VALIDATION OF FUZZY INFERENCE MODELS FOR SPATIAL LOAD FORECASTING

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Abstract: This paper reports the experiments conducted in order to compare the performance of Artificial Neural Networks and Takagi-Sugeno Fuzzy Inference Systems, in predicting consumer growth in Spatial Load Forecasting. These procedures are used in a GIS-Geographic Information System environment, and the objective is to determine feasible or attainable targets of quality in the load prediction by Fuzzy Inference Systems.

Key words: spatial load forecasting, fuzzy sets, fuzzy inference, neural networks, neuro-fuzzy systems

1. INTRODUCTION

Spatial Load Forecasting (SLF) methods have been developed to predict where, when and how much load growth will occur in a utility service area. They have been used to model the process of load growth in order to predict load evolution in a spatial and temporal basis, and have proved their value in distribution expansion planning. The first important systematic works in SLF have been conducted by Willis [1][2]. They are the basis for a consistent distribution network planning procedure.

However, the reasoning behind the models was, in some respects, still modelled in a crude way and not supported by a formal theoretical frame. In order to build a new approach to SLF based on a system with explicit rules, some of the authors of this paper developed a model joining the characteristics of a Fuzzy Inference System and Cellular Automata [3][4]. The Fuzzy Inference model captures the geographical patterns of influence factors, estimating the potential for development, and the Cellular Automata model the dynamics and spreading process over the geographical region, forecasting the development or consumer growth (Figure 1).

Spatial Load Forecasting (SLF) refers to models used to predict load growth in a region based on the influence of several control factors, defined as “influence factors”. Examples of those factors are, for instance, the radial distance to an urban centre or the distance to a waste treatment centre. Therefore, one of the best ways to implement SLF methods is use of Geographical Information System (GIS). The GIS is an ideal environment to SLF models because of its ability to: manage spatial information; model and simulate the phenomena behaviour; visualize data and simulation results and establish the interaction between the planner and simulation environment.

In spite of the interest of the classical SLF approach, there were aspects of the SLF model that depended too much on the *a priori* definition of numerical constants, values or parameters. However, one could feel that there could be perhaps a more appropriate approach that would directly include the representation of uncertainties, and that would be built upon learning from experience, i.e., from past data.

The Fuzzy Inference System is very appropriate to model spatial growth behaviour 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 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 translate to other space and time environments, giving its property of generalization.

The Fuzzy Inference Systems in this paper are of the Zero and First Order Sugeno type, organized in a Neuro-Fuzzy scheme. In the Zero-Order Sugeno type, a rule base is built such that the antecedent of each rule is fuzzy and the consequent is numerical and crisp. The strength of firing of each rule is given by the membership value of its antecedent and the contribution of each rule to the final result is mediated through a constant weight. In First-Order Sugeno models the output of each rule is now a linear function of the rule input values instead of a fixed weight. The rules are generated automatically, within the environment of a GIS – Geographical Information System, by defining the influence factors (examples: distance to roads; distance to urban centre; saturation level within the geographical unit; neighbourhood of other classes of consumers) and their linguistic values (examples: large; moderate; mediu m; small).

Results for a Zero-Order and a First-Order Sugeno Fuzzy Inference System and a pure Artifical Neuro-Network Model, based on data from a region represented on a GIS, are presented in this paper. The hybrid algorithm is used to achieve all the necessary coefficients in FIS instead of backpropagation training algorithm, similar to the one usually adopted in the process of training Artificial Neural Networks. The way to build a new generation of Spatial Load Forecasting systems, governed by a set of rules understood by the planners and with a linguistic interface, is now identified

