Takagi-Sugeno Fuzzy Model for Greenhouse Climate

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Abstract
This paper investigates the identification and modeling of a climate greenhouse. Given real climate data from greenhouse installed in the LAPER laboratory in Tunisia, the objective of this paper is to propose a solution of the problem of nonlinear time variant inputs and outputs of greenhouse internal climate. Based on fuzzy logic technique combined with least mean squares (lms) a robust greenhouse climate model for internal temperature prediction is proposed. The simulation results are presented to demonstrate the effectiveness of the identification approach and the power of the implemented Takagi-Sugeno Fuzzy model based Algorithm.

Keywords:
TS fuzzy modeling, Greenhouse climate, fuzzy clustering, Identification.

1. Introduction

Greenhouse cultivation has been of a great importance in agriculture supplies for many years. It is a way to protect plants from bad meteorological conditions and to take advantage of the internal climate to guarantee the high-quality and the low-cost of production. The optimal management of the greenhouse climate is the most appropriate way to meet the needs of industrial agricultural production.

This management is essentially based on the efficient use of solar energy, air heating, ventilation and cooling. For these different reasons, the modeling of the greenhouse is very difficult in terms of the non-linearity that describes the function between the outputs (internal humidity, internal temperature) and the inputs (external temperature, external humidity, solar radiation, wind speed...) [1].

To develop a control technique, a good model of the greenhouse is needed for the simulation and also for real time control. Various methods have been proposed in the past for modeling the greenhouse. In the literature, there are two main categories of mathematical modeling techniques for real processes [2]: Physical modeling and system identification. The first is based on the physical laws involved in the process and

the second is based on the analysis of the input-output data of the model. In [3,4] the dynamic temperature model is based on the energy balance. The author in [5] developed the physical model of the greenhouse by conducting research on thermal radiation and ventilation. The modeling of the system was described from the process of mass-energy exchange in [6]. The work in [7] studied the heat exchange by internal convection, plant transpiration and natural ventilation to establish a greenhouse model. An analysis in [8] was performed on auto-regressive models with external data based on the GDGCM model. In [9] the modeling of the internal temperature of the greenhouse is based on a hybrid system to obtain several greenhouse models. An identification was used in [10] based on Takagi-Sugeno (TS) fuzzy model. In [11] clustering brings back the main parameters for modeling the greenhouse. In [12] hierarchical strategy is used to minimize the number of fuzzy rules in the modeling of the system. A fuzzy modeling using neural network learning techniques was developed in [13,14]. To obtain the consequences of the rules, we can see the use of least squares for the modeling in [15,16]. In [17] the Calculus of variations and nonlinear optimization-based algorithm for optimal control of hybrid systems with controlled switching.

In this paper, we focus principally on the modelling phase. The contribution is dedicated to the modeling of a class of nonlinear dynamic processes by merging local linear models. These local linear models are the fuzzy models of Takagi-Sugeno type [18]. The output of these fuzzy systems is obtained by simple interpolation of locally approved linear models. This approach allows firstly, a linguistic interpretation of the fuzzy rules. On the other hand, classical methods of linear control can be applied to local fuzzy models [19,20]. The information system from fuzzy models can be used by a great variety of command methodologies. Thus, the performance of the control depends heavily on the accuracy of the model used. Therefore, a large part of the design effort must be dedicated to modeling. So, our objective is to have the simulation results of a FIS system that seeks to generate a linguistic model optimized by back-propagation and the least mean squares algorithm for predicting the climate of the greenhouse.

This work is organized as follows: the second section, deals with a description of the experimental setup studied

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for the greenhouse with the measurement equipment. The third section, describes the Takagi-Sugeno (TS) fuzzy model strategy that was developed and applied to the greenhouse to identify the internal temperature model. In the fourth section, a fuzzy model presentation of the greenhouse is given followed by simulation results. Finally, this study will be complemented by a conclusion.

2. Experimental set-up

2.1 Description of the experimental greenhouse

In this work, for the experimental part, the real greenhouse is located at the Laboratory of Application for Energy Efficiency and Renewable Energies (LAPER). The external structure of the greenhouse is oriented east-west and has the form of a chapel, as illustrated in Figure 1. The geometric characteristics of the greenhouse are: length = 150 cm; width = 100 cm; height = 115 cm.

Fig. 1. Experimental Greenhouse.

