

Research Article

Stabilization Using a Discrete Fuzzy PDC Control with PID Controllers and Pole Placement: Application to an Experimental Greenhouse

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This paper proposes a control strategy for complex and nonlinear systems, based on a parallel distributed compensation (PDC) controller. A solution is presented to solve a stability problem that arises when dealing with a Takagi-Sugeno discrete system with great numbers of rules. The PDC controller will use a classical controller like a PI, PID, or RST in each rule with a pole placement strategy to avoid causing instability. The fuzzy controller presented combines the multicontrol approach and the performance of the classical controllers to obtain a robust nonlinear control action that can also deal with time-variant systems. The presented method was applied to a small greenhouse to control its inside temperature by variation in ventilation rate inside the process. The results obtained will show the efficiency of the adopted method to control the nonlinear and complex systems.

1. Introduction

In the last few decades the Takagi-Sugeno (TS) fuzzy systems have become an important means for both modeling and control, and their performance in these two domains is proved in the research especially in the application of complex and nonlinear systems. TS fuzzy systems use a multimodel approach by fitting enough local linear models each describing an operating functional zone of the process [1]. The final output of the fuzzy system is the fuzzy weighted contribution of all the local output models guaranteeing precision and stability.

Such a tool can be used for control purposes; in fact when dealing with complex systems classical methods become inefficient and so emerges the need for other control techniques. The PDC controllers [2] are a convenient solution, having the same structure as a TS fuzzy system, where every rule is associated with a local linear controller synthesized from the local model with the same rule [3]. The result is a nonlinear control action, which is a fuzzy blending of each individual linear controller. Many applications using TS

model and PDC controller [3, 4] were presented, and several propositions of new techniques of PDC control appear in the literature [5]. Where the most proposed approaches present a state feedback for each rule, the stability is proved by finding a common Lyapunov function which can satisfy all the fuzzy subsystems [6]. However, in case of a large number of rules describing the system it is very difficult to apply this approach [7].

In the continuous domain, a solution was presented using a PD or a PID controller for each rule. The denominator of the closed loop system is treated as an uncertain polynomial with affine linear uncertainty structure where the stability can be verified using a frequency domain criterion [7]. In the discrete domain, there is not an efficient solution to deal with the stability problem which is one of the objectives of this paper that will be discussed in Section 3. Another goal that will be described in the same section is to find the appropriate parameters of the controller for each rule using pole placement approach. But before that, in Section 2, an introduction to the TS fuzzy model and the PDC controller will be presented. In Section 4, a



FIGURE 1: Greenhouse process.

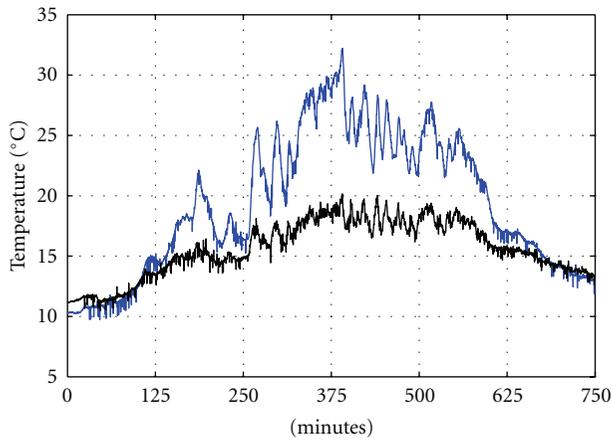


FIGURE 2: Difference between inside and outside temperatures during daylight.

practical application will be presented where the proposed control strategy is used in an adaptive fuzzy control scheme. The process is an experimental greenhouse that was fuzzy identified and controlled in real time. Finally, Section 5 will conclude this paper.

2. Takagi-Sugeno Fuzzy Systems

There are different classes of fuzzy systems; the most often used are Mamdani fuzzy systems [8] and Takagi-Sugeno fuzzy systems [1]. The latter differ from the former in the rules consequents: it is not a fuzzy set but it is a local model of the system (submodel related to the rule that describes an operative zone of the process) to be approximated. For the j th rule a TS fuzzy system has the following form:

$$R^{(j)}: \text{if } z_1(k) \text{ is } \Omega_{j1} \text{ and } \dots \text{ and } z_n(k) \text{ is } \Omega_{jn},$$

$$\text{then } \begin{cases} x_j(k+1) = A_j x(k) + B_j u_c(k) + L_j v(k), \\ y_j(k) = C_j x_j(k), \end{cases}$$

$$j = 1, \dots, N. \quad (1)$$

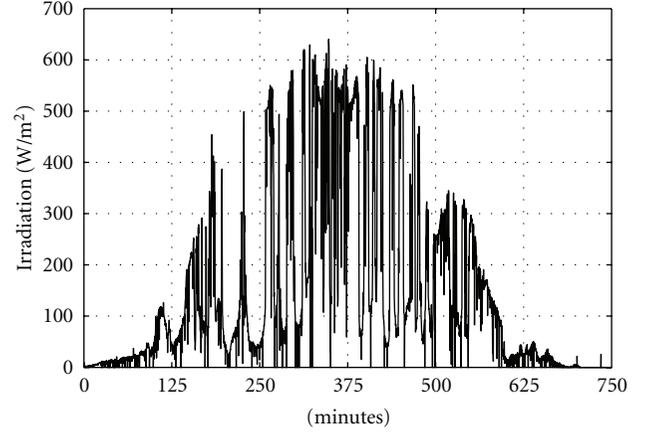


FIGURE 3: Solar radiation intercepted during daylight.

