VALIDATION PROCESS FOR FUZZY SPATIAL LOAD FORECASTING

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Abstract – This paper reports the method used to validate a spatial load forecasting model based on Fuzzy Inference Systems (FIS) and implemented in a Geographical Information System. The validation process not only confirms the adequacy of the rule base but is necessary to define confidence intervals to the predicted spatial demand.

Keywords – Spatial Load Forecasting, Geographic Information Systems, Fuzzy Inference, Forecasting validation.

1. INTRODUCTION

Spatial Load Forecasting (SLF) aims at predicting where, when and how load growth will occur in a utility service area, maintaining a full geographical representation. This information is useful for distribution expansion planning purposes, serving as basis for establishing the evolution of the design of a distribution system in a given region.

SLF methods must be implemented on a Geographical Information System (GIS). The GIS environment provides an ability to: manage spatial information; model and simulate phenomena behavior; visualize data and simulation results; and establish interaction between planners and simulation environment.

The first and important systematic works in SLF have been conducted by Willis and are described in a remarkable series of publications - see for instance [1][2]. More recently, the authors of this paper have developed a successful approach to Spatial Load Forecasting based on Fuzzy Inference Systems (FIS) and Cellular Automata, with important results [3-8].

The classical SLF approach depended too much on the *a priori* definition of numerical constants, values or parameters. The recent SLF models based on FIS rely instead on capturing knowledge from past maps and building a rule base describing the interaction among influencing factors that explain the evolution of demand along time.

Two concepts are therefore fundamental in modern SLF: the extraction of knowledge under the form of rules (from past or analog cases with geographical representation) and the application of the set of rules to generate the simulation of load growth (in maps of future development).

The questions remain: how accurate are the rules? How faithful is the prediction? How important is the uncertainty associated with the spatial forecast?

This paper presents the methodology used to validate a rule base used together with a FIS to produce a SLF.

2. SPATIAL LOAD FORECATING WITH FIS

2.1 The Fuzzy Inference System

A FIS is extremely adequate to model spatial growth behavior because:

- it allows knowledge representation by linguistic concepts such as "close to road", "location with high environment protection" or "medium saturation status for urban development";
- it allows knowledge representation by comprehensive rules, where cause and consequence are represented by *if-then* fuzzy rules; rules allow a better interaction between the system and human experts, because of their self-explanatory characteristics;
- a comprehensive knowledge base stored as a rule base may be applied to other space and time environments, due to its capacity of generalization.

There are some basic data whose definition is prior to the application of a FIS prediction system. One of the most important is a global growth forecast, valid for the geographical region as a whole - generated from some economic or aggregated model, external to the SLF process (trending, econometric, diffusion of innovation model).

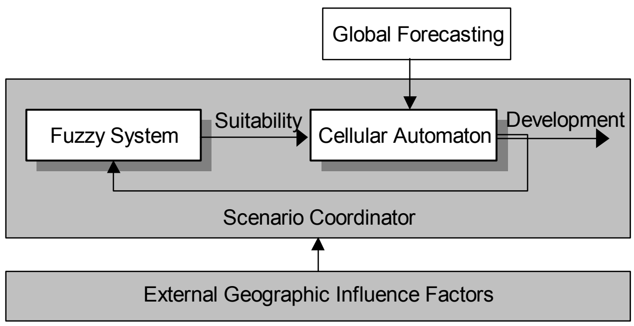

Figure 1 - Structure of the Fuzzy Spatial Model

Figure 1 sketches the organization of the FSM concept, composed of two main models. The first is the Fuzzy System (FS); it estimates the suitability or the potential for development at each map cell. The second is the Cellular Automaton (CA); it spreads the global forecast over all the region based on the preferences indicated by the suitability maps. The results of the CA module are the effective geographic distribution of the development.

The Scenario Coordinator (SC) links the FSM with the forecasting environment and with externally imposed conditions and coordinates the dynamics of the simulation, namely the inputs of the Fuzzy System and Cellular Automaton along the several time stages.

