Hierarchical Fuzzy Model

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Abstract: – A hierarchical fuzzy model is proposed in this paper. The concept of relevance has enabled the measurement of the relative importance of rule sets and the Separation of Linguistic Information Methodology (SLIM) provided a means to organize its information in different structures. Based on this methodology a new SLIM-PCS algorithm is proposed for the Parallel Collaborative Structure (PCS). As demonstrated in the experimental tests, the proposed SLIM algorithm has been successfully applied to modelling the temperature of agricultural greenhouses.

Keywords: – Hierarchical model, fuzzy model.

1. Introduction

Fuzzy modelling is a very important and active research field in fuzzy logic systems. Compared to traditional mathematical modelling and pure neural network modelling, fuzzy modelling possesses some distinctive advantages, such as the mechanism of reasoning in human understandable terms, the capacity of taking linguistic information from human experts and combining it with numerical data, and the ability of approximating complicated non-linear functions with simpler models. In recent years, a variety of different fuzzy modelling approaches have been developed and applied in engineering practice [1][2][3]. These approaches provided powerful tools to solve complex non-linear system modelling and control problems. However, most existing fuzzy modelling approaches concentrate on model accuracy that simply fit the data with the highest possible accuracy, paying little attention to simplicity and interpretability of the obtained models, which is considered a primary merit of fuzzy rule-based systems. Often, users require the model to not only predict the system's output accurately but also to provide useful description of the system that generated the data. Such a description can be elicited and possibly combined with the knowledge of experts, helping to understand the system and validate the model acquired from data. Thus, it is desired to establish a fuzzy model with satisfactory accuracy and good interpretation capability.

In order to organize the fuzzy rules and reduce its number, it is of utmost importance to define metrics to quantify each one of the fuzzy rules that describes the process.

This work addresses this fundamental aim of fuzzy modelling. As result of a new concept recently proposed [4], namely the relevance of the rule set, this objective is near at hand. This new concept, bounded by a set of intuitive axioms, opens the doors for new types of fuzzy modelling, based on called Separation of Linguistic Information Methodology, or SLIM [4][5]. It is useful for organizing the information in a fuzzy system: a system $f(x)$ is organized as a set of n fuzzy systems $f_1(x)$, $f_2(x)$, ..., $f_n(x)$, in a particular structure. Each of these systems may contain information related with particular aspects of the system $f(x)$. Taking this into account the SLIM-PCS algorithm is proposed for tuning the Parallel Collaborative Structure (PCS) and evaluated against a real world case study.

The practical goal of this work is to model an agriculture greenhouse under process control [6]. The process model is highly non-linear and is not completely known. To accomplish the fuzzy identification task, the RLS-Nearest Neighbourhood Fuzzy adapter method is employed, which combines the Nearest Neighbourhood Fuzzy Method with RLS algorithm [3][7][8]. As expected, the identification procedure for such kind of process model leads to a set with a very high number of rules. Afterwards, the information is organized by the SLIM algorithm in order to improve its readability and reduce the number of rules with no loss of valuable information. As demonstrated, the experimental results obtained with this strategy perform at least as well as the mechanistic models. A different SLIM-PCS algorithm was successful tested in the modelling of pilot plant chemical reactor [9].

The paper is organized as follows. The concept of the relevance and the Parallel Collaborative Structure are briefly presented in sections 2. The RLS-Neighbourhood Fuzzy Method, used in fuzzy identification procedure, is described in section 3. The SLIM methodology is presented and its SLIM-PCS algorithm is proposed in section 4. In section 5 the greenhouse climate model where the experimental tests took place is described, and the experimental results are presented. Finally, in section 6, the main conclusions are outlined.

2. Relevance and the Parallel Collaborative Structure

The SLIM methodology organizes a fuzzy system $f(x)$ as a set of n fuzzy systems $f_1(x)$, $f_2(\boldsymbol{x})$, …, $f_n(\boldsymbol{x})$. Each of these subsystems may contain information related with particular aspects of the system $f(\boldsymbol{x})$. The subsystems may be organized under different structures. In this case, a PCS has been used. Therefore, the output of the SLIM model is the integral of the individual contributions of each fuzzy subsystem:

$$f(\boldsymbol{x}) = \int_{i=1}^{n} f_i(\boldsymbol{x}) \cdot \Re_i(\boldsymbol{x}) \qquad (1)$$

where $\Re_i(\boldsymbol{x})$ represents the relevance function of the i^{th} fuzzy subsystem covering the point $\boldsymbol{x}$ of the Universe of Discourse, and the $\int$ an aggregation operator.

