For each rule map we compute a stack of maps with membership values $G_j(x_i)$.

These membership values are functions of the geographical value for the input variables (influence factors). All the calculations associated with each rule j are computed based on zonal functions available on GIS, in which the zones are the regions where rules are activated.

The method was implemented on *ArcView GIS* programmed on *Avenue* language. We needed 17.5 minutes to training 3 output classes with 3 geographical input variables using 67000 training points (area with 4000 km²) on a Pentium II 200Mhz.

The set of rules (variable labels, codification index and weights) is stored on a GIS database to be used on other time-space scenarios.

Every time changes are made on input maps (e.g. new roads, new demographics and new industries) the output maps for development potential must be recalculated using the database of rules. Such recalculation must be done in each stage of the forecasting time. This stage varies between 0.5 and 5 years depending of the urban development dynamics. The recalculation of new maps for development potential takes approximately 2/3 of the training time.

A new training is necessary if the new region uses different urban planning philosophies (different rules and different variables). If the urban planning rules change through time it is also recommended the retraining of the fuzzy inference model. If no data exists to describe the urban planning behaviour the planner experts can define their own rules and insert them directly on the database.

The obtained maps of development potential are continuous on space and static in time. To solve the SLF problem, which is discontinuous and dynamic, we use a cellular automata model. There are several possible approaches. In this paper, we sketched our experiments with CA.

IV. CELLULAR AUTOMATA

The CA theory was first introduced by Jon Von Neuman [21] and is ideally applied for dynamic discrete modeling [22]. A CA is a discrete dynamical system because space time and system states are discrete and this states changes

sequentially over time and space. Each point in a rectangular spatial grid, called a cell, can have any one of a finite number of states. The states of the cells in the lattice are updated according to a local rule, which depends of they own state and the state of its neighbors on the previous time step. The state of the entire lattice is updated synchronously in discrete time steps.

In our formulation at any specific point of time t , the automaton is a collection of states s_{ij} characterized by the saturation levels for the several consumers classes and the cell location (i, j) .

$$CA = \{s_{ij}^t\}, \quad 0 < i \leq r; \quad 0 < j \leq c; \quad \forall s_{ij}^t \in S \quad (8)$$

CA is the cellular automaton, S is the finite set of states, n and m are the number of rows and columns.

The possible states are the combination of possible saturation level for the several consumer classes.

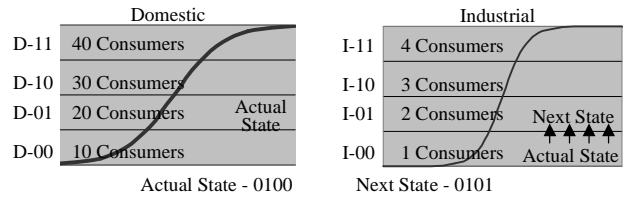


Figure 3 – State transition and load growth S curves.

For each consumer class the change must be between adjacent states. The sum of developed area must be lower than the saturation level (e.g. if the industrial development change from 2 to 3 consumers the domestic set must decline from 20 to 10 consumers). This method allows the simulation of growth, decline and redevelopment. An appropriated classification of the consumers according with load consumption, area utilized and time-scale for typical development is very important.

The state transition is done according to a set of heuristic rules. In this model the state transition function depends on the functions of potential-to-development and potential-to-decline obtained from the fuzzy inference model.

For each consumer class, one computes the potential for development and potential for decline using 3 component factors:

- positive feedback of the cell on the previous iteration, weighted by α ;
- neighborhood effect based on the 8 adjacent neighborhoods [23], weighted by β ;
- innovation factor modeled as random noise, weighted by λ .

$$P_i(t+1) = \alpha \cdot P_i(t) + \beta \cdot \frac{1}{8} \cdot \sum_{j \in \Omega_i} P_j(t) + \lambda \cdot \varepsilon_i(t) \quad (9)$$

$$D_i(t+1) = \alpha \cdot D_i(t) + \beta \cdot \frac{1}{8} \cdot \sum_{j \in \Omega_i} D_j(t) + \lambda \cdot \varepsilon_i(t) \quad (10)$$

Where α , β and λ are the weights for each component, with values $[0,1]$ and $\alpha+\beta+\lambda=1$, $P_i(t+1)$ is the potential to development in time stage $(t+1)$ on site i , $D_i(t+1)$ is the potential-to-decline in time stage $(t+1)$ and site i ; Ω is the set of adjacent neighbors cells.