The Takagi-Sugeno structure of the Fuzzy System (FS) organizes its rules in a neural-like form, the inputs propagating throughout the network until an output is generated. In the Takagi-Sugeno inference model, the antecedent of a rule is fuzzy, but the consequent is crisp, and a function of the input values.

The FSM problem is characterized by a very large set of geographical cells (may reach a million cells per map). On the other hand the number of significant variables is in general limited (a typical value would be of 5 variables). This characteristic motivated us to do an implementation based on the GIS spatial analysis functions instead of a GIS coupling with external fuzzy system modules.

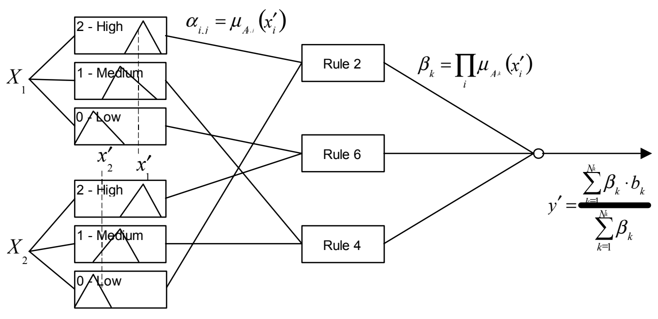

Figure 2 - Graphic representation showing the zero-order Takagi-Sugeno inference method.

The neural structure of the zero-order Takagi-Sugeno FS is represented in Figure 2. The matching on the fuzzy proposition "x'_i is $A_{i,j}$", is given by $\alpha_{i,j}$, where x'_i is the numerical input for variable x_i and $A_{i,j}$ is the membership labeled j on this variable. The support value for rule r_k is given by β_k. The final output y' is the weighted sum for all rules, where b_k is the zero-order function coefficient for rule r_k and N_k is the number of rules.

The implementation of this fuzzy system with GIS spatial functions is especially interesting because the operations are applied simultaneous on all the geographical cells. The implementation requires: maps with activated membership labels (two for each variable); maps with matching values $\alpha_{i,j}$ (two for each variable); maps with coding for activated rule (2^{N_v} maps, where N_v is the number of variables); maps with the support values β_k (as much as the number of maps for coding activated rules); maps with lookup values b_k associated with support values β_k (as much as the maps with the support values). The rule codification is important to identify the rules and access the lookup tables containing the rule database. The codification of the rule r_k is done by *Cod*$_i$ where $L_{i,j}$ is the membership label for label j on variable X_i, the $N_{L\max}$ is the maximal number of membership labels for variables X_i, and N_v is the number of variables.

Here's one example of a rule:

IF *(distance to road is CLOSE)* ***AND***
(distance to urban center is MODERATE CLOSE) ***AND***
(terrain slope is MODERATE) ***AND***
(domestic saturation is MEDIUM) ***AND***
(industrial saturation is LOW)
THEN
DomesticPfD is 20 consumers per stage per km^2 ***AND***
Industrial PfD is 0.1 consumers per stage per km^2

These rules are automatically generated and used by the spatial model and are easily understood by human specialists. The rules are stored in the GIS database and are used as in a lookup table in the process.

2.2 Cellular Automata

The application of the FIS rules leads to the production of maps of potential for developent. These maps must be transformed into maps of prediction of actual development, and this is done through a Cellular Automata (CA) model.

The CA theory was first introduced by Jon Von Neuman [9] and is ideally applied for dynamic discrete modeling [10]. In our formulation, at any specific point of time t the CA is a collection of binary states e^t_{ij} in cell location (i,j), with value 1 if a new consumer is added to the site and 0 if no consumer is added:

$$CA = \{e^t_{ij}\}, \quad 0 < i \le r; \;\; 0 < j \le c; \;\; \forall e^t_{ij} \in E \qquad (7)$$

where E is the finite set of states, r and c are the number of rows and columns of the map grid.

The CA is an iterative process computing development based on potential for development and computing new potential based on previous iteration development.