The relevance of aggregated system is given by:

$$\Re_i(\boldsymbol{x}) = \Re_i(\boldsymbol{x}) \cup \cdots \cup \Re_n(\boldsymbol{x}) \qquad (2)$$

Naturally, if the i^{th} fuzzy subsystem covers appropriately the region of the point $\boldsymbol{x}$, its relevance value is high (very close to one), otherwise the relevance value is low (near zero or zero).

Fig.1 shows an example of the application of the SLIM methodology to fuzzy modelling using two fuzzy subsystems. The fuzzy system $f_2(\boldsymbol{x})$ may describe the general aspects of the original system $f(x)$ (usually with a small number of rules), while the fuzzy system $f_1(\boldsymbol{x})$ describes all the remaining aspects, in order to improve the accuracy of the model. As the process evolves, part of the information of $f_1(x)$ is transferred to $f_2(x)$. The identification of $f(x)$ and the internal transference of information from $f_1(x)$ to $f_2(x)$ are two independent processes that can operate in parallel and may be used on-line.

The separation of information may be used to organize the information of a system, namely to reduce the number of rules representing the original system by discarding sets of rules with lower relevance values. For these purposes, the relevance function $\Re_i(\boldsymbol{x})$ is expected to measure the relative importance of the fuzzy rules in the specified context.

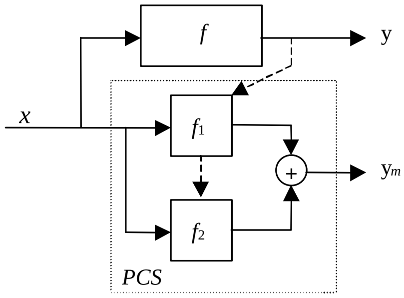

Fig. 1. A practical implementation of PCS.

Definition 1: Consider $\Im$ a set of rules from the input space U, into the output space V, covering the region in the product space $S = U \times V$. Any function defined as a measure of relevance must be of the form

$$\Re_S : \tilde{P}(\Im) \rightarrow [0\ ,\ 1] \qquad (3)$$

where $\tilde{P}(\Im)$ is the power set of $\Im$. The function $\Re_S$ must obey a set of five axioms [4][5].

Next, the definition of relevance for two particular situations is reviewed. A measure of relevance for a rule in a *single point* of the product space is given in definition 2, and definition 3 identifies a measure of relevance for a rule in a *region of the space*.

Definition 2: The relevance of a rule $l \in \Im$ in a point of the product space $(x, y) \in S$ is defined as

$$\Re_S(l,(x,y)) = \max_y (G_l / G) \qquad (4)$$

i.e., the relevance in (x, y) is the maximum of the ratio between the value of the output membership function of rule l in (x, y), and the value of the membership of the union of all the functions in (x, y).

Definition 3: The *relevance* of a rule $l \in \Im$ in S is defined as:

$$\Re_S(l) = \max_{x,y} \Re_S(l,(x,y)) \qquad (5)$$

i.e., the maximum of the value for all points $(x,y) \in S$, of the ratio between the membership output function of rule l, and the value of the union of all the output membership functions.

3. RLS-Neighbourhood Fuzzy Method

Consider a collection of N data points $\{P_1, P_2,..., P_N\}$ in a n+1 dimensional space that combines both input and output dimensions. A generic fuzzy model is presented as a collection of fuzzy rules in the following form:

R^i: IF x_1 is A_{il} and x_2 is A_{il} ... and x_i is A_{in} THEN y=$z_i(\vec{x})$

where $\vec{x} = (x_1, x_2, \cdots, x_n)^T \in U$ and $y \in V$ are linguistic variables, A_{ij} are fuzzy sets of the universes of discourse $U_i \in \boldsymbol{R}$, and $z_i(\vec{x})$ is a function of the input variables. Typically, z can take one of the following three forms: singleton, fuzzy set or linear function. Fuzzy logic systems with center of average defuzzification, product-inference rule and singleton fuzzification are of the following form:

$$f(\vec{x}_k) = \sum_{l=1}^{M} p^l(\vec{x}_k) \cdot q^l \tag{6}$$

where $p^l(\vec{x}) = m^l(\vec{x}) \Big/ \sum_{l=1}^{M} m^l(\vec{x})$ is the *fuzzy basis functions* (FBF), M represent the number of rules, q^l is the point at which the output fuzzy set l achieves its maximum value, and m^l is the membership of antecedent of rule l.