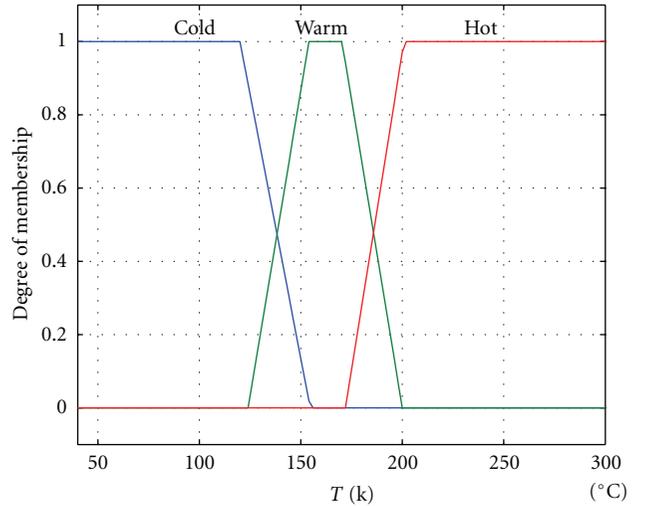


FIGURE 4: Membership function of the inside temperature.

The fuzzy proposition “ z is Ω ” is the antecedent of the rule, the system of equation in the second part of (1) is the consequent, “ $z = (z_1, \dots, z_n)$ ” are the inputs of the TS fuzzy system, they can be the states “ $x = (x_1, \dots, x_{n_a})$,” the input “ $u_c = (u_1, \dots, u_{n_a})$,” or the disturbances inputs “ $v = (v_1, \dots, v_{n_v})$,” “ Ω_{ji} ” is the membership function representing the fuzzy subset with a corresponding membership value “ $\Omega_{ji}(z_i)$,” and N is the total number of rules.

Assume that all the subsystems considered are completely controllable and completely observable. Also, denote the following states and inputs variables:

$$x_1(k) = y(k), \quad x_2(k) = y(k-1), \dots, \quad x_{n_a}(k) = y(k-n_a+1),$$

$$u_1(k) = u(k), \quad u_2(k) = u(k-1), \dots, \quad u_{n_a}(k) = u(k-n_a+1). \quad (2)$$

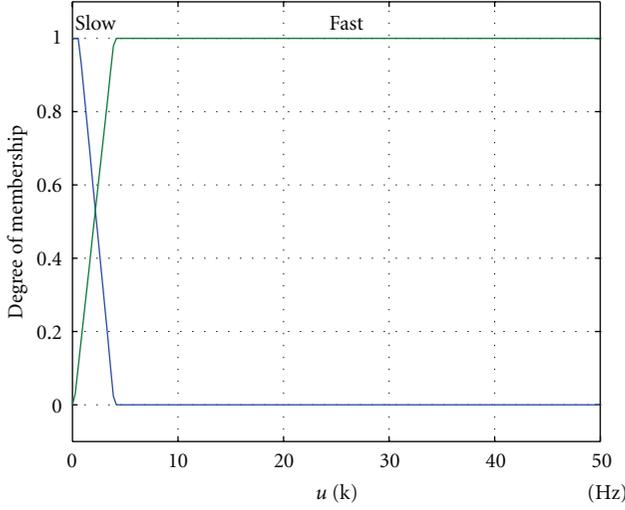


FIGURE 5: Membership function of the delivered frequency.

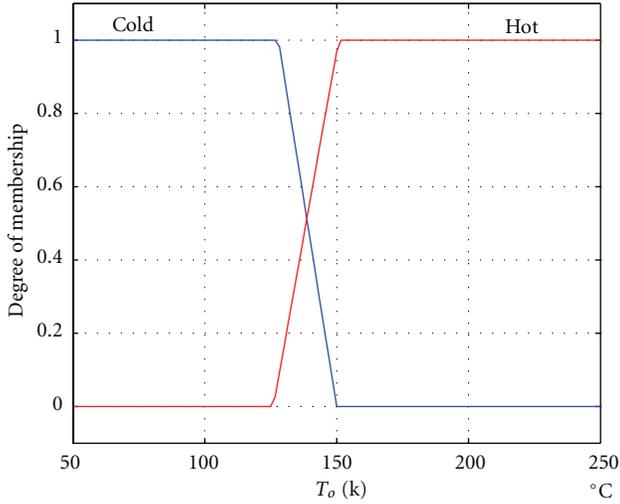


FIGURE 6: Membership function of the outside temperature.