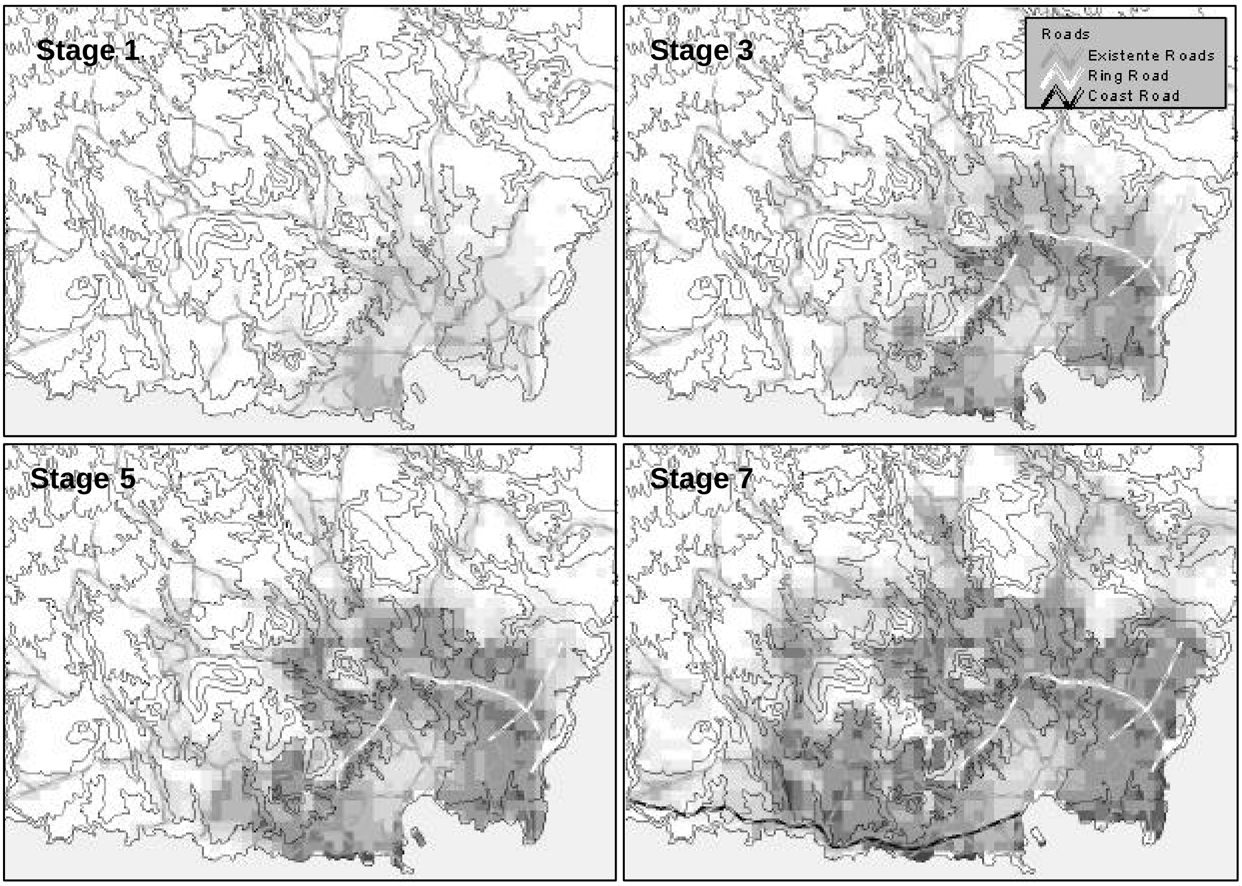

Figure 1: Example of the application of a TS Fuzzy Inference System to generate maps predicting load growth in a region, over a GIS (for illustration purposes, only [5]). This region, in the island of Santiago, Republic of Cabo Verde, Africa, was the one selected for the tests described in the paper.

2. THE *ANFIS* ARCHITECTURE

The acronym ANFIS derives its name from *adaptive neuro-fuzzy inference system* [6]. The basic idea behind neuro-adaptive techniques is very simple. These techniques provide a method for a TS fuzzy model to *learn* information about a data set, in order to compute the membership function parameters that best allow the fuzzy inference system to track the given input/output data relationship. This learning method works similarly to the bacpropagation algorithm of neural networks.

In order to present the ideas clearly, and without loss of generality, we assume now that the fuzzy inference system under consideration has two inputs x and y and one output f To fix ideas on reality, admit that x measures the proximity to a road, y measures the proximity to an urban center and f measures the electric power demand.

A rule set with two fuzzy if-then rules for a first-order Sugeno fuzzy model may be:

Rule 1:
If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$,

Rule 2:
If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$.

Figure 2 illustrates the reasoning mechanism for this Sugeno model. The corresponding equivalent ANFIS architecture is shown in where nodes of the same layer have similar functions, as described below.