The Potential for Development (PfD) is initially set by the fuzzy system. The PfD is represented as a stack of continuous maps, one for each consumer type, representing the potential growth number of consumer per stage and per geographic unit (e.g. 20 domestic consumers per stage and per km^2). The Development, which is the output of the CA, represents the effective number of consumer growth. A global geographical trending controls the global development, the sum of all developments in the region. The CA process finishes when the sum of all cell developments reaches the global trending value (e.g. the growth for year 2001 in the whole region tends to 250 industrial consumers and 5000 domestic consumers).

The iterative process of the CA is based on state transitions $S_i(t)$; in our model, these will be transitions from non developed to developed. The state transition is done according to a set of rules such as

$$\text{if} \;\; P_i(t) > P_b(t) \;\; \text{then} \;\; S_i(t) = 1 \;\; \text{else} \;\; S_i(t) = 0$$

In our model a transition exists if the cell has a PfD value

$P_i(t)$ higher than a specified boundary value $P_b(t)$. The boundary value is specified by the system by ranking PfD intervals.

The development $D_i(t)$ is recalculated in each iteration incrementing the number of consumers, by steps D_{step} (measured in number of consumers), only on cells marked as developed $S_i(t)=1$.

$$D_i(t) = D_i(t-1) + S_i(t) \cdot D_{step} \quad (8)$$

Development maps may then be generated such as in Figure 3.

The new potential $P_i(t+1)$ is recalculated based in three components:

- positive feedback of the cell on the previous iteration, weighted by α;
- neighborhood effect based on the 8 adjacent cells [11], weighted by β;
- innovation factor λ modeled as random noise

and is given at time t+1 by

$$P_i(t+1) = \alpha \cdot P_i'(t) + \beta \cdot \frac{1}{8} \cdot \sum_{j \subset \Omega_i} P_j'(t) + \lambda \cdot \varepsilon_i(t) \quad (9)$$

where α, β and λ are the weights for each component, with values [0,1] and $\alpha+\beta+\lambda=1$, and Ω is the set of adjacent neighbors cells. $P'_i(t)$ is the updated potential to development in time stage t on site i, computed based on the output of the fuzzy inference model $P_i(0)$ and on the development computed by the CA on iteration t:

$$P_i'(t) = P_i(0) - D_i(t)$$

At the end of each stage the PfD maps may be recalculated, using the fuzzy inference model and the new geographic data computed with the CA or introduced by the planner.

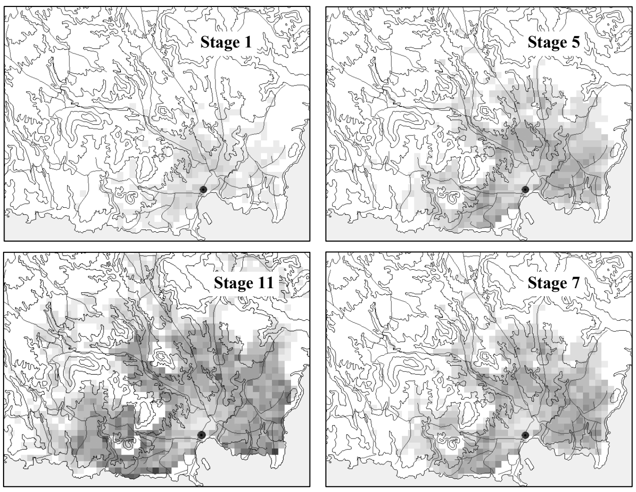

Figure 3– A sample of 4 out of an 11 stage simulation maps of forecasted number of consumers (of domestic type) after the action of the cellular automata.

3. VALIDATING PROCESS

The Fuzzy Spatial Load Forecasting model has particular characteristics that require appropriated validation processes. These characteristics are the spatial behavior, the capability to model judgmental information and the temporal behavior. To evaluate these three characteristics we have formulated decoupled tests to independently validate the several aspects: spatial validation, temporal forecasting validation, temporal backcasting validation and validation of the merging of judgmental information.