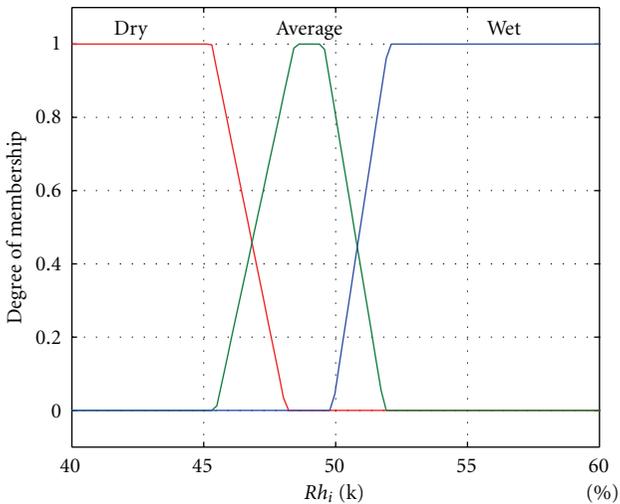


FIGURE 7: Membership function of the inside humidity.

The matrix ($A_j \in \mathbb{R}^{n_a \times n_a}$, $B_j \in \mathbb{R}^{n_b \times 1}$, and $D_j \in \mathbb{R}^{n_d \times n_d}$), represents the parameters of the TS fuzzy system (1) with the following Frobenius canonical structure:

$$A_j = \begin{pmatrix} 0 & 1 & 0 & \cdots & 0 \\ \vdots & 0 & 1 & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \cdots & \cdot & \cdots & \cdot \\ a_{j0} & a_{j1} & \cdots & \cdots & a_{jn_a} \end{pmatrix},$$

$$B_j = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \\ b_{j1} & b_{j1} & \cdots & b_{jn_a} \end{pmatrix}, \quad (3)$$

$$L_j = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \\ l_{j0} & l_{j1} & \cdots & l_{jn_v} \end{pmatrix}, \quad C_j = (1 \ 0 \ \cdots \ 0).$$

The output level x_j of each local model is weighted by the firing strength $\mu_j(z(k)) = \prod_{i=1}^n (\Omega_{ji}(z_i(k)))$. The final output of the system is the weighted average of all the rule's outputs, the computed as

$$x(k+1) = \frac{\sum_{j=1}^N \mu_j(z(k)) y_j(k+1)}{\sum_{j=1}^N \mu_j(z(k))}. \quad (4)$$

Assuming that

$$\frac{\mu_j(z(k))}{\sum_{j=1}^N \mu_j(z(k))} = \beta_j(z(k)), \quad (5)$$

the output of the TS model becomes

$$x(k+1) = \sum_{j=1}^N \beta_j(z(k)) x_j(k+1) \quad (6)$$

with $0 < \beta_j(z(k)) < 1$ and $\sum_{j=1}^N \beta_j(z(k)) = 1$.

On the other hand, the controller is a TS fuzzy system, having the same antecedent of the fuzzy model and differing from it in its consequent. A linear controller is developed for each rule, and the global control action is synthesized in the same way as the TS fuzzy model output [2] as follows:

$$u(k) = \sum_{j=1}^N \beta_j(z(k)) u_j(k) \quad (7)$$

with u_j representing the local output control.

3. Stability of a Closed-Loop TS System

The stability problem of (1) can be solved in general using the Lyapunov approach [9–11]. In this case, the proposed control law of the PDC controller is a state feedback having the following expression:

$$u = -\sum_{j=1}^N \beta_j(z) K_j x. \quad (8)$$

Replacing (8) into (1) without considering the disturbance inputs leads to the following expression:

$$\begin{aligned} x(k+1) &= \sum_{j=1}^N \beta_j(z(k)) \left[A_j x(k) - B_j \sum_{i=1}^N \beta_i(z(k)) K_i x(k) \right] \\ &= \sum_{j=1}^N \beta_j(z(k)) \left[A_j \sum_{i=1}^N \beta_i(z(k)) x(k) \right. \\ &\quad \left. - B_j \sum_{i=1}^N \beta_i(z(k)) K_i x(k) \right] \\ &= \sum_{j=1}^N \sum_{i=1}^N \beta_i(z(k)) \beta_j(z(k)) [A_j - B_j K_i] x(k), \end{aligned} \quad (9)$$

$$\begin{aligned} x(k+1) &= \sum_{j=1}^N \beta_j(z(k))^2 G_{jj} x(k) \\ &\quad + 2 \sum_{j<i}^N \beta_i(z(k)) \beta_j(z(k)) \frac{G_{ji} + G_{ij}}{2} x(k) \end{aligned} \quad (10)$$

with $G_{ji} = A_j - B_j K_i$.

The following theorem gives a sufficient stability condition for a system of the form of (11) [12].

Theorem 1. *The closed-loop TS fuzzy system of the form of (10) is quadratically stable for some state feedback K_j (via PDC scheme) if there exists a common positive definite matrix P such that*

$$G_{jj}^T P G_{jj} - P < 0 \quad \text{for } j = 1, \dots, N, \quad (11)$$

$$\left(\frac{G_{ji} + G_{ij}}{2} \right)^T P \left(\frac{G_{ji} + G_{ij}}{2} \right) - P < 0 \quad \text{for } j < i. \quad (12)$$

The problem arises when the TS fuzzy system has a great number of rules, for it is difficult to find matrix P that verifies the stability condition (see (11) and (12)) [7].

