Fuzzy model and control of a fan-coil

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Abstract

Fuzzy models and controllers are represented by *if-then* rules and thus can provide a user-friendly and understandable representation of combined quantitative and qualitative description. The *qualitative* rules result in a *quantitative non-linear controller* well suited to nonlinear systems controlling thermal comfort with vague defined objectives as fan-coils used in solar energy systems. The fuzzy models are achieved through identification by varying the inputs so that the fan-coil reaches the states encountered in normal operation. These models may be used for control or for simulation. On its domain of validity, the fuzzy controller behaves better then a classical controller. In fact, the main advantage of fuzzy controller is the easiness of introducing operating modes and poor defined objectives specific for solar energy systems such as freeze and over-temperature protection, or draining.

Key words: artificial intelligence, fuzzy logic, nonlinear control, thermal comfort

Introduction

Solar energy heating systems convert the solar radiant energy and use air or, more commonly, liquid to transfer the resulted heat to the building. The objectives of solar energy systems are temperature, humidity, air movement, and air purity control. Besides clear objectives (e.g. room air temperature value), other vaguely defined operating rules and objectives characterize the control of solar energy systems, such as heat collection, heat rejection, power outage, freeze protection, and auxiliary heating [1].

Room air temperature is controlled by varying the supply air temperature and flow. Supply air temperature control presents interest in evaluating the comfort and in control system design: models for evaluating the thermal comfort consider the supply air temperature as input [2], and cascade control of room temperature has the control of supply air temperature as inner loop. Hence the interest of controlling supply air temperature and also having the possibility of including operating rules, specific for the solar energy systems, in the overall algorithm.

Fuzzy controllers are represented by vague *if-then* rules (such as *if the temperature is small then slightly open the control valve*) and thus can provide an easy and understandable knowledge representation. The *qualitative* rules in a fuzzy controller result in a *quantitative non-linear controller*. As there is no unique relation between a qualitative expression and a quantitative value, a loss of information results in the translation. However, it is an advantage that complex control strategies available in the form of expert knowledge can be implemented in automatic controllers. Generally, the computer implemented controllers with time-invariant parameters may be considered as static functions. The measurements are performed at certain sampling time and the dynamic behavior is achieved by considering time differences of inputs and outputs. The linear controller yields a control (hyper)plane. Fuzzy controllers are in most cases non-linear static functions. They provide a *user-friendly* method to implement non-linear functions and "*interpolative mechanisms, not only in small, but also in very large and complex problems."* [3] The comfort control systems require the combination of comfort parameter control with operating and scheduling rules, in order to achieve poor defined objectives, which are well represented in fuzzy logic.

Fuzzy controllers are usually claimed to be more robust and adequate for nonlinear control. Nevertheless, there is no demonstration of the robustness of fuzzy controllers. A fuzzy algorithm is in fact a multivariable nonlinear static function; if a system controlled with such a function is robust or not depends on the rules that define the function. When the variation of parameters is known (even partially), the fuzzy control algorithm may be designed to be less sensitive to parameter variation. The other claim, that the fuzzy control algorithms are better suited for nonlinear control is true only for that type of systems in which the nonlinearities depend on the error (i.e. the difference between the output and set point) and its derivates. But in many cases, the process nonliniarities depend on other variables, which should be measured. Consequently, using a fuzzy controller requires knowledge of the process, even if it is not expressed in a clear mathematical form [4].

An important problem in fuzzy control is the stability. As fuzzy controllers are nonlinear functions, the stability is difficult to be analyzed [5], but, practically, the stability analysis is replaced by prototype tests [6].