A fuzzy adaptive system is constructed from a set of changeable fuzzy IF-THEN rules. These fuzzy rules come either from human experts or by matching input-output pairs through an adaptation procedure. The adaptive algorithms update the parameters of membership functions, which characterize the fuzzy concepts in the IF-THEN rules by minimizing some criterion functions.

The present algorithm combines the Nearest Neighbourhood Fuzzy Method with RLS algorithm. The former is used to find the appropriate fuzzy basis functions and its placement, namely of the inputs memberships, while the RLS algorithm adjusts the linear function parameters [7][10].

For our RLS fuzzy adaptive system we have the following problem: for each time point k=0, 1, 2,…, determine an adaptive fuzzy model of equation (6) such that

$$J(k) = \sum_{i=0}^{k} l^{k-1} \left[d_i - f(\vec{x}_i) \right]^2 \tag{7}$$

is minimized, where $l \in (0,1]$ is a forgetting factor.

The preceding problem is quite general. If we constrain the f_k's to be linear functions of q 's parameters, the problem becomes an RLS adaptive design problem:

$$f(\vec{x}_k) = \boldsymbol{p}^T(\vec{x}_k) \cdot q \tag{8}$$

where $\boldsymbol{p}$ and q are the vectors of FBF's and q 's parameters, respectively.

Choosing the appropriate FBF requires the placement of the inputs memberships. For that reason, we proposed the use of the Nearest Neighbour methodology [3][8]. This identification method consists in establishing a single radius of influence r. Starting with the first sample point $(\boldsymbol{x},y)$, a cluster with center $\bar{\boldsymbol{x}}^{\boldsymbol{l}}$ is created in $\boldsymbol{x}$. A sample point for which the distance to the nearest clusters is greater than r becomes the center of a new cluster:

$$IF\ \left\| x_k - \bar{x}^l \right\| > r\ THEN \begin{cases} \bar{x}^{l+1} = x_k \\ q^{l+1} = 0; \\ M = M+1; \end{cases} \tag{9}$$

$$for\ k = 1, \cdots, n, \forall l \in \{1, \cdots, M\}$$

The radius r determines the complexity of the adaptive fuzzy model. For smaller radius there are more clusters resulting in a more complex non-linear regression that demands more computational effort.

The vector $\boldsymbol{q}$ can be updated using the RLS algorithm shown bellow [7][10]:

$$q_k = q_{k-1} + \boldsymbol{S}_k \boldsymbol{p}_k \left(\boldsymbol{d}(k) - \boldsymbol{p}_k^T q_{k-1} \right) \tag{10}$$

$$\boldsymbol{S}_k = \frac{1}{l} \left(\boldsymbol{S}_{k-1} - \frac{\boldsymbol{S}_{k-1} \boldsymbol{p}_k \boldsymbol{p}_k^T \boldsymbol{S}_{k-1}}{l + \boldsymbol{p}_k^T \boldsymbol{S}_{k-1} \boldsymbol{p}_k} \right) \tag{11}$$

where k=1, 2, … is the iteration number.

The initial values for the iterative process can be chosen as $\boldsymbol{q_0} = \boldsymbol{0}$ and $\boldsymbol{S_0} = g.\boldsymbol{I}$, where g is a large number.

4. The SLIM-PCS algorithm

As depicted in Fig.1, the present algorithm is proposed for two subsystems. The generalization for more than two subsystems is obvious. The relevance function of the fuzzy rules used here is as stated in *Definitions* 2 and 3. Other relevance functions can be used as well.

Let f_1 be a fuzzy subsystem obtained by using the RLS-Neighbourhood algorithm, and f_2 a fuzzy subsystem with early null output values for all domain (or relevance null). M_1 and M_2, are the number of rules of the f_1 and f_2, respectively.