The solution presented in this paper deals with a transfer function form of the TS fuzzy system. Combining (1) and

(6) without considering the disturbance inputs, we obtain the following NARX form:

$$y(k) = \sum_{j=1}^N \beta_j(z) \left(\sum_{m=1}^{n_a} a_{jm} y(k-m) + \sum_{l=1}^{n_b} b_{jl} u(k-l) \right). \quad (13)$$

Since $\sum_{j=1}^N \beta_j(z) = 1$, the following expression can be obtained:

$$\begin{aligned} \sum_{j=1}^N \beta_j(z) \left[y(k) - \sum_{m=1}^{n_a} a_{jm} y(k-m) \right] \\ = \sum_{j=1}^N \beta_j(z) \left[\sum_{l=1}^{n_b} b_{jl} u(k-l) \right]. \end{aligned} \quad (14)$$

The Z transformation leads to the new form:

$$\begin{aligned} \sum_{j=1}^N \beta_j(z) \left[1 - \sum_{m=1}^{n_a} a_{jm} q^{-m} \right] Y(q^{-1}) \\ = \sum_{j=1}^N \beta_j(z) \left[\sum_{l=1}^{n_b} b_{jl} q^{-l} U(q^{-1}) \right]. \end{aligned} \quad (15)$$

Let

$$\begin{aligned} A_j(q^{-1}) &= 1 - \sum_{m=1}^{n_a} a_{jm} q^{-m}, \\ B_j(q^{-1}) &= \sum_{m=1}^{n_b} b_{jm} q^{-m}, \end{aligned} \quad (16)$$

and so the transfer function of the TS fuzzy system is as follows:

$$H(q^{-1}) = \frac{Y(q^{-1})}{U(q^{-1})} = \frac{\sum_{j=1}^N \beta_j(z) B_j(q^{-1})}{\sum_{j=1}^N \beta_j(z) A_j(q^{-1})}. \quad (17)$$

Let us also consider the transfer function of the PDC controller to be

$$P(q^{-1}) = \frac{\sum_{j=1}^N \beta_j(z) D_j(q^{-1})}{\sum_{j=1}^N \beta_j(z) C_j(q^{-1})}, \quad (18)$$

where $D_j(q^{-1}) = \sum_{m=0}^{n_a} d_{jm} q^{-m}$ and $C_j(q^{-1}) = \sum_{m=0}^{n_b} c_{jm} q^{-m}$ are the numerator and the denominator of local controllers correspondent to each rule j of the PDC controller.

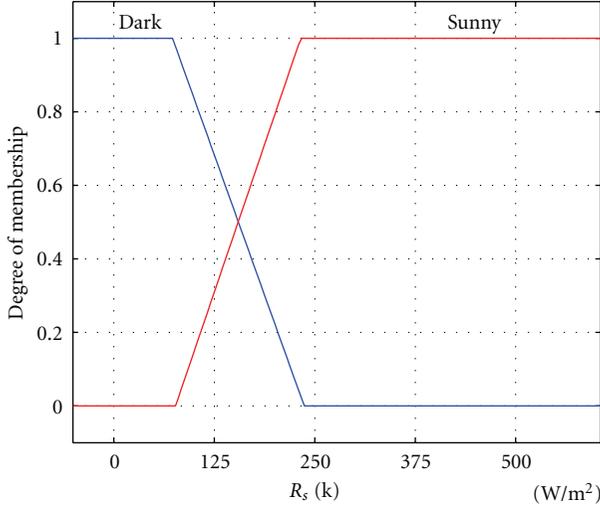


FIGURE 8: Membership function of the intercepted solar radiation.

The transfer function of the closed-loop fuzzy system will be

$$G(q^{-1}) = \frac{(\sum_{j=1}^N \beta_j B_j)(\sum_{i=1}^N \beta_i D_i)}{(\sum_{j=1}^N \beta_j A_j)(\sum_{i=1}^N \beta_i C_i) + (\sum_{j=1}^N \beta_j B_j)(\sum_{i=1}^N \beta_i D_i)}. \quad (19)$$

This leads to the following expression:

$$G(q^{-1}) = \frac{(\sum_{j=1}^N \beta_j B_j)(\sum_{i=1}^N \beta_i D_i)}{\sum_{j=i}^N \beta_j^2 (A_j C_j + B_j D_j) + \sum_{j \neq i}^N \beta_j \beta_i (A_j C_i + B_j D_i)}. \quad (20)$$

From (20) we can see that the controller related to a rule j , initially designed to stabilize the local model related to the same rule, has an influence on the stability of the other submodel related to different rules as indicated by the expression $\sum_{j \neq i}^N \beta_j \beta_i (A_j C_i + B_j D_i)$ located in the

denominator of the closed-loop transfer function. There is a high probability that the local controller for a particular rule is not suitable for a local model associated with a different rule. Thus, the stability of the overall closed-loop system with the current structure cannot be guaranteed especially when the TS fuzzy system has a great number of rules.