Two different measures of accuracy are used: the Coefficient of Variation (CV) to measure the accuracy on *level*; and the Turning Point (TP) to measure the accuracy on *changes*. These two measures of accuracy are required because for Electricity Distribution Planning one needs to assess the level of load development (*levels*) and the changes from green-field to new load developed area (*changes*).

The Coefficient of Variation (CV) relates the Root Mean Square Error (RMSE) to the average value of the actual data.

$$CV = \frac{RMSE}{\sum_{i=1}^{h} V_i / h} \quad (1)$$

The RMSE is the Root Mean Square Error given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{h} (V_i - F_i)^2}{h}} \quad (2)$$

where i is the index of the forecasted output (representing a geographical cell in a specific time period), h is the number of forecasted points (number of cell in the geographical coverage times the number of periods), V_i is the actual result for point i and F_i is the forecasted value for point i.

The Turning Point (TP) measures the accuracy of prediction in the change from green-field to developed area. The four possible turning point situations are the following:

		Did the change occur? Yes	No
Was a change predicted?	**Yes**	$TP_1=a/o$	$TP_2=b/p$
	No	$TP_3=c/o$	$TP_4=d/p$

The value ***a*** represents successful predictions when change occurs; ***d*** represents successful predictions when no change was forecasted; ***c*** represents errors when change occurs and was not predicted; ***b*** represents errors when change was predicted but did not occur; ***o*** represents the number of change occurrences (a+c), and p represents the number of change predictions (a+b). Change prediction ***p*** is not necessarily equal to change occurrence ***o***.

3.1 Spatial Validation - example

To validate the spatial behavior, a cross validation procedure is used. A spatial random selection is used to separate a calibration sample [C_j] from a validation sample [V_i], where $i \neq j$. The calibration sample is used to train the system and build the fuzzy rule knowledge base. Using this knowledge base, the forecasting method is applied producing the forecast sample [F_i] in the point corresponding to [V_i].

We will describe a validation procedure applied to a given region in the island of Santiago, in Cabo Verde (Africa).

The historical data consists in the development observed along 3 time periods and corresponds to 3 geographical coverages of domestic development in Santiago. To decouple the spatial behavior from the temporal behavior, the selection of the calibration and validation samples was done for the three temporal stages.

From this geographical coverage we've randomly selected half of the points for a calibration sample [C_j] (near 15000 points per period) and the other half for a validation sample [V_i]. The system was trained with a calibration set [C_j] of 45000 points, using six variables as influence factors and generating approximately 2500 fuzzy rules.

After the training step, using only historical information, we produced a forecast for a following time period using the same input variables and labels and adopting a given value for a global forecast. The global forecast (number of new consumers for all the coverage) was previous obtained from the development maps in each period (p_1=1000; p_2=1500; p_3=2000). We've produced three maps of forecasting values covering the entire region in the three periods. Using the forecasting results [F_i] and the validation sample [V_i] for the validation points (points not used for calibration), we estimated the accuracy measures CV and TP.

The results in Table 1 show that the spatial mean error (CV) reaches 11%. Comparing the values for the three periods we observe that Period P2 has lower error because the three periods where used for calibration and P2 is the intermediary period that probably benefits of better fitting.

The error is not the same for different saturation levels. Saturation is a concept illustrated in Figure 4. In our FIS model, one *observes* the evolution of saturation, instead of defining its curve externally.

Table 1 - Spatial Validation results to measure the accuracy on the forecasting level. Including the Root Mean Square Error (RMSE), and the coefficient of variation (CV).

	$\sum_{i=1}^{h} V_i / h$	RMSE	CV
Period P1	1.502	0.163	10.90%
Period P2	1.511	0.156	10.30%
Period P3	1.520	0.171	11.35%
Global	1.512	0.163	10.80%

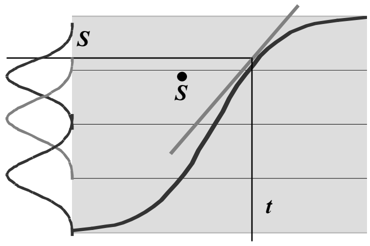

Figure 4 – The number of consumers as a function of time defines the Saturation curve at a location; its derivative is seen as the potential for development PfD. The saturation level at stage t is characterized through fuzzy descriptors.