The first subsystems can be expressed by:

$$f_{\Re,1}(\vec{x}) = \boldsymbol{q}_{\Re}^T(\vec{x}) \cdot \boldsymbol{Y} \tag{12}$$

where

$$\boldsymbol{q}_{\Re}(\vec{x}) = \boldsymbol{q}(\vec{x}) \otimes \Re_l \tag{13}$$

i.e., $\boldsymbol{q}_{\Re}(\vec{x}) = \left[q^{l_1}(\vec{x}) \cdot \boldsymbol{a}^{l_1}, q^{l_2}(\vec{x}) \cdot \boldsymbol{a}^{l_2}, \cdots, q^{l_{M_1}}(\vec{x}) \cdot \boldsymbol{a}^{l_{M_1}} \right]^T$ is the inner product between the FBF vector and the relevance vector. $\boldsymbol{Y} = \left[\bar{y}^{l_1}, \bar{y}^{l_2}, \cdots, \bar{y}^{l_M} \right]^T$ is the vector (or matrix) of all the centers of output membership functions.

The parameter $\boldsymbol{a}^{l_1}$ is closely connected to the relevance of the rule in the fuzzy system. When $\boldsymbol{a}^{l_1}$ is equal to unity, rule l_1 has maximum relevance, while for null

a^{l_1}, the rule loses its relevance. If $a^{l_1} = 1$ for all $l_1 = 1,...,M_1$, then $f^*_1 = f_1$. If parameter a^{l_1}, associated to rule l_1, converges to null, rule l_1 is eliminated from function $f_{\hat{A},1}$. If this is possible for all rules of f_1 then f_1 is eliminated ($\lim_{a\to\infty} f_1 = 0$).

Similarly, the second fuzzy system is expressed by

$$f_{\Re,2}(\vec{x}) = \boldsymbol{p}^T(\vec{x}) \cdot q_{\Re} \tag{14}$$

where $q_{\Re}$ is the inner product between the q vector and the relevance vector.

Initially, f_1 contains all the information, $\Re_l(l_1) = 1$, $\forall l_1 \in \{1, 2, \cdots, M_1\}$ while f_2 is empty, *i.e.*, $\Re_l(l_2) = 0$ $\left(q_{\Re}^{l_2} = 0\right)$, $\forall l_2 \in \{1, 2, \cdots, M_2\}$, $f_{\hat{A},2}(x_k) = 0$.

The relevance of the rules of f_1 decreases at the same proportion that f_2 assumes a greater importance. Thus, during this transfer of process information there is no change in the sum of the models. By the end of this process, all or part of the rules of model f_1 may have null or almost null relevance and under these circumstances they should be eliminated. Those who keep a significant relevance index should not be eliminated, as they still contain relevant information.

Considering what was stated, the problem consists on the optimisation of the cost function *J:*

$$\min J(\vec{a}) = \min \ (\vec{a})^T \cdot \vec{a}$$

$$\text{subject to } \ f(\vec{x}) = f^i_{\Re,1}(\vec{x}) + f^i_{\Re,2}(\vec{x}) \tag{15}$$

The purpose is then to keep the invariability of the identification model (i = 1, 2, …, iteration) and, simultaneously, to reduce the importance of model f_1 in favour of f_2. In order to achieve this, the Lagrange multipliers technique has been used.

Obviously, if the radius of the rules of f_1 is so small that the center of the rule is a point representative of the region covered by the rule, then the resolution of the problem has been constrained to the set of M_1 points. Under these circumstances, the solution of the problem is obtained by solving the following system of nonlinear equations:

$$a_k = 1 - \frac{1}{\bar{y}^k} \cdot (\vec{p})^T \cdot \vec{q}, \quad \text{for } k = 1, \cdots, M_1 \tag{16}$$

$$\vec{q} = Q^{-1} \cdot \sum_{k=1}^{M_1} \frac{\vec{p}(\vec{x}_k)}{\bar{y}^k} \tag{17}$$

where

$$Q = \sum_{k=1}^{M_1} \frac{1}{\bar{y}^k} p(\vec{x}_k) \cdot \left(p(\vec{x}_k)\right)^T \tag{18}$$

is a symmetric matrix with $M_1 \times M_1$ dimension.

If the inputs membership functions are static then equations (16)-(17) provide a systematic way of transferring the information from system f_1 to system f_2 in one step. Otherwise, the tuning of memberships parameters will improve the minimization of J cost function. An iterative procedure can be used:

$$a_p^{i+1} = a_p^i - h \cdot \frac{\partial J}{\partial a} \tag{19}$$

where a_p, with $p = 1, \cdots, np$, are parameters of input memberships function, with np the total number of parameters liable to optimisation procedure, and i the current number of the iteration optimisation step. In this work we used gaussian memberships.

The SLIM-PCS algorithm results in the association of tuning of the input memberships functions, eq. (19), with the tuning of the center of fuzzy outputs sets, eqs. (16)-(17).