In fact, the cross-coupling and possible instability are created by the two multiplications $(\sum_{j=1}^N \beta_j A_j)(\sum_{i=1}^N \beta_i C_i)$ and $(\sum_{j=1}^N \beta_j B_j)(\sum_{i=1}^N \beta_i D_i)$; if we manage to eliminate the multiplication, then the problem can be solved.

In order to fulfill this objective the chosen local controllers must have the same order as the local models. For instance, if the system is a first-order one, then the local controllers must be a PI, and if the system is a second-order one, then the correspondent local controllers should be a PID. For higher-order systems, one can choose an RST controller to each local model with an equivalent order having the polynomial $R(q^{-1})$ equal to the polynomial $T(q^{-1})$.

Also, assuming all stable zeros of the transfer function (17), the denominator $C_j(q^{-1})$ of each local controller must include the numerator of the local model having the same rule j . So let us consider the denominator of a local controller related to a rule j :

$$C_j(q^{-1}) = e(q^{-1}) \tilde{B}_j(q^{-1}) \text{ with } e(q^{-1}) = 1 - q^{-1} \text{ and}$$

$$\tilde{B}_j(q^{-1}) = \sum_{m=1}^{n_a} b_{jm} q^{-(m-1)}. \quad (21)$$

Here all the local controllers share the same polynomial $e(q^{-1}) = 1 - q^{-1}$ representing the numerical expression of an integrator that will allow the rejection of disturbances. This expression already exists in a PI, a PID, or an RST controller having an integrator in the open loop [13].

We have also

$$B_j(q^{-1}) = q^{-1} \tilde{B}_j(q^{-1}). \quad (22)$$

Replacing (21) and (22) in (19) leads to the following transfer function of the closed-loop fuzzy system:

$$G(q^{-1}) = \frac{q^{-1} (\sum_{j=1}^N \beta_j \sum_{m=0}^{n_a} d_{jm} q^{-m})}{(1 - q^{-1}) (\sum_{j=1}^N \beta_j (1 - \sum_{m=1}^{n_a} a_{jm} q^{-m})) + (q^{-1} \sum_{j=1}^N \beta_j \sum_{m=0}^{n_a} d_{jm} q^{-m})} \quad (23)$$

$$= \frac{q^{-1} \sum_{j=1}^N \beta_j \sum_{m=0}^{n_a} d_{jm} q^{-m}}{\sum_{j=1}^N \beta_j (1 + (d_{j0} - 1 - a_{j1}) q^{-1} + \sum_{m=1}^{n_a} (a_{jm} - a_{j(m+1)} + d_{jm}) q^{-(m+1)})}.$$

In the transfer function (23) of the closed-loop system, the multiplication was eliminated and so the cause of the interaction or cross-coupling is removed. However, the

stability is not yet guaranteed. We still need to find the appropriate numerator's parameters $D_j(q^{-1})$ of each local controller. A pole placement strategy is adopted with an

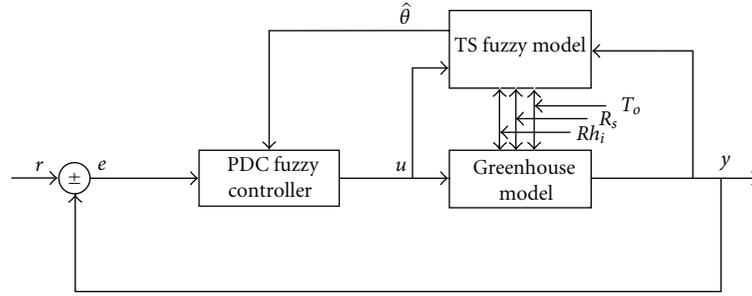


FIGURE 9: Adaptive fuzzy control scheme.

appropriate polynomial $F(q^{-1}) = 1 + \sum_{m=1}^{n_a+1} l_m q^{-m}$, having its roots inside the unit circle, to be identified with the denominator of every closed-loop subsystem as follows:

$$\begin{aligned} 1 + (d_{j0} - 1 - a_{j1})q^{-1} + \sum_{m=1}^{n_a} (a_{jm} - a_{j(m+1)} + d_{jm})q^{-(m+1)} \\ = 1 + \sum_{m=1}^{n_a+1} l_m q^{-m}, \quad \forall j = 1, \dots, N. \end{aligned} \quad (24)$$

The result is the following system of equations:

$$\begin{aligned} d_{j0} &= l_1 + 1 + a_{j1}, \\ d_{j1} &= l_2 + a_{j2} - a_{j1}, \\ &\vdots \\ d_{jn_a} &= l_{n_a+1} + a_{jn_a+1} - a_{jn_a}, \quad \forall j = 1, \dots, N. \end{aligned} \quad (25)$$

The denominator of the transfer function (23) becomes invariant whatever the rule j , and since we have $\sum_{j=1}^N \beta_j = 1$, the new form of the transfer function (23) becomes

$$G(q^{-1}) = \frac{\sum_{j=1}^N \beta_j \sum_{m=0}^{n_a} d_{jm} q^{-(m+1)}}{F(q^{-1})}, \quad (26)$$

with the poles located inside the unit circle which guarantees the stability of the system. Also, with the described method, whatever the number of rules is, it is possible to take advantage of both: the performance of a classical controller like a PI, a PID, or an RST and in the same time the multicontrol approach given by the PDC controller. The result is a robust nonlinear controller that can even deal with complex system with time-variant parameters when using a recursive fuzzy identification of the TS fuzzy model. A simulation of the proposed method will be presented in the next section to control such a system.