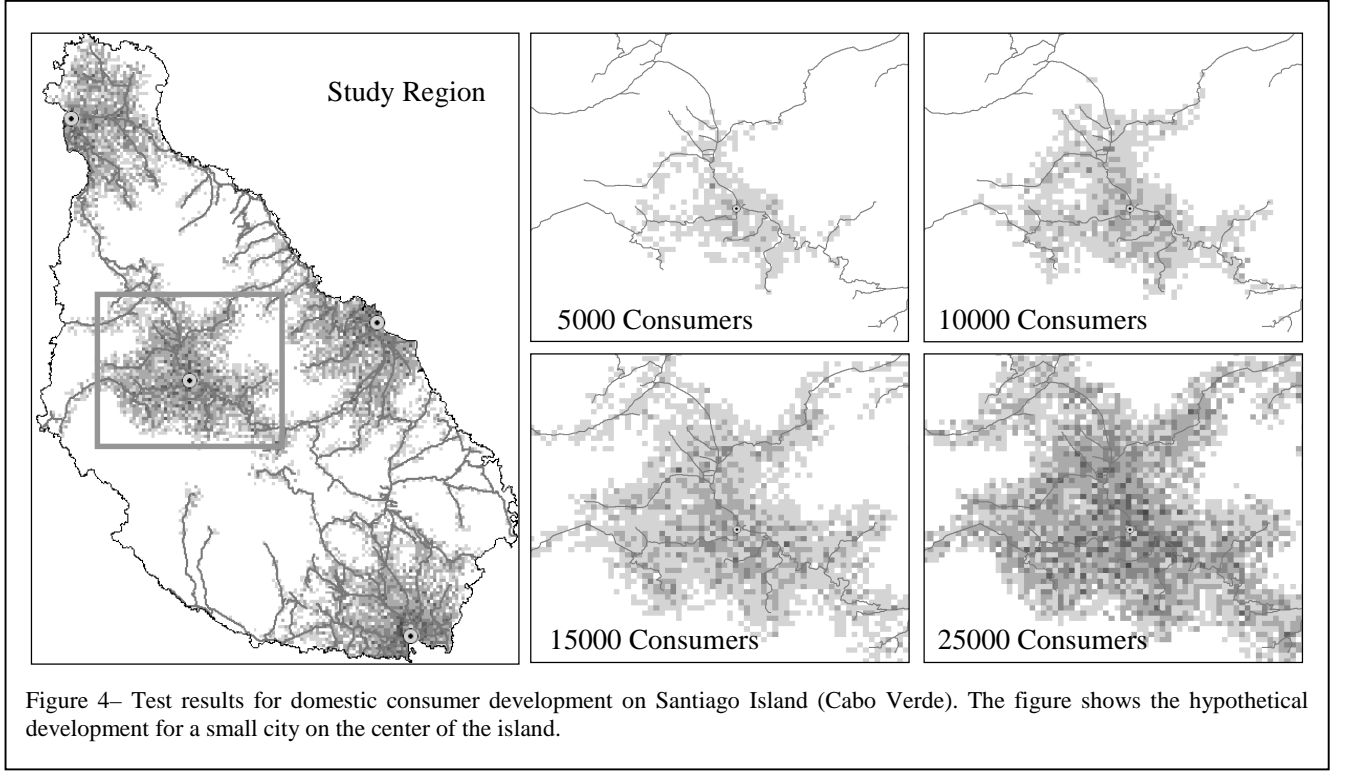


Figure 4— Test results for domestic consumer development on Santiago Island (Cabo Verde). The figure shows the hypothetical development for a small city on the center of the island.