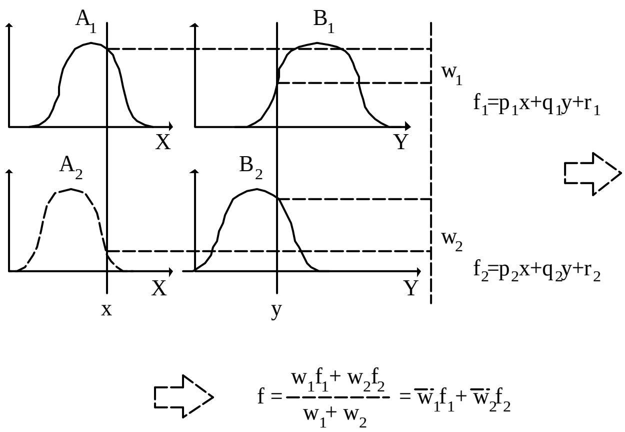

Figure 2: A two-input first-order Sygeno fuzzy model with two rules

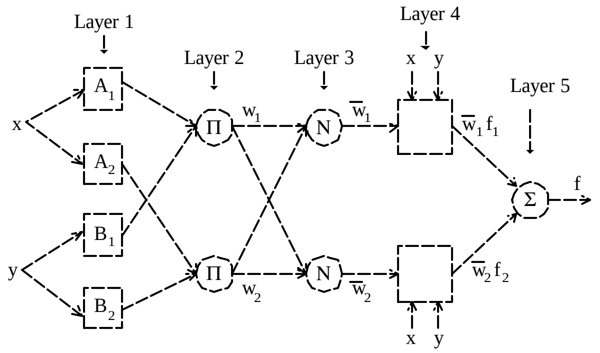

Figure 3: Equivalent ANFIS architecture for a two-input first-order Sugeno fuzzy model with two rules

Layer1

Each node *i* in this layer is an adaptive node with function:

$O_{1,i} = \mu_{A_i}(x)$, for i = 1, 2

$O_{1,i} = \mu_{B_{i-2}}(y)$, for i = 3, 4

where x or y is the input to node *i* and A_i or B_{i-2} is a linguistic label (such as “small” or “large”) associated with this node.

In other words, $O_{1,i}$ is the membership grade of fuzzy set A (= A_1, A_2, B_1 or B_2) and it specifies the degree to which the given input x or y satisfies the quantifier. The membership function for A can be any appropriate parameterised membership function such as the Gaussian function:

$$\mu_A(x) = e^{-\frac{(x-c_i)^2}{2\sigma_i^2}}$$

where c_i and s_i belong to the parameter set. Parameters in this layer are called *premise parameters*.

Layer2

Each node *i* in this layer is a fixed node labeled Π, whose output is the product of all the incoming signals:

$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y)$, for i= 1,2.

This can be interpreted as the adoption of the T-norm “product” for the conjunction or intersection of fuzzy sets. Each output node represents the *firing strength* of a rule.

Layer3

Each node *i* in this layer is a fixed node labeled N. The *i*th node calculates the ratio of the *i*th rule’s firing strength to the sum of all rule’s firing strengths:

$O_{3,i} = \overline{w}_i = \frac{w_1}{w_1 + w_2}$, for i= 1,2.

These outputs are called *normalized firing strengths*.

Layer 4

Each node *i* in this layer is an adaptive node with function:

$O_{4,i} = \overline{w}_i \; f_i = \overline{w}_i\left(p_i x + q_i y + r_i\right)$, for i=1, 2.

where $\overline{w}_i$ is a normalized firing strength from layer 3 and p_i, q_1 and r_1 represent the parameter set of this node. Parameters of this layer are *consequent firing parameters*.

Layer 5

The single node in this layer is a fixed node labelled Σ, which computes the overall output as the summation of all incoming signals:

$$overall\ output = O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}.$$

Thus we constructed an adaptive network that is functionally equivalent to a Sugeno fuzzy model.

3. NEURAL NETWORKS

Neural networks are systems that try to make use of some of the known or expected organizing principles of the human brain. It is a massively parallel-distributed processor that has a natural propensity for storing experimental knowledge and making it available for use [7]. The most interesting properties of the neural net are that they are universal approximators. They can approximate to any desired degree of accuracy any real valued, continuous function. The Figure 4 shows a multilayered feedforward neural network.