4. Application to an Experimental Greenhouse

The presented method was applied to control the inside temperature of a small greenhouse (Figure 1). The inside climate is subjected to various phenomena like the solar

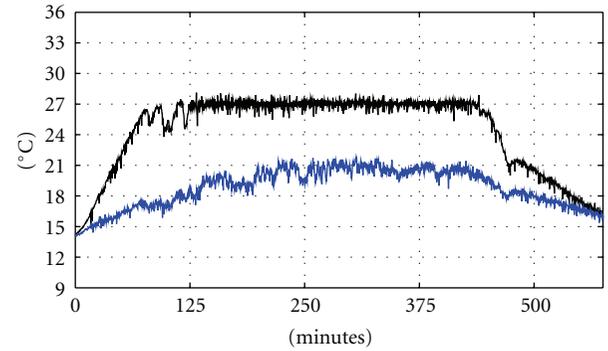


FIGURE 10: Practical results: outside temperature (blue line) and inside temperature (black line).

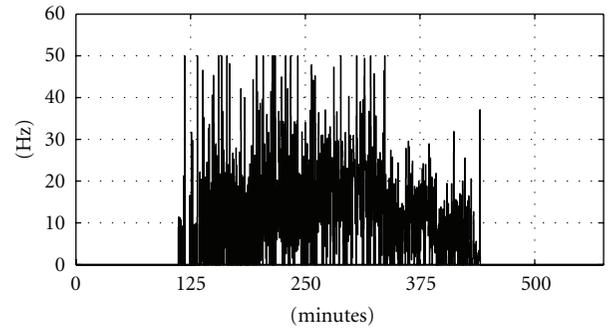


FIGURE 11: Action control of the fuzzy controller.

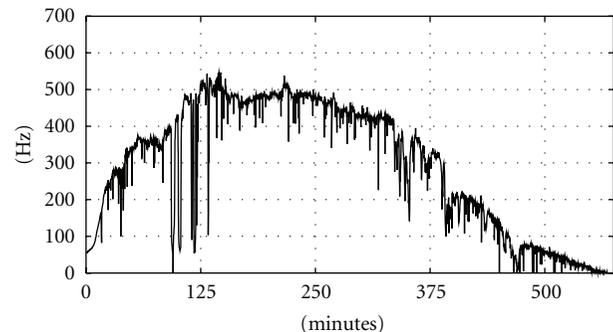


FIGURE 12: Intercepted solar radiation.

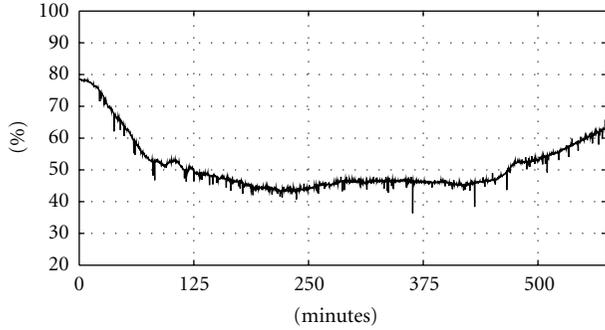


FIGURE 13: Inside humidity.

radiation transfer, heat and mass transfer between the soil, the cover, the canopy and the outside climate. There is also the ventilation conducted by two three-phase motors that interfere to cool the inside temperature.

The effect of the solar radiation is preponderant during daylight; in fact, the components of the greenhouse absorb the radiation energy and convert it to heat energy released in the air by heat transfer [14], which enhances the inside temperature that will surpass the outside temperature (Figures 2 and 3).

All these factors result in a nonlinear evolution with time-varying parameters of the climate inside the greenhouse [15]. The use of ventilation to cool down the climate during daylight is very common. In fact, with an adequate and skilful management it can be possible to maintain suitable climate-state variables (temperature, humidity, and CO₂ concentration) [16]. Also, the ventilation represents an alternative and cheap solution to the air conditioner that consumes an important electrical power.

But the complexity of the system makes it hard to achieve successful results, and so most of the farmers use an on-off control action between two boundary temperature values. But, this kind of control is unhealthy to the canopy. On the other hand, the time where the ventilation is effective is related to the weather. In fact, the possible constraints that oppose the use of this method all along the year are

- (i) the presence of solar radiation that will enhance the inside temperature and make it surpass the outside temperature,
- (ii) the desired temperature of the climate inside the greenhouse that must be greater with several degrees than the outside temperature. The choice of the desired temperature depends on the requirement of the cultivation inside the greenhouse.