For each consumer class, one checks if the saturation level is reached (if the sum of all consumer on cell i occupies more than the global saturated level s_{Ti}) and if conditions to redevelopment are filled ($Z_1 \cap Z_2$); where Z_1 is the set of cells with highest potential-to-development and Z_2 is the set of cells with highest potential-to-decline. If the cell i is saturated the consumer class with higher potential-to-development C develops (increase state s_C) but the consumers class with higher potential-to-decline D must decline (decrease state s_D) in order to maintain the global saturation level.

$$\text{if } \sum_C s_{Ci} > s_{Ti} \begin{cases} s_{Ci}(t+1) = s_{Ci}(t) + 1, & i \in (Z_1(t) \cap Z_2(t)) \\ s_{Di}(t+1) = s_{Di}(t) - 1, & i \in (Z_1(t) \cap Z_2(t)) \\ Z_1 = \max_j \{P_{Cj}(t+1)\} & Z_2 = \max_j \{D_{Dj}(t+1)\} \end{cases} \quad (11)$$

If the cells are not saturated, one increases the saturation in the areas with higher potential-to-development. If the cell is not empty, one decreases the saturation level on cells with higher potential-to-decline.

$$\text{else } \begin{cases} s_{Ci}(t+1) = s_{Ci}(t) + 1, & \text{developed if } i \in (Z_1) \\ s_{Di}(t+1) = s_{Di}(t) - 1, & \text{decline if } i \in (Z_2) \\ s_i(t+1) = s_i(t), & \text{not change if } i \notin (Z_1 \cup Z_2) \end{cases} \quad (12)$$

This operation is repeated until all the global growth and global decline, for each consumer class in each stage, was allocated.

Trending models must estimate the global growth and global decline, for each consumer class, (e.g. the growth for year 2001 in all region is 250 industrial consumers and 5000 domestic consumers). On the end of each stage the maps of potential-to-development and potential-to-decline may be recalculated, using the fuzzy inference model and the new geographic data computed with the CA and introduced by the planner.

On figure 4 we can see the test results, a prototype demonstration for four different stages of domestic consumer development in one city (located on the island center) in an African country (Cape Verde). The influence factors to compute the potential-to-development were the distance to the roads and the distance to the urban centers.

The pattern of evolution follows the pattern of potential, more intense growth near the urban center and near roads.

V. CONCLUSIONS

The major problem of simulation methods is capturing and retaining the richness of the simulated system. The fuzzy inference approach allows the automatic identification of the chains of cause/effect in the form of rules. These rules can be transposed to other time-space environments, with similar planning philosophies. Other advantage of the fuzzy inference model is the ability to store new planning rules directly specified by the planner. The generalization ability of fuzzy systems allows the generation of continuous and stationary maps of potential-to-development and potential-to-decline.

From maps of potential, one needs to take a step into generating scenarios of development, conditioned by the set of rules establishing an environment for growth.

In the paper we have explore the possibilities offered by cellular automata in providing a massive parallel mechanism of simulating evolution.

The results are preliminary but promising. However, one recognizes that further research is necessary to understand the coupling of automata behavior with the inference model and the rules derived, and to control the characteristics of this coupling.

With this approach, we hope to have opened a way to represent the dynamics and discrete characteristics of urban and rural development, seen from the point of view of the

energy planner. Hopefully, final model will satisfy and simulate the growth, decline and redevelopment of several classes of consumers in a territory.

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VI. BIOGRAPHIES

Vladimiro Miranda received his Licenciado, Ph.D. and Agregado degrees from the Faculty of Engineering of the University of Porto, Portugal (FEUP) in 1977, 1982 and 1991, all in Electrical Engineering. In 1981 he joined FEUP and currently holds the position of Professor Associado Agregado. In 1985 he joined also INESC, a research and development institute, having held for many years the position of Head of Information and Decision in Energy Systems. In 1996 he was appointed President of the Executive Board of INESC-Macau (South China) and Full Professor in the University of Macau. He is currently the President of the Scientific Board of INESC Porto and Executive Board Adviser for Power Systems. He has been a member of several Expert Committees in Power Systems. He has had responsibility over several research projects within the European Union programmes and also in cooperation with Latin America and Portuguese speaking African countries, and he is the chairman of the Luso-Afro-Brazilian Cooperation Network in Power. He has also acted as consultant for the promotion of projects with China, within the framework of the EUREKA initiative. He has authored or co-authored many papers, namely in his areas of interest, related with Power System planning and the application of fuzzy sets and other soft computing techniques to Power Systems.

Cláudio Monteiro was born in France, on March 14th, 1968. He received his Licenciado and MSc. degrees from FEUP in 1993 and 1996, in Electrical Engineering and Computers. In 1993 he joined INESC as a researcher in the Power System Unit. Presently is working in his Ph.D. related integrating distribution planning models and Geographical Information Systems under uncertain reasoning.