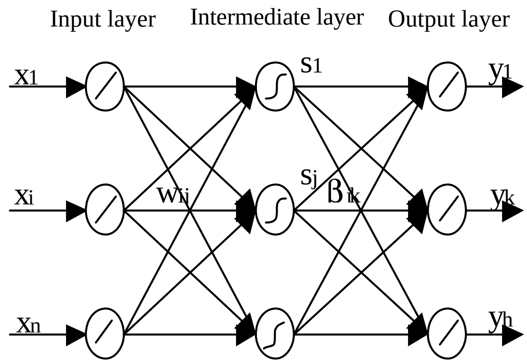

Figure 4: Multilayered feedforward neural network

The simple processor named neuron, communicate with others via weighted connections, the synaptic weights. Each neuron in intermediate layer calculates:

$$s_j = f(\sum_{i=1}^{n} x_i w_{ij}),$$

where x_i is the i-th input to the net, w_{ij} is the weight of the connection from neuron x_i to neuron s_j and f is named function activation.

Each output neuron calculates:

$$y_k = g(\sum_{j=1}^{m} \beta_{jk} s_j),$$

where g is the identity function, β_{jk} is the weight of the connection from neuron s_j to neuron y_k.

The knowledge is acquired trough the so-called learning process where the neural net learns from examples and solves problems by processing a set of training data. In the training process the synaptic weights are modified in an orderly fashion so as to attain a desired design objective [8].

4. HYBRID LEARNING ALGORITHM

For parameter tuning in an adaptive network one can apply a backpropagation algorithm, which is well known and is based on the steepest decent principle. This simple optimisation method, although enhanced by a number of algorithmic improvements, usually takes a long time before it converges. However, we may observe that the adaptive network's output is linear in some parameters; therefore, we can tune these linear parameters using an analytical Least-Squares method. This Least-Squares approach may be directly used in tuning TS FIS output parameters, when the parameters in the input membership functions (mf) remain constant.

We have, therefore, developed a hybrid algorithm, described in [9], consisting of a series of forward and backward passes. In the forward pass, the input parameters remain fixed, node outputs are propagated forward until layer 4 and the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by a gradient descent procedure, analog to the backpropagation in neural networks. Table I summarizes the characteristics of each pass.

TABLE I: Two passes in the hybrid learning procedure for anfis

	Forward pass	***Backward pass***
Premise parameters	Fixed	Gradient descent
Consequent parameters	Least-square estimator	Fixed
Signals	Node outputs	Error signals

5. EXAMPLE

The selected study region is the island of Santiago (Republic of Cabo Verde, Africa). This region is represented in Figure 1 where, for illustration purposes only, we have represented successive maps of prediction of load growth, resulting from the application of a Fuzzy Spatial Load Forecasting System, as described in [5].

The region size is 39km x 50,5km. The resolution in the GIS spatial representation was of square cells of 250 m, aggregated in a cell-based map with 31512 cells. Each cell contains information about influence factors as inputs and potential for development as the output.
We have divided these data into a training set and a test set of equal size (15756 points each), and controlled the convergence of the training processes in the usual way, avoiding phenomena of over-fitting, while minimizing the mean square error between actual data and predictions.

An example of a rule generated for a 0-order Takagi-Sugeno FIS with 5 influence factors would be:

IF (distance to road is (CLOSE)) **AND**
IF (distance to main urban center is (MODERATE CLOSE)) **AND**
IF (distance to secondary urban centre is (CLOSE)) **AND**
IF (terrain slope (VERY SMALL)) **AND**
IF (saturation level is (MEDIUM))
THEN Domestic PfD is 25 consumers per stage per km^2

The qualifiers "CLOSE", "VERY SMALL", etc., represent the linguistic labels that are modeled by fuzzy set membership functions. All tests examples have been made in MatLab.

The following figures present the results for a Zero-Order and a First-Order Sugeno Fuzzy Inference System and a pure Artificial Neuro-Network Model. All the necessary coefficients in FIS were calculated using the hybrid algorithm.