Finally, if the a_k value for rule k is a null value or near zero, then the rule can be discharged.

5. The greenhouse model

The greenhouse climate model describes the dynamic behaviour of the state variables by the use of differential equations of temperature, humidity and CO2 concentrations. In this paper the temperature model is considered.

The model equations can be written by deriving the appropriate energy balance

$$\frac{dT_{est}}{dt} = \frac{1}{C_{Temp}}\left(Q_{T,h} - Q_{T,out} + Q_{T,soil} + Q_{T,rad}\right) \tag{20}$$

where C_{Temp} [J m^{-2} ^{o}C^{-1}] is the heat capacity per square meter.

The energy balance in the greenhouse air is affected by the energy supplied by the heating system, $Q_{T,h}$ [W m^{-2}], by energy losses to outside air due to transmission through the greenhouse cover and forced ventilation exchange, $Q_{T,out}$ [W m^{-2}], by the energy exchange with the soil, $Q_{T,soil}$ [W m^{-2}], and by the heat supplied by sun radiation, $Q_{T,rad}$ [W m^{-2}]. The energy transport phenomena at greenhouse cover and the contribution of ventilation, induced by temperature differences between the inside and outside air is only significant at very low wind speeds [11], and consequently they are neglected in this model.

This model requires a great domain of the physical process and measurement accuracy on the process variables. Fuzzy modelling can be an alternative representation for describing the process and is easily interpretable by anyone.

The model can be significantly improved if it is divided in sub models. The temperature model is broke in two parts: the daylight and night sub models.

- Daylight Temperature (DT) sub model (RAD>0)

$$\frac{dT_{est}}{dt} = f_{Temp}\left(\Delta T, Rad, Q_{T,h}, Q_{T,out}\right) \qquad (21)$$

- Night temperature (NT) sub model

$$\frac{dT_{est}}{dt} = f_{Temp}\left(\Delta T, Q_{T,soil}, Q_{T,h}\right) \qquad (22)$$

where:

- $\Delta T(t) = T_{est}(t) - T_{ext}(t)$ is the difference between inside and outside temperatures.

- *Rad* is the sunlight radiation intensity.

- $Q_{T,h}(t) = U_{T,h}(t)\cdot\left(T_p - T_{est}(t)\right)$ is the heat flux from the heating system. T_p is the temperature of the coil water of the heating (about 60 °C).

- $Q_{T,out}(t) = U_{T,out}(t)\cdot\left(T_{ext}(t) - T_{est}(t)\right)$ is the heat flux exchange with the outside air.

- $Q_{T,soil}(t) = \left(T_{soil}(t) - T_{est}(t)\right)$ is the heat exchange with the greenhouse soil.

Here, the required task is to develop the above fuzzy systems that can match all the N pairs of collected temperature data to any given accuracy.

The structural and parametric identification of the above model can be implemented using the RLS-Neighbourhood fuzzy algorithm, described in section 3, by using daily input-output data points collected from the process.

6. Experimental results

The SLIM methodology has been applied to the identification of the dynamic behaviour of temperature in an agricultural greenhouse located at the UTAD campus. Three different fuzzy identification techniques have been applied to model the data: back propagation [2], RLS (section 3) and SLIM-PCS. The idea is to compare a system organized by the SLIM methodology against the systems produced by the reference methods: The structure for the organization of information adopted in this case was a Parallel Collaborative Structure (PCS). This structure uses two fuzzy subsystems whose outputs are added to produce the global output. SLIM is used to transfer information between the subsystems. The rules with lower relevance values are discarded.

The identification of the above models was realized by using daily input-output data points collected from the process, between January 15 and February 4, 1998, at 1-minute sample time. Fig. 2 shows, for this period, the evolution of actuation variables of the greenhouse heating, ventilation and screen system. Two other data periods were used to test the models: 8 to 14 of January and 5 to 11 of April.

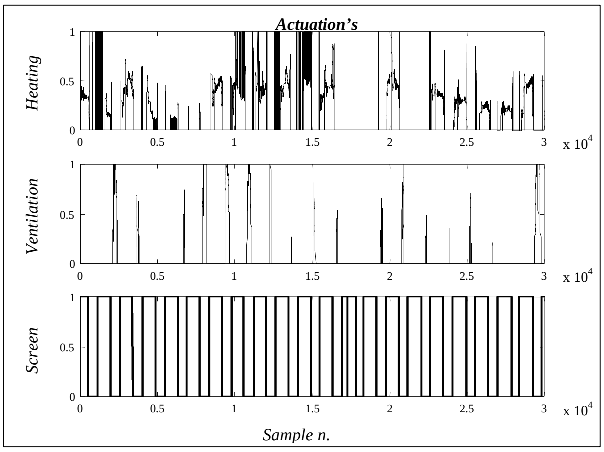

Fig. 2. Evolution of actuation variables of the greenhouse heating, ventilation and screen systems.