These conditions can be met in 3 to 4 months of the year. When the outside temperature is near the desired inside temperature, the farmers use the pad cooling system; it is a combination between fans and a wet pad that decreases the introduced air with several degrees [17–19]. Thus, the ventilation use is effective for another one or two months depending on the quality of the pad.

In this paper, we focus on the evolution of the inside temperature by manipulating the ventilation rate to obtain

a desired behavior of the process. As described in Section 2, the TS fuzzy system is able to describe this kind of system and can be used to control the inside temperature using the fans during daylight.

4.1. Materials and Measurements. The process is a greenhouse with the following geometrical characteristics: 1.5 m height, total width of 1 m, and total length of 1.5 m.

The inputs of the system are obtained from several sensors located inside and outside the greenhouse as follows.

- (i) The inside and outside temperatures were measured by two LM35 transistors; both have an AD 620 amplifier to amplify the delivered signal.
- (ii) The inside humidity was measured using a humidity sensor (SY-HS-230BT).
- (iii) The solar radiation was obtained by a pyranometer type LP-PYRA 03 module.

In order to control the ventilation rate, the greenhouse was equipped with two fans driven by two three-phase motors. These engines have a power supply delivered by a frequency converter (microdrive FC 51 Danfoss). The rotational speed of the fans is proportional to the frequency of the three-phase power supply and so the ventilation rate inside the greenhouse depends on the frequency of the power supply. Thus, the control input will be the frequency that will be computed by the fuzzy controller.

The communication between MATLAB, the sensors, and the frequency converter is carried by the data acquisition module (KUSB-3100).

4.2. Fuzzy Identification. The structure of the discrete TS fuzzy system that will be approximated will have a local model for every rule j having the following form [20]:

$$R^{(j)} : T_j(k+1) = \alpha_{j1}(k)T(k) + \alpha_{j2}(k)u(k) + \alpha_{j3}(k)T_o(k) + \alpha_{j4}(k)R_s(k) + \alpha_{j5}(k)Rh_i(k) + \alpha_{j6}(k) \quad \text{for } j = 1, \dots, N, \quad (27)$$

where u is the frequency delivered by the frequency converter to the motors equipped with fans to control the ventilation rate inside the greenhouse.

The fuzzy identification is performed in two steps. The first one is the determination of the appropriate membership functions of each input to set the antecedent part of the TS fuzzy system, which is done using fuzzy clustering based on C-means algorithm. The membership functions were fixed and *would not* change during the control application. For that purpose, on the day of 25-02-2011, we gave a random action control to collect the data needed under the sample time of 15 seconds; after that we set the membership functions in Figures 4, 5, 6, 7, and 8.

The second step is the estimation of (27) that represents the consequent part of the TS fuzzy system. For a time-variant system like a greenhouse, the more convenient way

is an online fuzzy identification using the following recursive equations based on the recursive least square algorithm [20]:

$$\begin{aligned} K_j(k) &= \frac{P_j(k-1)z_e(k-1)}{\lambda/\beta_j(z(k-1)) + z_e^T(k-1)P_j(k-1)z_e(k-1)}, \\ \hat{\theta}_j(k) &= \hat{\theta}_j(k-1) + K_j(k)(y(k) - z_e^T(k-1)\hat{\theta}_j(k-1)), \\ P_j(k) &= \frac{1}{\lambda}(P_j(k-1) - K_j(k)z_e^T(k-1)P_j(k-1)), \end{aligned} \quad (28)$$

where λ is a forgetting factor, $z_e^T = (T \ u \ T_o \ R_s \ Rh_i \ 1)$ is the regression vector of inputs, $\hat{\theta}_j^T = (\hat{\alpha}_{j1} \ \hat{\alpha}_{j2} \ \hat{\alpha}_{j3} \ \hat{\alpha}_{j4} \ \hat{\alpha}_{j5} \ \hat{\alpha}_{j6})$ is the estimated vector of parameters, and y is the output representing the inside temperature T .

$P_j(0)$ and $\hat{\theta}_j(0)$ are obtained from an offline fuzzy identification based on an ordinary weighted least square method [20], where the data used are those collected during the day before the recursive identification and also served to build the membership functions.

The estimated vector $\hat{\theta}$ will be used in an adaptive fuzzy control scheme (see Figure 9) to bring the inside temperature T to the desired temperature r using the fuzzy controller output u .