Figure 5 shows the variation of the error for the different levels of saturation (of growth in a map cell). The error increases when in the growth part of the saturation curve, because for this saturation level (40% to 70%) the area develops very fast and the forecasting is more difficult. When the growth approximates saturation the development becomes slow, as if restricted by a maximum value, and consequently the forecast becomes more accurate.

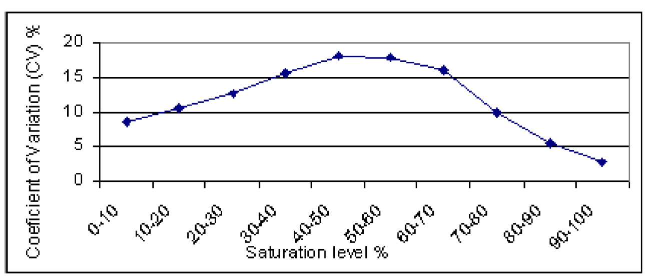

Figure 5 - Variation of accuracy (CV) with the saturation level.

As explained before, measuring the level of error is not enough for Spatial Load Forecasting; it is also very important to have accuracy in predicting changes from green-field to developed area. This accuracy is evaluated with Turning Point (TP) measures (TP_1; TP_2; TP_3 and TP_4), described previously. The TP_2 and TP_3 are measures of unsuccessful predictions and TP_1 and TP_4 are measures of successful predictions.

Table 2 - Spatial Validation results to measure the accuracy for forecasting change. TP_1 represents successful predictions when change occurs; TP_2 represents errors when change was predicted but did not occur; TP_3 represents errors when change occurs and was not predicted; and TP_4 represents successful predictions when no change was forecasted.

	Period P1	Period P2	Period P3	Global
Observed changes	48	73	108	229
Predicted changes	47	65	102	214
TP1	88.8%	85.9%	84.1%	86.3%
TP2	9.3%	11.5%	13.8%	11.5%
TP3	11.2%	14.1%	15.9%	13.7%
TP4	98.3%	97.1%	95.8%	97.1%

The number of observed changes and of predicted changes are quite close with an error between 7% and 10%. Observing the Turning Point measures of error TP_2 and TP_3 we conclude that the error sums up to approximately 25%. These values are considerably high but we must recognize that forecasting behaviors of "spatial pioneer" consumers is extremely difficult because usually these consumers display unusual behavior. We note that the change accuracy along the three periods decreases in opposition with the accuracy in level, that has better values for the intermediate period P_2. For the latest periods, more innovative behaviors at development borders are activated and the changes occur mostly in these regions, and consequently these are more exposed to error.

3.2 Temporal Validation – forecast and backcast

To validate the temporal behavior we used two different procedures: the forecast validation and the backcast validation. The forecast validation consists in using the forecasting models, calibrated with the historical information excluding the latest period, and measuring their success in forecasting the latest known data sample. This test is almost as good as the real forecast. However, only uses historical behavior for calibration and is unable to model forward changes on behavior.

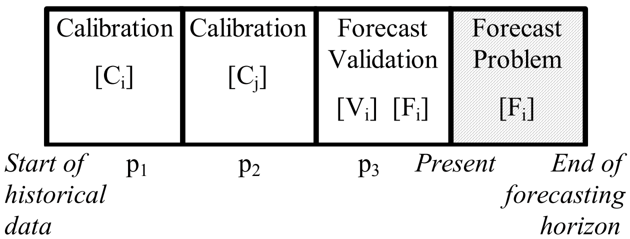

Figure 6 - Scheme identifying, for forecast temporal validation process, the data sets used for calibration validation and forecasting.