Applications of classical fuzzy controllers (as introduced by Zadeh and using Mamdani type inference algorithm) in heating, ventilating and air conditioning systems is reported in both research papers and industrial applications. Tobi and Hanfusa [5] describe an experimental test of fuzzy control of an air conditioning system. The controller has two inputs (the temperature and the humidity of the air-conditioned space) and three outputs (the valves of the heating and cooling coils, and of the humidifier) and uses 22 rules. Pedrycz [8] gives an example of fuzzy control implementation on an air conditioning system at Mitsubishi Heavy Industry. To develop this system of 25 rules for heating and 25 rules for cooling, three days were necessary to write down the initial rules, a month to determine the membership functions shapes and about three months to finally tune the controller. Altrock *et al.* [9] claim that a control system based on heuristic rules is efficient for heating systems. Dounis *et al.* [10] develop and test (on a numerical model of the building) a fuzzy controller having the comfort criteria (Predicted Mean Vote, PMV) and the outdoor temperature as inputs, and heating, cooling and window opening angle as outputs. Fraisse, Virgone and Roux [11] present comparison between classical and fuzzy controllers for a tertiary building, achieved by simulations with TRNSYS software. *Sousa et al.* [12] present a more sophisticated approach of a predictive Sugeno-fuzzy controller tested on the same experimental stand as the one used to test the model and controller presented in this paper.

Without being exhaustive, the above presentation of fuzzy control applications to heating, ventilating and air conditioning systems reveals the importance of having a model of the system, even if it is not expressed in a mathematical form. The fuzzy model may be achieved through heuristic methods or, as an alternative, by using identification techniques.

Identification of fuzzy models

The techniques for identifying fuzzy models are developed for fuzzy linguistic models, as defined by Zadeh [13], which use Mamdani inference algorithm [14], or fuzzy linear models, as introduced by Sugeno [15, 16]. The models are achieved based on measured inputs and outputs; they may be used for simulation or for designing controllers. Identifying linguistic models and relations of Mamdani type, based on input-output data, is similar to determining a look-up table [17]; consequently, more rules are required for a better approximation of a given function. The training data should be relevant for the input and output spaces otherwise the model reaches states never attended during the training, states for which the output is unpredictable. When the model is used for recursive prediction (i.e. the output is computed based on the output given by the model at previous time steps), the model easily gets in unidentified states where it may be unstable or deadlocked. The first methods for identifying the Sugeno type fuzzy models consider that the membership functions are trapezoidal and their number is given; membership functions vertices are found by minimizing a criterion, usually the error square mean [18]. Another approach is based on the fact that the input-output relation for a multi-input single-output system forms a surface in the space defined by the Cartesian product of inputs and outputs. The identifying algorithm approximates this surface with a number of planes *a priori* specified [19, 20]. The form of membership functions may be based on clustering methods, when the number of clusters is given [21-23]; the number of clusters may be reduced to a minimum, prior to determining the membership functions [24, 25].

The identification algorithm of a Sugeno type fuzzy system considers a set of rules with fuzzy sets in the premise and a linear equation in the consequent:

$$\textbf{If } x_1 \textit{ is } A_1 \textbf{ and } \ldots x_k \textit{ is } A_k \textbf{ then } y=p_0+p_1\, x_1+\ldots+p_m\, x_m \tag{1}$$

Each rule may be interpreted as a local linear model of the system. Identifying the system described by a set of rules of the type (1) using input and output data implies choosing:

1. $x_1, \ldots x_k$ the variables in the fuzzy implicants;
2. $A_1, \ldots A_k$ the membership functions of premise fuzzy sets;
3. $p_0, \ldots p_m$ the parameters of the consequent.

The membership functions may be chosen arbitrarily or may be obtained algorithmically, using the fuzzy ISODATA or Fuzzy C-Mean Clustering algorithm [22, 23, 26, 27]. This algorithm considers M vectors $x_1, \ldots, x_M$ seen as elements in an r-dimensional space where the distance $d(\bullet,\bullet)$ between two elements is defined. The main notion of this algorithm is the partition matrix, $\mathbf{F}$, with c rows and m columns, having the properties:

$$
\begin{aligned}
&0 \le f_{ik} \le 1 \\
&\sum_{i=1}^{c} f_{ik} = 1,\ \forall k,\ 1 \le k \le M \qquad (2)\\
&0 < \sum_{k=1}^{M} f_{ik} < M,\ \forall i,\ 1 \le i \le c
\end{aligned}
$$

The i-th row of the matrix **F** represents a discrete membership function, while f_{ik} shows the degree of membership of element x_k to the set i. The second condition shows that every fuzzy set is not empty and does not include all the elements. Noting v_i the center of fuzzy sets, the index to be minimized is:

$$= \qquad = \quad \| \quad \| \quad = \qquad (3)$$

where **M** is a positive defined matrix [25, 26]. The index Q is in fact the sum of the dispersion of the elements around the center of the fuzzy sets; by minimizing this index, the partition matrix, **F**, can be found.