In the first series of tests for Sugeno Fuzzy Inference Systems, the input variables are: distance to main urban center (5 linguistic labels), distance to road (5 linguistic labels) and distance to secondary urban centers (5 linguistic labels); and the output is the potential for development (PfD), represented by the number of consumers identified in each cell of the map generated by the GIS. In this structure there are 125 rules, while the number of linear and non-linear parameters depends on the types of membership functions and the order of the Sugeno model. For examples displayed below, we have adopted gaussian membership functions (mf).

0-order TS FIS

Figure 5 shows the output (PfD) for a zero-order Sugeno model with gaussian mf and its error for the training data set.

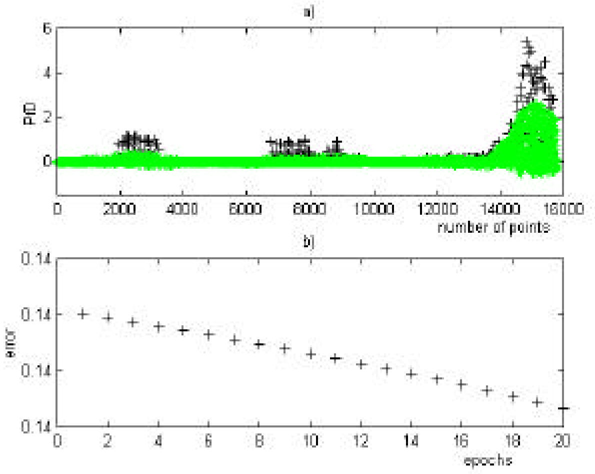

Figure 5: a) Output-potential for development for three-inputs zero-order Sugeno model with gaussian mf (+ - real pfd; * - modelled PfD); b) Error for training data set

1st-order TS FIS

Figure 6 shows the output for a first-order Sugeno model with gaussian mf and its error in training data set.

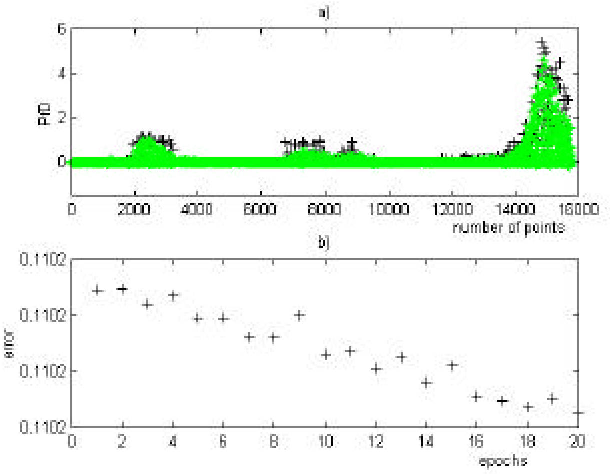

Figure 6: a) Output-potential for development for three-inputs first-order Sugeno model with gaussian mf (+ - real PfD; * - modelled pfd); b) Error in training data set

Neural-network model

A neural network was trained with the same three input variables (distance to main urban center, distance to road and distance to secondary urban centers) and one output (potential for development). The neural network is constructed of four layers: input layer, two intermediate (hidden) layers (4 neurons in first intermediate layer with activation function 'logsig' and 12 neurons in second intermediate layer the same activation function) and output layer (1 neuron with activation function 'purelin'). The algorithm used for training process is the usual backpropagation algorithm. Training data set is the same as for TS FIS.

The Fig. 2 shows the output (potential for development) for the neural network trained. The error for the training set was 0.0866.

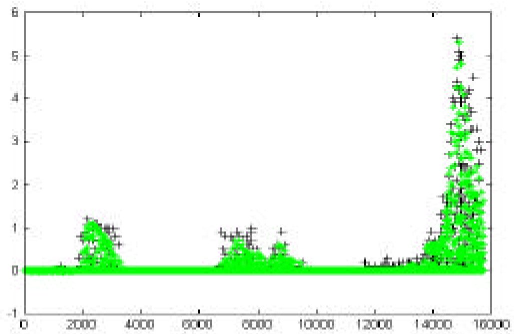

Figure 7: Output-potential for development for three-inputs neural networks (+ - real pfd; * - modelled PfD);

Tests on a heavier model

In order to confirm the generality of the conclusions to be extracted, we increased number of inputs in the FIS model by enlarging the number of influence factors considered. This time, we used as inputs: distance to main urban center (4 linguistic labels), distance to roads (4 linguistic labels), distance to any urban center (4 linguistic labels) and cell saturation (3 linguistic labels), keeping potential for development as the output of zero and first-order Sugeno models. There are 192 rules in these models. The gaussian mf is chosen for input variables, again.