As Shown in Figure 6, for forecasting validation we use the data samples from periods P_1 and P_2 to calibrate the forecasting model. The knowledge base generated with this historical data is used to validate the latest data sample available P3. In this test the forecasting model doesn't know any information about the behavior of the latest period P3. The [C_j] data sample (periods P_1 and P_2), used to calibrate the knowledge base totalize approximately 60000 points. After the training step, we used the model to forecast the period P3 and we obtained the forecasting map with forecasting values for approximately 30000 points. With the forecasting map [F_i] and with validation sample [V_i] in period P3 we measured the accuracy. We used the Coefficient of Variation (CV) to measure the forecasting level accuracy and the Turning Point (TP) to measure the accuracy in forecasting changes.

One of the interesting aspects of the Fuzzy Spatial model is its capability to capture and store the knowledge base and the possibility of applying this rule base to other region with region with similar behavior but shifted in time. This is only possible if the model has good backcasting validity. With the backcast validity we test if the model still predict efficiently earlier behavior based on a knowledge base constructed with recent data sets. Obviously, this approach may suffer from contamination because the knowledge base is influenced by what happens recently, but it is this kind of contamination that we wish to evaluate.

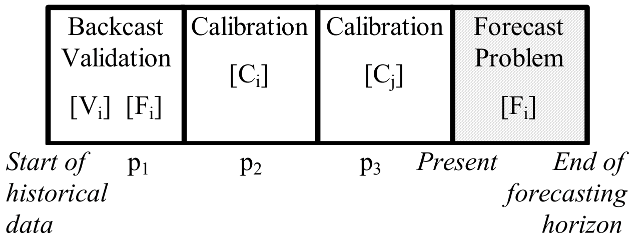

Figure 7 - Scheme identifying, for forecast temporal validation process, the data sets used for calibration validation and forecasting.

As shown in Figure 7, contrarily to forecasting validation, in backcasting validation we use the data samples from period P2 and P3 to calibrate the model knowledge base. The model calibrated with this historical data is used to validate the earlier data sample correspondent to period P1. The calibration data sample (periods P_2 and P_3) adds up to approximately 60000 points, and the validation data sample (period P_1) contains approximately 30000 points.

Table 3 – Temporal validation results for forecasting and backcasting.

	$\sum_{i=1}^{h} V_i / h$	RMSE	CV
Forecasting P3	1.520	0.228	15.00%
Backcasting P1	1.502	0.177	11.08%

In *Table 3* we observe that the accuracy for foreward validation is lower than the one observed for backward validation: the CV measure increases from 11% to 15%. This increase is expected because, contrarily to the spatial validation process, the forecasting knowledge base has no information about the behavior of the forecasted period. Other reason for this decrease in forecasting accuracy is the possible changes in behavior resulting for multiple factors. Obviously these changes in behavior could not be captured from historical information. This accuracy of the model could be significantly improved by merging judgmental information.

For backcasting we observe and error of 11,8%. As expected, these values are higher than values observed for spatial validation (*Table 1*) because, contrarily to spatial validation using cross validation, in this backward validation the period P_1 is completely unknown for the knowledge base. The accuracy of the backcast (11.8%) is considerably better than of the forecast (15.0%). This shows that the future behavior continues keeping in storage the past behavior and this could be efficiently captured. The predictions from forecasting are worse than the predictions from backcasting because future data samples contain both the past and future behavior but past data sample don't contain a complete characterization of the future behavior.

To test the accuracy on changes we used the several Turning Point (TP) measures. The measures use the forecasting sample [F_i] and the validation sample for period P_3 for forecasting validation and for period P_1 for backcasting validation.

As shown in *Table 4*, for forecasting validation, the accuracy in the number of predicted changes is approximately 90%, with lower number of predicted than occurred changes. The total forecasting validation error in change (TP_1 and TP_2) totalizes approximately 30%. Comparing the values obtained for temporal validation (*Table 4*) with values obtained for spatial validation (*Table 2*) for period P3, we observe that TP_2 is lower for the temporal validation test and TP_3 is considerably higher. This happens because the behavior for period P_3 was affected by innovative changes not known by the model knowledge base, but the behavior from previous periods P1 and P2 is still valid and consolidated. Thus the knowledge base remains valid to predict changes following the historical behavior (failing less for predicted/non-occurred) but is unable to predict the changes corresponding to the innovative behaviors (failing more for occurred/non-predicted).