Knowing the fuzzy sets in the premises of the rules, the parameters of the consequences are found by minimizing the quadratic criterion of the difference between the output of the model and the output of the system. The parameters of the consequences are found from:

$$\mathbf{P}=(\mathbf{X}^{\mathbf{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{Y} \qquad \mathbf{(4)}$$

where **P** is the vector of parameters, **X** is a matrix formed by the fuzzy sets of the antecedents of the rules, and **Y** is the output vector.

As a simple example, let us consider a nonlinear function defined as follows:

$y=0.25x, \quad 0<x\leq 3.3$

$y=x^2+0.75, \quad 3.3<x\leq 6.6$

$y=0.25x+8.25, \quad 6.6<x\leq 10$

Using the membership functions A_1, A_2, and A_3 defined in Figure 1 (b), the resulted Sugeno type fuzzy model is:

If *x is* A_1 **then** $y=1.50x+0.82$

If *x is* A_2 **then** $y=3.57x-12.86$

If *x is* A_3 **then** $y=0.97x$

For the same system, the fuzzy membership functions obtained using Fuzzy C-Means Clustering are shown in Figure 2 (b). In this case, the model is:

If *x is* A_1 **then** $y=0.13x+ 0.34$

If *x is* A_2 **then** $y=2.83x -9.39$

If *x is* A_3 **then** $y=0.12x+ 9.34$

Comparing the behavior of the initial system and of the identified fuzzy model reveals that the model obtained using Fuzzy C-Means Clustering is better than using predefined membership functions due to the non linearities introduced by the membership functions.

The identification method of Sugeno fuzzy models presented by Babuska [28] was used to model a fan-coil; based on this model, a fuzzy control algorithm of the supply air temperature was designed.

Sugeno-type fuzzy model of a fan-coil

Solar energy systems that use liquid in the collector loop have convective radiation heating terminal units that may be of fan-coil type. Fan-coils move air by forced convection through the conditioned space, filter the circulating air, and introduce outside ventilation air in order to control the temperature, humidity, air speed, and air purity [1]. The fan-coil unit capacity must be related to the room thermal load and to the power provided by the solar energy collector by controlling the coil water flow, air bypass, fan speed, or a combination of these. However, air bypass and fan speed are imposed by humidity and air speed requirements. Room temperature is controlled by fan-coil air supply temperature that may vary in a range imposed by thermal comfort criteria.

The experiments needed for modeling were carried out on a commercial type fan-coil. The fan-coil has two separate coils for heating and cooling, equipped with control valves, and two adjustable dampers, for outdoors and recirculated air. Each damper has three parts, covering one seventh, two sevenths, and four seventh of the damper cross-section. The model has in the consequent of the rules the prediction of the output at the next time step as a linear function of inputs and output at the current time step:

If $y(k)$ *is* A_i **then** $y(k+1) = b_1u_1(k) + b_2u_2(k) + b_3u_3(k) + ay(k)$

where:

u_1	is the position of the control valve;
u_2	-the position of the indoor air damper;
u_3	-the position of the outdoor air damper;
y	-the outlet temperature of the fan-coil;
A_i, $_{i=1,..,5}$	-the fuzzy sets defined on the universe of discourse of the output.

The control valve position and the fuzzy sets defined on the universe of discourse of the output are given in Figure 3 (b). The universe of discourse of the output equals the output range, in this case 20 … 70°C. For a correct identification, the input variables should contain the frequency specter and amplitude range characteristic for the normal working conditions of the system; in other words, the system should reach representative states for the normal working conditions during the identification. The command of the control valve position was chosen as a sum of sine functions with different amplitudes and frequencies, representative for the normal operating conditions of the fan-coil (Figure 3 (a)). The aim is to cover the output range (30…60°C), mainly in the zones of interest (40 … 55°C).