2.2 Description of the measuring equipment

The database is obtained using the following apparatus:

-Air temperature is measured by an LM35 sensor, with an accuracy of 0.4°C in the temperature range between -24°C and 48°C.
- The relative humidity is measured by a SY-230 sensor. These sensors have an accuracy of about 3% in the measurement range between 0 and 95%.
- Pyranometer type LPYRA03 was used to measure the global solar radiation level on a horizontal surface. The accuracy is about 5%. The measuring range 0 to 2000 W/m2 and the typical sensitivity is about 10 µV(W/m^2).

3. Takagi-Sugeno fuzzy model

3.1 Basic structure

The fuzzy logic can provide an interesting alternative to mathematical modeling for many physical processes that are too complicated to be described by precise and simple mathematical equations or formulas. There are several classes of fuzzy systems, the most commonly used are Mamdani fuzzy systems [10] and Takagi-Sugeno (TS) fuzzy systems. The particularity of these systems is that the consequence of each rule does not correspond to a fuzzy set but to a local model of the system to be estimated. The TS model is composed of if-then rules with fuzzy antecedents and mathematical functions in the consequent part [21]. The antecedents of fuzzy sets that divide the input space into a number of fuzzy regions, while the consequent functions are used to describe the behavior of the system in these regions [22]. For an i^{th} rule, a TS fuzzy system has the following form:

$$If\ x(k)\ is\ M_i,\ then\ x(k+1) = A_i x(k) + B_i u(k) \quad (1)$$

With, $x(k)$ represents the state vector and M_i represents the vector of the fuzzy set of the i^{th} rule. The output of the TS model corresponds to every rule. Therefore, it is necessary to attribute a weight to describe the similarity ratio of each rule to the actual behavior of the process:

$$w_i\left(x(k)\right) = \prod_{j=1}^{p} M_{ij}\left(x_j(k)\right) \quad (2)$$

With, $M_{ij}\left(x_j(k)\right)$ is the membership degree of the j^{th} state variable to the i^{th} rule. In addition, $w_i\left(x(k)\right)$ is the product of all the membership degrees of the i^{th} rule, which shows the weight of this rule in the whole model. Therefore, the output can be defined by the weighted average of all rules:

$$x_i(k+1) = \frac{\sum_{i=1}^{n} w_i\left(x(k)\right)\left(A_i x(k) + B_i u(k)\right)}{\sum_{i=1}^{n} w_i\left(x(k)\right)} \quad (3)$$

Thus, in the whole TS fuzzy system, the weighting of the element $x(k)$ is described in the form :

$$\phi_i\left(x(k)\right) = \frac{w_i\left(x(k)\right)}{\sum_{i=1}^{n} w_i\left(x(k)\right)} \quad (4)$$

So, the output of the TS model is:

$$x(k+1) = \sum_{i=1}^{n} x_i(k+1)\phi_i(x(k)) \quad (5)$$

3.2 Fuzzy clustering

Fuzzy clustering consists on identifying natural groupings of data from a large data set to produce accurate representation of a system's behavior. It is useful to divide a fuzzy data set into a certain number of groups by mapping membership probabilities to each object [23]. The membership of each data item to each group is illustrated by the membership matrix with size $c?$ for grouping the data set $X = \{x_1, x_2, \ldots x_l\}$:

$$U = \begin{bmatrix} u_{11} & \cdots & u_{1\beta} & \cdots & u_{1l} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ u_{\alpha 1} & \cdots & u_{\alpha\beta} & \cdots & u_{\alpha l} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ u_{c1} & \cdots & u_{c\beta} & \cdots & u_{cl} \end{bmatrix} \quad (6)$$

With, $u_{\alpha\beta}$ corresponds to the membership degree of the $\beta^{th}(\beta=1,2,\ldots l)$ element to α^{th} clustering.
In the present matrix, there are several limitations:

- $u_{\alpha\beta} \in [0,1]$
- $\sum_{\alpha=1}^{c} u_{\alpha\beta} = 1$
- $0 \prec \sum_{\beta=1}^{l} u_{\alpha\beta} \prec l$

The objective function is defined as follows during the clustering:

$$J(U,V) = \sum_{\beta=1}^{l}\sum_{\alpha=1}^{c} (u_{\alpha\beta})^m (d_{\alpha\beta})^2 \quad (7)$$

With, $V = (v_1, \ldots, v_c)$ represents a vector whose elements representing the center of each clustering. m is the weight factor which usual value is 2. The euclidean distance between the β^{th} element and the center of the α^{th} fuzzy clustering is defined by $(d_{\alpha\beta})^2 = \|x_\beta - v_\alpha\|^2$. Thus, the objective function aims are to calculate the sum of the weighted values. To obtain the minimum of the objective function, it is necessary to search for the partial derivatives and make them equal to zero. Finally, the limit conditions are:

$$v_\alpha = \frac{\sum_{\beta=1}^{l} (u_{\alpha\beta})^m x_\beta}{\sum_{\beta=1}^{l} (u_{\alpha\beta})^m} \quad (8)$$

$$u_{\alpha\beta} = \frac{\|x_\beta - v_\alpha\|^{\frac{2}{m-1}}}{\sum_{\alpha=1}^{c} \|x_\beta - v_\alpha\|^{-\frac{2}{m-1}}} \quad (9)$$