Figure 8 and Figure 9 present the output (PfD) for zero and first-order Sugeno models with gaussian mf, respectively, and their error in the training data set.

All tests allow us to conclude that, in fact, an ANN model will provide a better fit to data. This sets a quality target for any prediction model.

Also, we have confirmed (as it would be expected) that 1st order TS-FIS will give better results than 0-order TS-FIS.

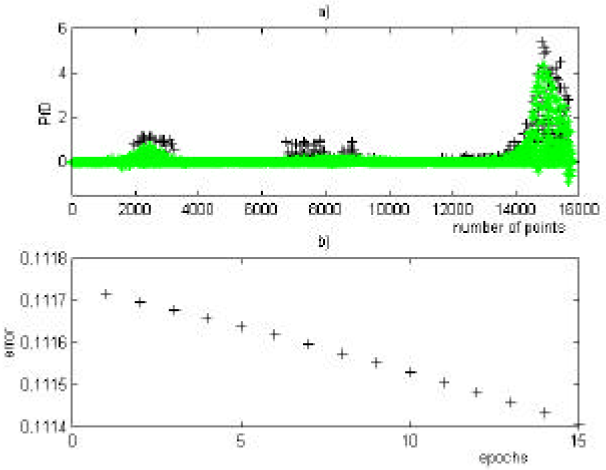

Figure 8: a) Output-potential for development for four-inputs first-order Sugeno model with gaussian mf (+ - real pfd; * - modelled PfD); b) Error in training data set

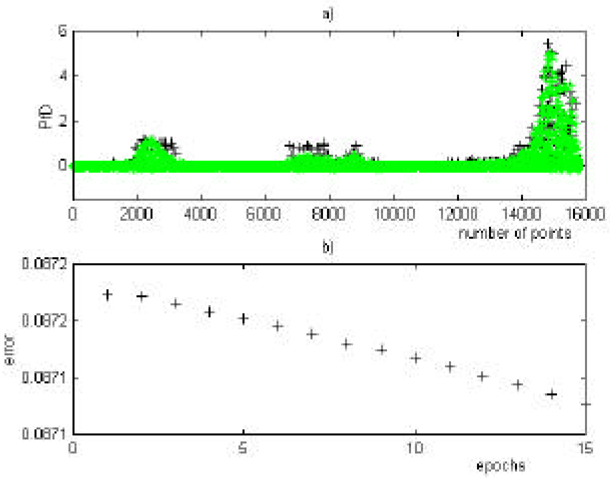

Figure 9: a) Output-potential for development for four-inputs first-order Sugeno model with gaussian mf (+ - real PfD; * - modelled pfd); b) Error in training data set

6. CONCLUSIONS

This report describes part of the work being done in order to develop consistent rule based inference systems that may assist planners in using GIS tools to perform spatial load forecasting exercises.

As a target for quality, one has selected the performance of well-trained Artificial Neural Networks. ANNs are universal interpolators and one hopes that a good one may be built to fit the data in the training and test sets. Besides, it is conceivable to admit that a suitable ANN will have larger degrees of freedom to become adapted to data than TS-FIS of the lowest orders. As expected, the neural network black box models designed gave better results than Takagi-Sugeno Systems with same number of inputs.

This allowed one to define a target for quality for the TS-FIS to be tested. A fuzzy inference system fitting the data with a small error regarding the output of the best ANN available would be taken as an acceptable inference engine, because one will not reasonably expect to largely beat the ANN in the fitting task. Therefore, one can determine a "level of acceptability" for the order of a TS-FIS that would perform the same duty.

This means that one will, in the end, remain with the same quality in the fitting as with an ANN and obtain knowledge explicitation through a rule set, based on linguistic based rules.

This paper demonstrates that this reasoning is feasible and that TS-FIS or 1st order with gaussian membership functions will produce results of quality comparable to neural network models.

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