Prior to use the experimental data for identification, the input and output were scaled and centered. The model identified for the mean values $y=40^oC$, $u_1=70\%$, $u_2=37\%$ and $u_3=65\%$, using a sample time $\Delta t=3\ s$, is:

if $y(k)$ *is* A_1

then $y(k+1) = -0.1569\ u_1(k) + 0.1608\ u_2(k) - 0.007851\ u_3(k) - 3.846y(k)$

if $y(k)$ *is* A_2

then $y(k+1) = 0.007371\ u_1(k) - 0.00127\ u_2(k) -0.000466\ u_3(k) + 0.9867\ y(k)$

if $y(k)$ *is* A_3

then $y(k+1) = 0.013834\ u_1(k) - 0.00385\ u_2(k) - 0.001104\ u_3(k) + 0.9791\ y(k)$

if $y(k)$ *is* A_4

then $y(k+1) = 0.01383\ u_1(k) - 0.00134\ u_2(k) -0.000292\ u_3(k) + 0.9878\ y(k)$

if $y(k)$ *is* A_5

then $y(k+1) = -0.01573\ u_1(k) + 0.0005\ u_2(k) + 0{,}001693\ u_3(k) + 1.0223\ y(k)$

It is easy to notice that the first and fifth rules are different as compared with the other rules. Analyzing the parameters in rule consequent reveals that these rules are apparently incorrect as their parameters indicate that the opening of the heating control valve results in temperature decreasing (the inverse relation between output $y(k+1)$ and input u_1); moreover, the fifth rule defines an unstable system (the sign of $y(k)$ is positive). Referring to Figure 3 (b), the poor quality of the first and fifth rules is foreseeable since the data used for their identification is irrelevant. The second, third and fourth rules define a simple and intuitive model by assigning to the fuzzy sets A_2, A_3, and A_4 of Figure 3 (b) the linguistic meanings *small, medium* and *high*, respectively.

The model was tested in two situations: control, as a one step predictor, and simulation, as a recursive predictor. The one step predictor test implies that the output at the next time step, *y(k+1)*, is predicted based on measurements at current time step, *k*; this type of test is relevant for control, since the measured output is known. The recursive predictor test requires only the initial value of the output; then, the output, *y(k+1)*, is computed based on previous value of the output, *y(k)*, resulted from the model output, not from measurement. This test is tougher because once the model gets in states that were unattained during the identification it may stuck or may evolve unpredictably. The results for the one step predictor are very good, the errors being within the measurement error range. The model gives also good results in simulation (recursive predictor), in tests conducted on input sequences different from those used in training (Figure 4).

Fuzzy control algorithm

The good adequacy of the identified model allows us to synthesize the control algorithm for each linear model of the consequent of the fuzzy rules using the well developed techniques of linear dynamic systems. Since the position of the dampers (inlet and recirculated air) is imposed by the indoor air quality requirements, the dampers are not input variables for the controller; they act as disturbances that the controller should reject. As a result, the model of the fan-coil in the consequence of the fuzzy rules is a first order one-input (control valve position) one-output (fan-coil outlet temperature) model. A more sophisticated model may be considered, taking into account, for example, the air temperature before the coil or the indoor and outdoor temperatures. Nevertheless, complex models require more transducers and the use of more complicated design technique [29].

The one-input one-output model was obtained by removing the variables corresponding to the dampers from the complete fuzzy model and the improper fuzzy rules (the first and the fifth). This form of the model allows us to have a geometric representation of the model surface and the measured points (Figure 5). For each of the three fuzzy rules, a linear PI control algorithm was designed for the linear model present in the rule consequent, by using the pole allocation method, though any other classical approach may be applied.

The performances of the fuzzy algorithm and of a PID with anti wind-up controller were compared in range of quasi-similar experiments over a month. Using Ziegler-Nichols procedure, the PID controller was tuned by trial and error around the working point. A comparison of the performance of the fuzzy and PID with anti wind-up control systems is given in Figure 6. For the test presented in Figure 6, the fuzzy algorithm achieves the imposed performance of 2.5°C overshot and has a settle time of about 100s (the initial time is 75s). On the other hand, the PID controller has a slightly smaller overshot but the settling time is about 225s. Both controllers reject the perturbation introduced by the outdoor air temperature. (Note that the temperature values used in experiments are higher with about 15°C than in normal operation. In fact, we tried to have differences of temperature that usual in normal operation.)