Where v_α is to calculate the center of α^{th}clustering while $u_{\alpha\beta}$ is to renew the membership degree of each element. In the clustering process, the iteration will be completed until it satisfies the convergence condition [24] or about the iteration times.

3.3 Parameter estimation

Generally, it is recommended to start with a linear model and determine the structure of the system based on the available tools to use the best model possible as a starting point for the nonlinear modeling. This is possible with the TS models' ability to use the local linear models obtained by fuzzy identification and interpolate them with each other to optimize the nonlinear structure of the systems and obtain optimal results.

The common way to identify the parameters is the least squares method which processes data in a similar way. However, the different rules play a different role in the TS fuzzy model. For this reason, the ordinary least squares lms method should be applied [10]. Firstly, the consequence must be rewritten in the following form:

$$x(k+1) = a_1x_1 + \cdots + a_px_p + b_1u_1 + \cdots + b_qu_q \quad (10)$$

Where $x\ (k+1)$ is the output of this rule, x and u are the system inputs. Thus, the data can be described as follows:

$$Y = \begin{bmatrix} Y(2) \\ \vdots \\ Y(k+1) \end{bmatrix} = \begin{bmatrix} x(2) \\ \vdots \\ x(k+1) \end{bmatrix}; \; X = \begin{bmatrix} X(1) \\ \vdots \\ X(k) \end{bmatrix} \quad (11)$$

The parameters of an ordinary lms identification are determined by the following equation:

$$\theta_i = \left[X^T Q_i X \right]^{-1} X^T Q_i Y \tag{12}$$

Where, θ_i represents the consequent parameter vector and Q_i represents the weight matrix that contains the weight of all the data:

$$Q = \begin{bmatrix} \phi_i(x(1)) & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \phi_i(x(n)) \end{bmatrix} \tag{13}$$

4. Greenhouse fuzzy modeling and simulation results

The main objective of fuzzy identification is to improve the accuracy compared of nonlinear physical model.

For this simulation, a database was recorded on 05/10/20 at the LAPER laboratory to do the greenhouse fuzzy modeling. The sampling rate is fixed to 15 seconds. For this analysis, from the data obtained we have fixed 2 membership functions for the inside temperature, the outside temperature, the humidity and the solar radiation. The data of each input will be classified and indexed using the C-Mean Fuzzy algorithm and then will be approximated by trapezoidal membership functions. The results obtained for each input are represented by the figures (Figure 2, Figure 3 and Figure 4, Figure 5), designating the membership functions of the discrete fuzzy model as well as the groupings established by the C-Mean Fuzzy algorithm. For each input, we select a small number of clusters to minimize the number of rules in the TS fuzzy system.

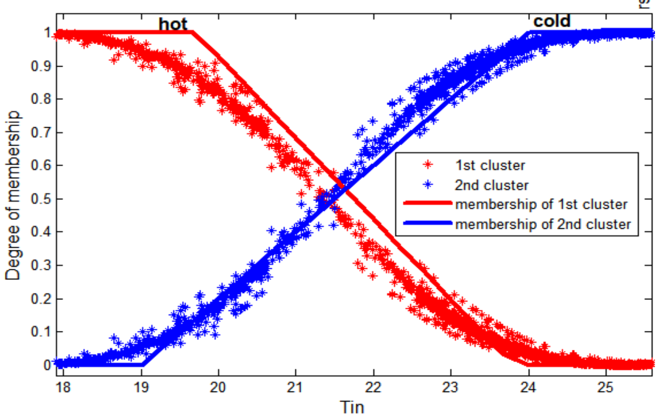

Fig. 2 Membership of internal temperature (°C) (solid line) and data clusters (points).