The first step is to capture the greenhouse models in a PCS system from real data. The identification process was performed with the RLS-Neighbourhood identification method, with a radius of 0.4 for the temperature model. Sets of 777 and 349 fuzzy rules have been used, respectively for the sub models (21) and (22).

In order to proceed, the information is transferred from the sub-system f_1 to f_2 in the PCS structure. Previously, all the original rules are placed in the first level. The next step consists in diminishing the relevance of the rules in level 1 in favour of the rules in level 2. This is accomplished by tuning the membership functions of level 2 to compensate for the relevance rules in level 1. The optimisation procedure is achieved using equations (16) to (19). The number of rules chosen for level f_2 is 10 for each sub-model.

The output of the resulting PCS system after applying the SLIM methodology is represented in Fig. 3 for temperature model: The results were obtained in the test period of 5 to 11 of April. Real data curves are also represented for comparison purposes.

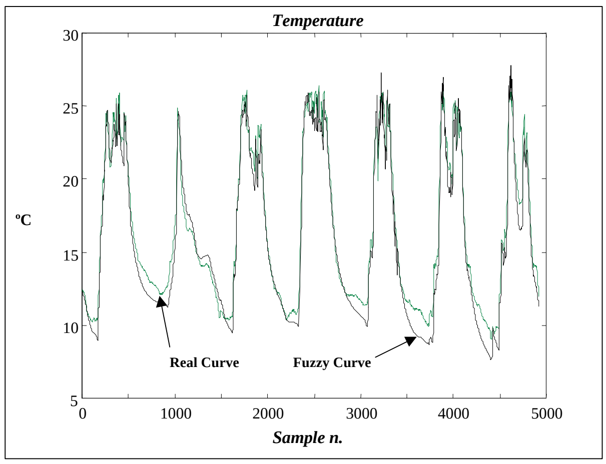

Fig. 3. Temperature Fuzzy model.

The variance of the errors between the simulations and the experimental temperature data is indicated in Table 1.

Experimental work shows that fuzzy identification systems created with the reference methods are made of a very large number of IF…THEN rules. The SLIM methodology, applied to the systems produced with the RLS method, has produced systems with a number of rules that varies between 2% and 20% of the number of rules of the other systems, with negligible differences in the behaviour, as illustrated in Table I. The "slimed" system, with a superior organization, contains the same level of information and uses a lower number of rules.

The only identification method which produces a number of rules comparable to the one obtained with SLIM is the back-propagation method. However, it uses 1000 iteration cycles for capturing the data behaviour. Even so, it produces 50 rules, against 10 rules in the system using the SLIM methodology.

Table 1: Errors, number of rules and iterations of the different temperature fuzzy system models.

			Temperature Error - $\hat{E}$ ($\bar{E}$) (ºC)		
Fuzzy Method	**n. of rules**	**n. of itera-tion**	**8 to 14 Jan.**	**15 of Jan to 4 of Feb**	**5 at 11 of April**
Back-Propaga-tion	**50 (day)**	**1000**	**0,98 (0,79)**	**0,81 (0,56)**	**1,01 (0,77)**
	50 (night)				
RLS	**777 (day)**	**1**	**0,88 (0,70)**	**0,74 (0,53)**	**1,07 (0,86)**
	349 (night)				
MSIL-PCS	**10 (day)**	**1**	**0.87 (0.72)**	**0.81 (0.64)**	**1.18 (1.02)**
	10 (night)				

7. Conclusions

An experimental evaluation of the concept of relevance and SLIM methodology was presented in this paper. Its applicability and the good results obtained demonstrate the success of this methodology for the separation of information (SLIM) in the PCS structure.

Two important advantages can be outlined: it is suitable for on-line use, and it is capable of describing the behaviour of the plant with a reduced number of linguistic rules. This implies better readability of the process model.

It is believed that the proposed approach for describing a system model by a set of fuzzy rules, which are then processed to extract relevant information, is viable for analysing and controlling real processes.

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