The goal of the present control algorithm is to regulate the fan-coil outlet temperature and to reject disturbances introduced by damper position and fan speed. Its set-point is imposed by the room temperature controller with which controls in cascade the room temperature. Supply air temperature is also an input to models that predict thermal comfort in air conditioning rooms [2].

The advantage of formulating the control algorithm as fuzzy rules resides not primarily in its performance, but mainly in its ability to accommodate operating rules and smoothly shift the operating point. A fuzzy control algorithm of Sugeno type is an interpolation of local linear algorithms; consequently, the fuzzy controller is at least as good as the corresponding linear algorithm. More than that, expert and/or operating fuzzy rules may be added. The expert rules, derived from reasoning and past experience rather than mathematical models, augment the validity range of the control algorithm. Solar energy system operating rules (such as freeze and over-temperature protection, draining, auxiliary energy to load, etc.) may be formulated as fuzzy rules and included in the control algorithm.

Conclusions

Practically, designing a Sugeno fuzzy controller based on an identified fuzzy model results in better and constant performance over all the operating range and eliminates the retuning procedure required by the classical PID controller for different working points.

The identified model is valid only for the range of inputs and states achieved during the identification; consequently, the control algorithm has the same range of applicability. Nevertheless, the identification procedure may continue during the normal functioning of the fan-coil, resulting in expanding the initial range of validity. The fuzzy Sugeno system is in fact a nonlinear function obtained by interpolating between linear systems; the interpolation is achieved through weighted mean, the weights being given by the membership functions.

The main advantage of fuzzy controller resides not mainly in performance but in the easiness of understanding and including linguistic scheduling and expert type knowledge; or, in Lofti Zadeh's words, *"in almost every case you can build the same product without fuzzy logic, but fuzzy is faster and cheaper."*

Acknowledgments

The experiments described in this paper were conducted in 1995 at the Indoor Climate-control and Refrigerating Engineering Laboratory of Delft University of Technology, The Netherlands, sponsored by the Netherlands organization for international cooperation in higher education (NUFFIC). The paper was finalized at University of La Rochelle, France, supported by the Council of Poitou-Charentes Region with a research scholarship. Special thanks are addressed to dr. ir. A.H.C. van Paassen and dr. ing. R. Babuška for their support.