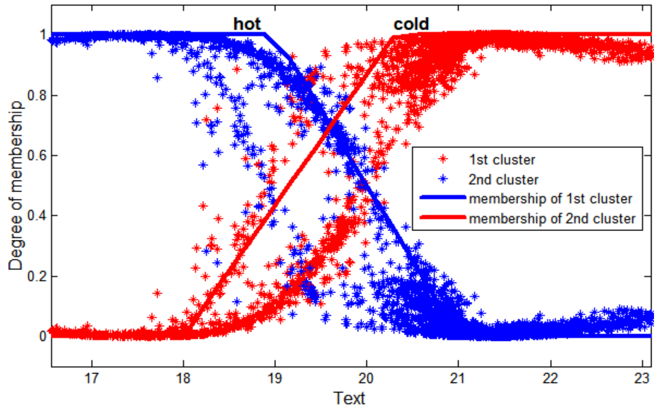

Fig. 3 Membership of external temperature (°C) (solid line) and data clusters (points).

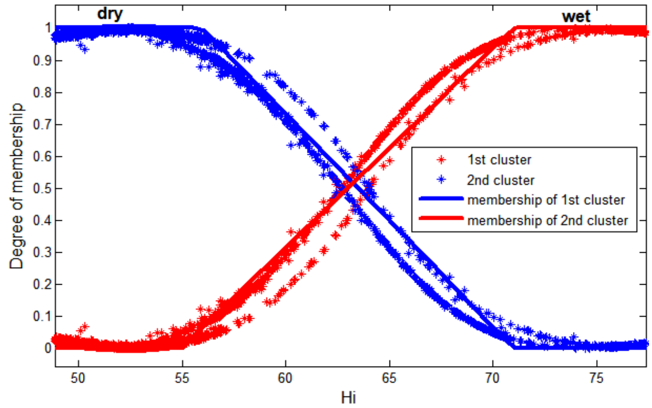

Fig. 4 Membership of internal humidity (%) (solid line) and data clusters (points).

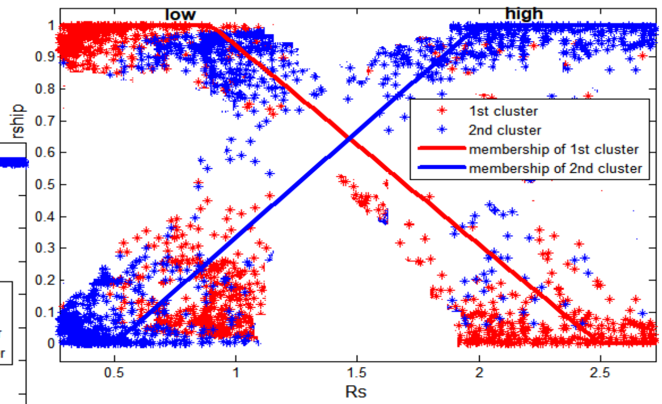

Fig. 5 Membership of radiation (W/m^2) (solid line) and data clusters (points).

The consequent output of a rule *i* of the TS fuzzy model to be identified has the form:

$$T_i(k+1) = a_{1i} + a_{2i}T_i(k) + a_{3i}T_e(k) + a_{4i}RH_i(k) + a_{5i}RH_e(k) + a_{6i}R_s(k) + a_{7i}V_i(k) + a_{8i}Q_{ch}(k) \quad (14)$$

Where T_i is the internal temperature, T_e is the external temperature, RH_i is the internal humidity, RH_e is the external humidity, R_s is the solar radiation, V_i is the internal air speed and Q_{ch} is the heat delivered by the thermal system.

Subsequently, the practical results show that the fuzzy identification systems generated with the LMS methods is more accurate than the dynamic modeling (Figure 8) because we observe a good convergence to the real data Figure 6. Moreover, we notice in Figure 7 the error is of the order of 1 % compared to the classical dynamic modeling which reaches an error value of (2%, -4%) (Figure 9), hence the efficiency of the model greenhouse obtained. Also, to evaluate the result quantitatively, we adopt the VAF function [25], to compare the difference degree between two signals. This function is given as follows:

$$VAF = \left\{ 1 - \frac{var(y_1 - y_2)}{var(y_1)}, 0 \right\} ? \quad 00\% \quad (15)$$

Where y_1 represents the real data, y_2 represents the simulation result and *var* is the variance. The result is more accurate if the VAF value is closer to 100%. On the contrary, the result is less accurate if the VAF value is closer to 0%. After the calculation, the temperature variation value for the physical model VAF=89.38 % and the temperature variation value for the fuzzy model VAF=97.47%. We can see that the performance of the proposed modeling method is successful for any kind of greenhouses.