4.3. Fuzzy Control. The system is a first-order one so the local controller for each rule will be a PI controller. From the previous section, the transfer function of the PDC controller can be deduced as follows:

$$P(q^{-1}) = \frac{\sum_{j=1}^N \beta_j(z)(d_{j0} + d_{j1}q^{-1})}{\sum_{j=1}^N \beta_j(z)(1 - q^{-1})b_{j1}}, \quad \text{with } b_{j1} = \alpha_{j2}. \quad (29)$$

Consider the following polynomial having its roots inside the unit circle of the complex plane:

$$F(q^{-1}) = 1 - 1.0164q^{-1} + 0.5102q^{-2}, \quad (30)$$

where its poles, having a complex form, are the following:

$$\begin{aligned} z_1 &= 0.5082 + 0.5020i, \\ z_2 &= 0.5082 - 0.5020i. \end{aligned} \quad (31)$$

The chosen polynomial is identified with the denominator of every closed-loop subsystem which leads to the following equality:

$$\begin{aligned} 1 + (d_{j0} - 1 - \alpha_{j1})q^{-1} + (\alpha_{j1} + d_{j1})q^{-2} \\ = 1 - 1.0164q^{-1} + 0.5102q^{-2}, \quad \forall j = 1, \dots, N. \end{aligned} \quad (32)$$

The solution of (32) gives us the numerator's parameters of the PDC controller as follows:

$$\begin{aligned} d_{j0} &= -0.0164 + \alpha_{j1}, \\ d_{j1} &= 0.5102 - \alpha_{j1}, \quad \forall j = 1, \dots, N. \end{aligned} \quad (33)$$

The transfer function of the PDC controller (30) leads to the following equalities:

$$\sum_{j=1}^N \beta_j(1 - q^{-1})\alpha_{j2}u(q^{-1}) \quad (34)$$

$$= \sum_{j=1}^N \beta_j(d_{j0} + d_{j1}q^{-1})E(q^{-1}),$$

$$\sum_{j=1}^N \beta_j(\alpha_{j2}u(q^{-1}) - \alpha_{j2}q^{-1}u(q^{-1})) \quad (35)$$

$$= \sum_{j=1}^N \beta_j(d_{j0}E(q^{-1}) + d_{j1}q^{-1}E(q^{-1})),$$

$$\sum_{j=1}^N \beta_j\alpha_{j2}u(q^{-1})$$

$$= \sum_{j=1}^N \beta_j(\alpha_{j2}q^{-1}u(q^{-1}) + d_{j0}E(q^{-1}) + d_{j1}q^{-1}E(q^{-1})). \quad (36)$$

From (36) a recurrent form of the control law can be deduced, which will be

$$\begin{aligned} u(k) &= \frac{1}{\sum_{j=1}^N \beta_j(k)\alpha_{j2}(k)} \\ &\times \sum_{j=1}^N \beta_j(k)(\alpha_{j2}(k)u(k-1) + d_{j0}(k)e(k) + d_{j1}(k)e(k-1)), \end{aligned} \quad (37)$$

where e represents the error between the reference output and the system output,

$$\begin{aligned} u(k) &= \sum_{j=1}^N \beta_j(k)(\tilde{\alpha}_{j2}(k)u(k-1) + \tilde{d}_{j0}(k)e(k) + \tilde{d}_{j1}(k)e(k-1)), \end{aligned} \quad (38)$$

where

$$\tilde{\alpha}_{j2} = \alpha_{j2}(k) / \sum_{j=1}^N \beta_j(k)\alpha_{j2}(k),$$

$$\tilde{d}_{j0} = d_{j0}(k) / \sum_{j=1}^N \beta_j(k)\alpha_{j2}(k),$$

$$\tilde{d}_{j1} = d_{j1}(k) / \sum_{j=1}^N \beta_j(k)\alpha_{j2}(k).$$

With this expression it is also possible to take into account the saturation of the control input since we deal with

local classical controllers with recurrent form [21], and so the new expression of the control law will be

$$u_s(k) = \sum_{j=1}^N \beta_j(k) (\tilde{\alpha}_{j2}(k) u_s(k-1) + \tilde{d}_{j0}(k) e(k) + \tilde{d}_{j1}(k) e(k-1)) \quad (39)$$

With

$$u_s = \begin{cases} 50 \text{ Hz} & \text{if } u \geq 50 \text{ Hz,} \\ u & \text{if } 0 < u < 50 \text{ Hz,} \\ 0 & \text{if } u \leq 0 \end{cases} \quad (40)$$

represent the saturated control input.

4.4. Practical Results. The desired output r is 27°C. The application was conducted with a sample time equal to 15 seconds on the day of 24 March 2011. It started at 8:39 AM and ended at 6:23 PM. The results of the proposed method are shown in Figures 10 and 11. Figures 12 and 13 represent the measured disturbance inputs of the system during the application. In the beginning and in the end of the application, where the values of the intercepted solar radiation and outside temperature are very low (corresponding to the morning and later in the evening before the sun set), the controller does not take action. This is because the value of the inside temperature is below the desired temperature.

Moreover, we can note from Figure 11 that the control signal presents high switching; it is because of some errors in measurements that affect the response of the controller; but, in spite of this, it still leads the process to the desired trajectory, which proves its robustness and efficiency.

5. Conclusion

TS fuzzy systems can assimilate the evolution of complex and nonlinear process and act consequently to provide acceptable results in terms of modeling and control. However, a stability problem arises because of the great number of rules used to model such systems. This paper offers a solution using classical controllers like a PI, a PID, or an RST for each rule and a pole placement strategy. The fuzzy controller presented combines the multicontrol approach and the performance of the classical controllers. The result is a robust nonlinear control action that can also deal with time-variant systems.

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