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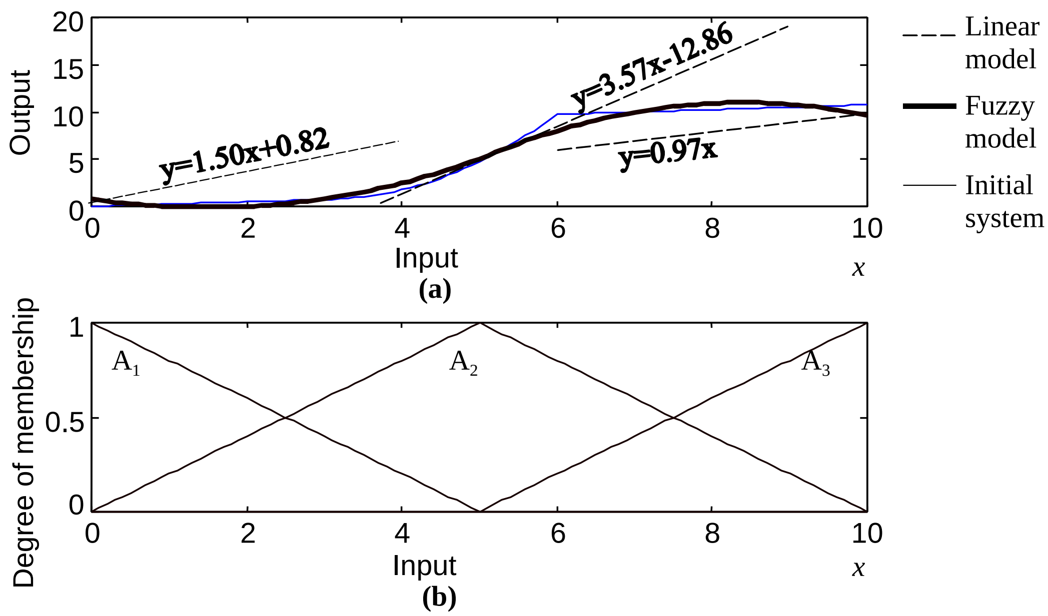
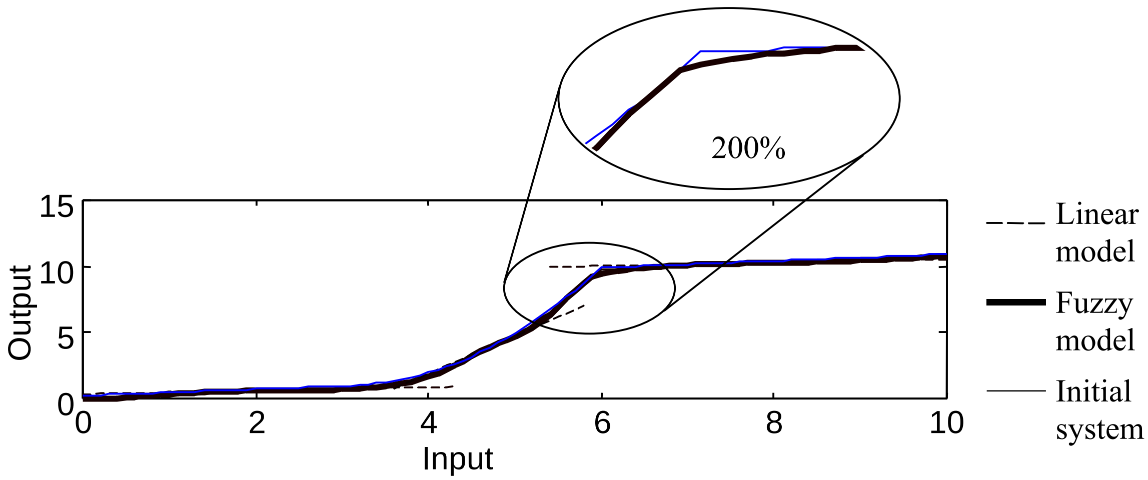
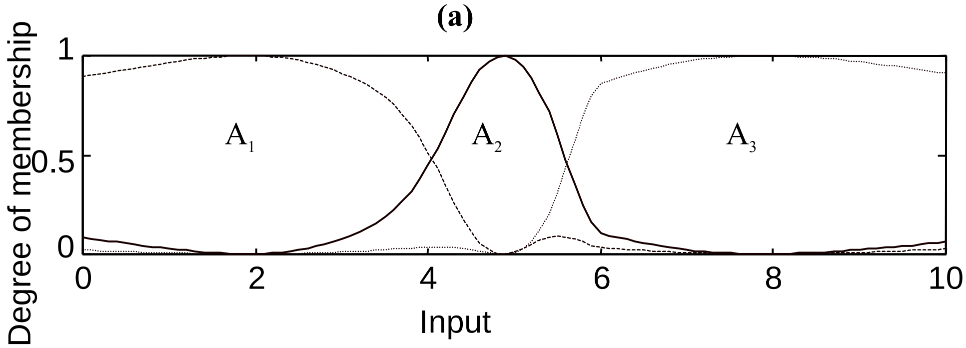


Figure 1 Identifying a Sugeno fuzzy model with given membership functions in the antecedents: (a) the given system, the linear models and the fuzzy model; (b) input membership functions.