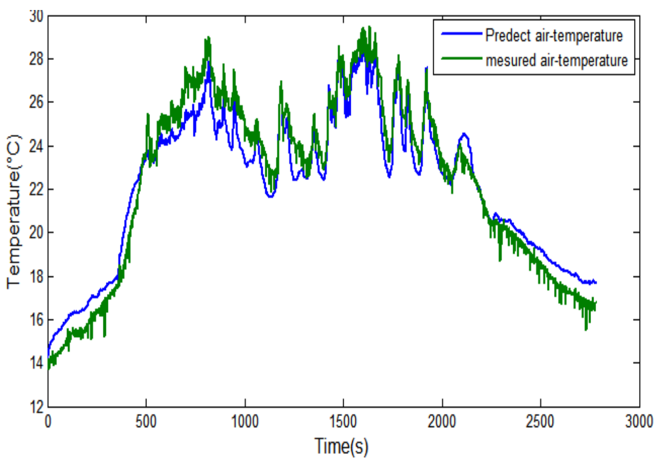

Fig.6 Inside temperature of the greenhouse and output of the fuzzy model.

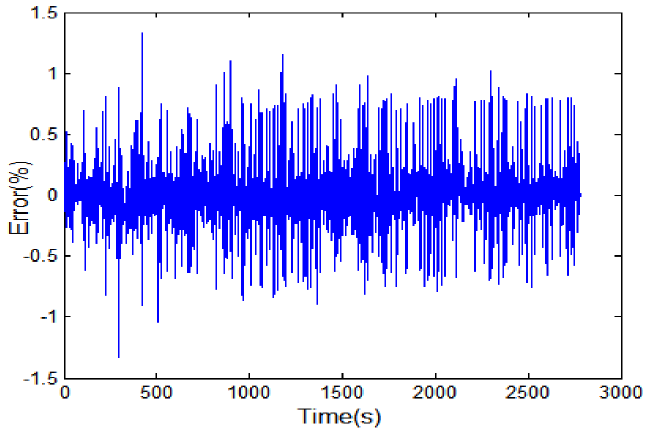

Fig.7 Difference between inside temperature of the greenhouse and output of the fuzzy model.

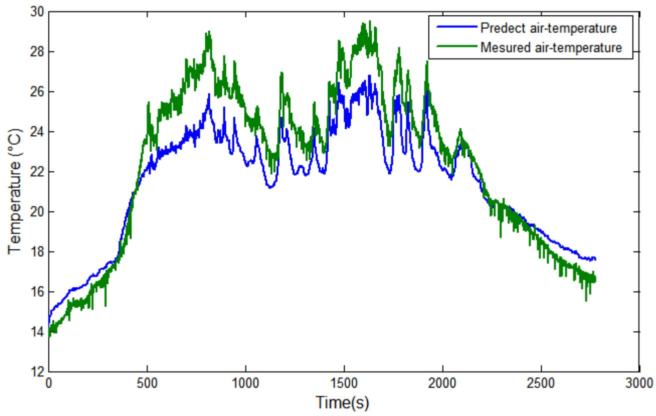

Fig.8 Inside temperature of the greenhouse and output of dynamic model.

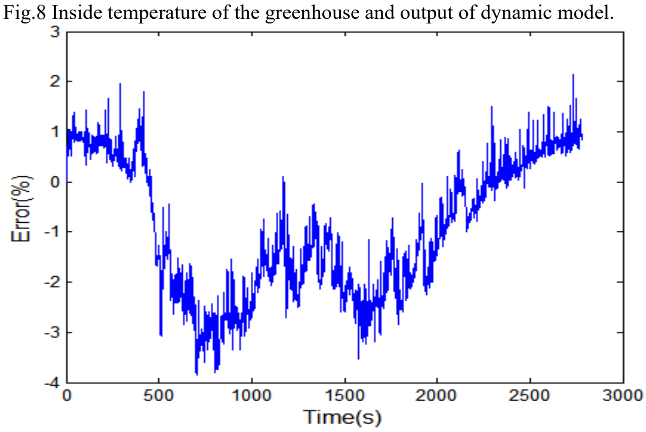

Fig.9 Difference between inside temperature of the greenhouse and output of the dynamic model.

5. Conclusion

This paper proposes a greenhouse model method based on a TS fuzzy model using the Fuzzy C-means algorithm for clustering and the least mean squares method for adjusting the model. This method has great advantages: it allows to modify the hierarchical structures by adding or removing a sub-model or rules at any time, without the need to repeat the whole identification process and to use all the data collected. These sub-models have similar correspondences in the physical modeling, which represent the contributions of the process mechanisms involved in the global process.

According to the comparison results obtained by the fuzzy model and the experimental results, we confirmed the efficiency and accuracy of the proposed model to predict the internal greenhouse climate.

In the next work, we think to integrate the developed model in an adaptive control system in order to obtain an increase in the production and quality of horticultural products and to reduce energy consumption.

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