Table 4 - Temporal validation results to measure the accuracy for forecasting change.

	Forecasting P3	Backcasting P3
Observed changes	108	48
Predicted changes	98	46
TP1	87.4%	89.8%
TP2	12.6%	10.2%
TP3	18.3%	14.7%
TP4	90.0%	91.0%

The total error obtained for backcast validation (TP_1 and TP_2) is approximately 22%. These values are significantly lower than the obtained for forecast validation but still slightly higher than values obtained for the spatial validation process (21%). This occurs because in backcast we don't have the additional difficulty of the innovative behaviors as these behaviors could also be captured from the future information samples. The difference observed between accuracy values in backcasting tests and spatial validation tests are a consequence of a better knowledge of the behavior in P1 for spatial validation tests due to the cross validation process.

4. CONCLUSION

In this paper we discussed the validation process for a spatial forecasting model. Four different tests are performed to validate the Spatial Load Forecasting model: spatial validation, forecast, backcast and temporal validation. Two different accuracy measures were used: the measure of the accuracy in forecasting level and the measure of the accuracy in predicting changes from green-field to developed area.

Our experience teaches us that validating Spatial Load Forecasting requires more complex analysis than usual aggregated forecasting models. The accuracy observe for the forecasting level varies from 80% to 90%, which we classify as good for the tested example and for distribution planning purposes. The inaccuracy observed for changes are higher, ranging from 65% to 80%. These change accuracy values, important for expansion planning, are a consequence of the difficult predictive characteristics of the "spatial pioneer" consumers.

These results are extremely helpful in building "confidence intervals" for demand growth at each geographical location.

REFERENCES

[1] L. Willis, "Spatial Load Forecasting", Marcel Dekker Inc., New York, 1996. ISBN: 0-8247-9425-7

[2] H. L. Willis, "Power Distribution Planning Reference Book", Marcel Dekker Inc., New York, 1997. ISBN: 0-8247-0098-8

[3] Vladimiro Miranda, Cláudio Monteiro, "Fuzzy Inference Applied to Spatial Load Forecast", Proceedings of IEEE Budapest Power Tech'99, paper BPT99-359-25, August, 1999

[4] Vladimiro Miranda, Cláudio Monteiro, "Fuzzy Inference in Spatial Load Forecasting", Proceedings of IEEE PES Winter Meeting 2000, January, 2000

[5] Cláudio Monteiro, Vladimiro Miranda, Maria Teresa Ponce de Leão, "Uncertainty Propagation in a Fuzzy Spatial Load Forecasting Model", Proceedings of PMAPS'2000 - 6th International Conference on Probabilistic Methods Applied to Power Systems, September, 2000

[6] Cláudio Monteiro, Vladimiro Miranda, Maria Teresa Ponce de Leão, "Scenario Identification Process in Fuzzy Spatial Load Forecasting", Proceedings of PMAPS'2000 - 6th International Conference on Probabilistic Methods Applied to Power Systems, September, 2000

[7] Vladimiro Miranda, Cláudio Monteiro, Tatjana Konjic, "Spatial Offer and demand forecasting with Neuro-Fuzzy Inference Systems in GIS", Proceedings of WM2001 - IEEE PES Winter Meeting, (IEEE CD-ROM 01CH37194C), January, 2001

[8] Cláudio Monteiro, Vladimiro Miranda, Maria Teresa Ponce de Leão, "Merging judgmental and statistical information to build Spatial Load Forecasting System knowledge bases ", Proceedings of ISAP'2001 - Intelligent Systems Applications to Power Systems Conference, vol.1, June, 2001

[9] J. Von Neuman, "Theory of Self-Reproducing Automata", edited by A.W. Burks, University of Illinois Press, 1966

[10] S. Wolfram, "Cellular Automata and Complexity", Addison-Wesley Publishing Company, 1994, ISBN: 0-201-62664-0

[11] T. Toffoly, N. Margolus, "Cellular Automata Machines", MIT Press, Cambridge, 1996