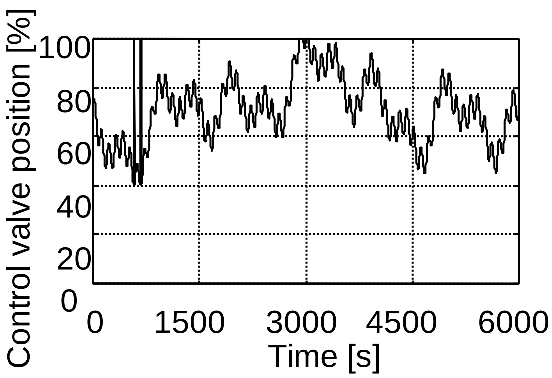


(a)

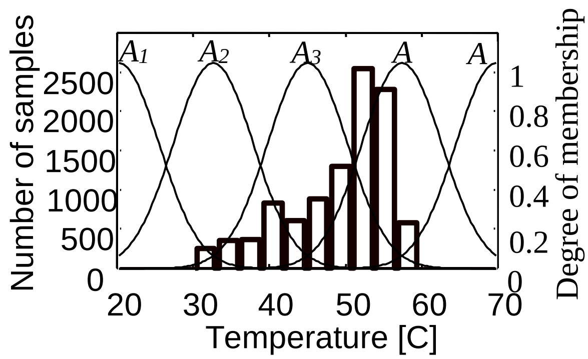


(b)

Figure 2 Identifying a Sugeno-type fuzzy model using membership functions determined by Fuzzy C-Means Clustering algorithm. The fuzzy model is better than in Figure 1. (a) The given system, the linear models and the fuzzy model. The fuzzy model is superimposed on the initial system. (b) Input membership functions.



(a)



(b)

Figure 3 Characteristics of the signals used for identification: (a) time sequence of the input signal; (b) histogram of the output signal superimposed with the membership functions.

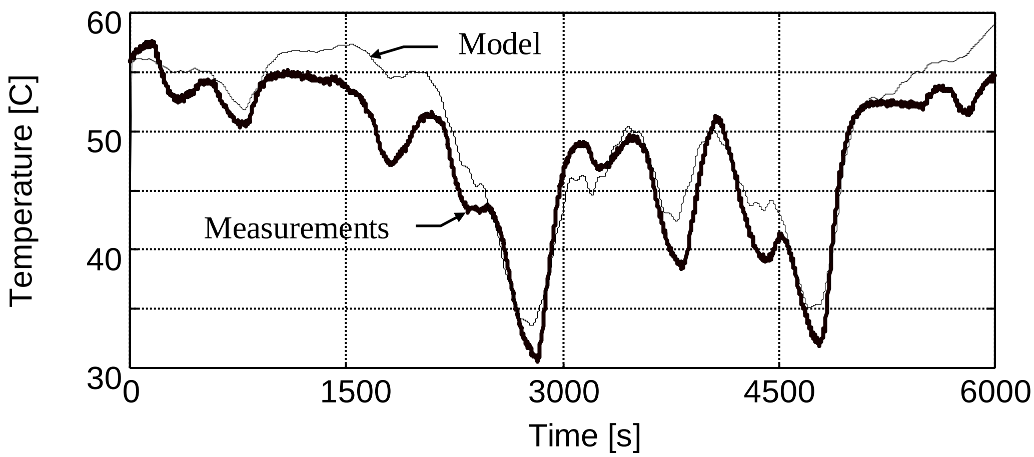


Figure 4 Comparison between the output of the fan-coil and of the model working in recursive prediction. In recursive prediction the model evolves in the next state from a state previously calculated (not measured).

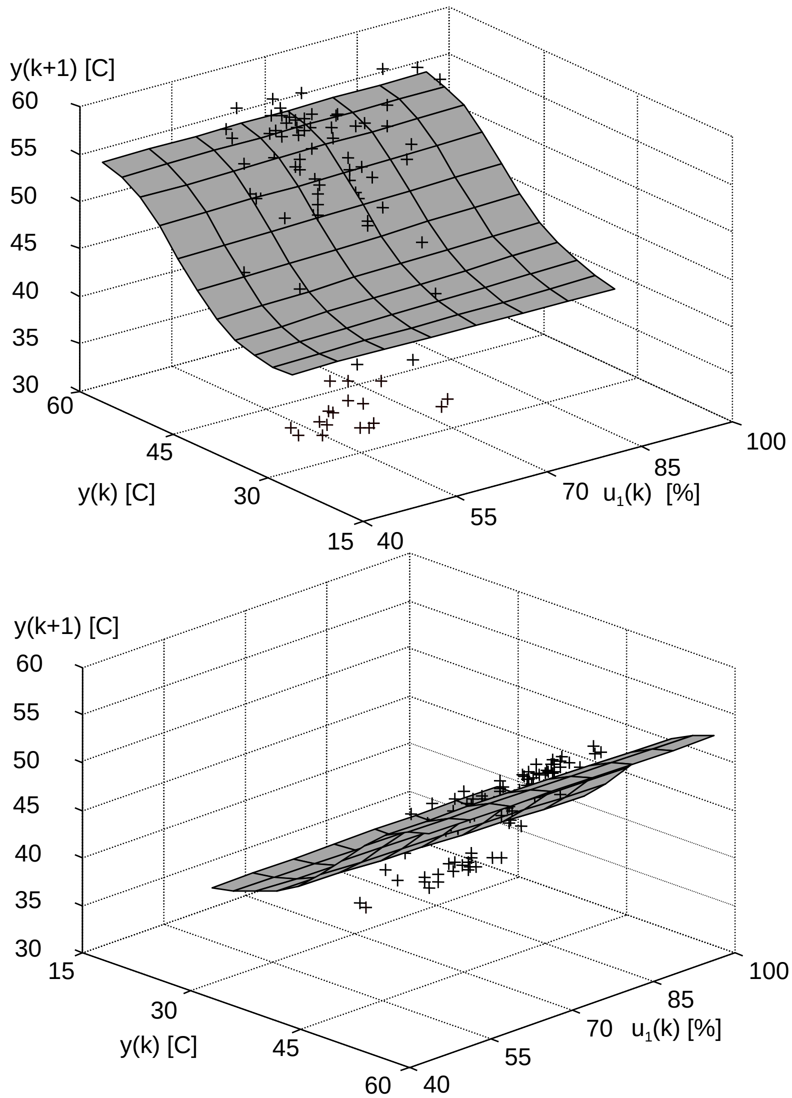


Figure 5 The surface of the identified fuzzy model (considering only the valve position as an input) and the experimentally measured points seen from two angles. The measured points are distributed in space around the surface. The dispersion of the measured points is due to the inputs not considered in the model.

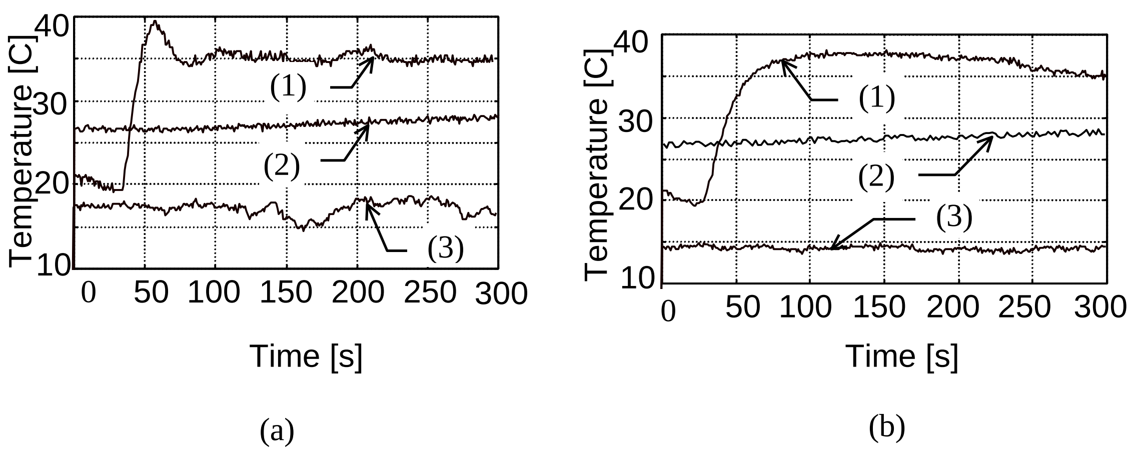


Figure 6 The controlled outlet temperature of a fan-coil when the set point is changed from 20ºC to 35ºC: a) Sugeno-fuzzy controller; b) PID with anti-wind up. The three temperatures represent: (1) the fan-coil outlet temperature; (2) the indoor air temperature of the test cell; (3) the outdoor air temperature.