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Self – Tuning Method of Fuzzy System: An Application on Greenhouse Process

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Abstract**—**The approach proposed here is oriented in the direction of fuzzy system for the analysis and the synthesis of intelligent climate controllers, the simulation of the internal climate of the greenhouse is achieved by a linear model whose coefficients are obtained by identification. The use of fuzzy logic controllers for the regulation of climate variables represents a powerful way to minimize the energy cost. Strategies of reduction and optimization are adopted to facilitate the tuning and to reduce the complexity of the controller.

Keywords**—**Greenhouse, fuzzy logic, optimization, gradient descent.

I. Introduction

THE agricultural greenhouse make parts of an important class of process agro food bio (greenhouses, cellars of fermentations…) that require the development of regulator multivariables to improve the development of a specific culture and to minimize the cost of production.

The production under greenhouse can contribute efficiently to increase the productivity.

To cover these needs it is therefore necessary to perfect the air-conditioning of the greenhouses in order to maintain the cultures in the conditions that are compatible with the agriculturist's agronomic and the economic objective. Seen the importance of such a process, systems of traditional air-conditioning used in the habitat (refrigerated machine) are too expensive and cannot be put in work in the conditions of production. Other methods such as the statistical ventilation (roofing), the screens of shadiness or the cooling evaporative (moistening) can be adopted. These methods, if they are less costly, they are too difficult to control and to optimize because they call on very complex physical mechanisms.

The interdependence of the temperature and the humidity requires a control strategy which takes into account the relationship between these two parameters, thus the approach proposed in this work is oriented in the synthesis of an intelligent climate controller based on the fuzzy logic.

The use of the fuzzy logic in this work is due to exploit the tolerance of imprecision, uncertainty and partial truth, the use of human contributions, low solution cost and better rapport with reality.

In recent fuzzy applications, it is getting more important to consider how to design optimal fuzzy controller from training data, in order to construct a reasonable and suitable fuzzy system. Due to the above reasons, it is natural and necessary to generate or tune fuzzy controller by some learning techniques like the gradient descent method.

The model that we use to simulate the greenhouse in this work is a linear model whose coefficients are obtained by an out line identification [7], [18] and [20].

In this paper, we propose two different approaches: a basic fuzzy controller and an optimised one.

This paper shows that the optimized fuzzy controller can be successfully applied to control the greenhouse environment.

II. Greenhouse Model

A greenhouse has one purpose: to provide and maintain the environment that will result in optimum crop production for maximum profit. This includes an environment which efficiently works as well as for crop growth. We are in presence of a Multi Input – Multi Output (MIMO) system, non linear and non stationary in which intervene the energizing exchanges of the biologic functions assuring the development of the plants. Many works have been done on the development of the models of the greenhouse [1], [2], [3], [4], [5], [6], [18], [20], [21].

Different works have been achieved on the agricultural greenhouses. Indeed, we can distinguish between two classes of models, the statistical models and the dynamic ones.

The statistical models have been studied by various authors [3], [5] and [6]. They are directly descended of the physics of the process; they present themselves under the shape of algebraic equations established from the energizing balances.
The dynamic models have been studied by various authors [4], [8] and [21]. The dynamic approach covers the set of the physical processe and describes the behaviour transient of it.

The clarification of a regulation of the greenhouse must take in consideration the evolution of the meteorological variables and the thermal state of the greenhouse.
The objective is to simulate the internal state of the greenhouse in order to test algorithms of control. We will present in this work a model of simulation of a greenhouse that uses the external weather to predict the internal state of the greenhouse.

To describe the different properties of the greenhouse, we take the model [7] and [20].

This model can be considered like linear and stationary around a particular operating point in which the parameter values are determined by dynamic identification.

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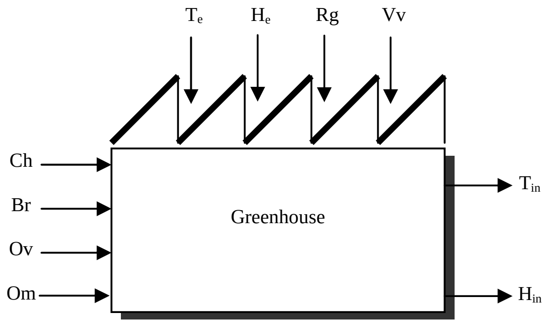

Fig. 1 The greenhouse model

The model possesses two types of variables of entries:

- The disruptions variables (weather) :
  - T_e : External temperature
  - H_e : External humidity
  - R_s : Solar radiation
  - V_v : Wind velocity
- The commands variables :
  - Ch : Heating
  - Br : Moistening
  - Ov : Roofing
  - Om : Shadowing

We intend to control:

- T_{in} : Internal temperature
- H_{in} : Internal Humidity.

The model can be described in the discrete – time domain by:

$$y(k+1) = f(\varphi(k)) \tag{1}$$

Where the regression vector:

$$\varphi(k) = [y_1(k) \cdots y_n(k) u_1(k) \cdots u_m(k) p_1(k) \cdots p_q(k)]^{T} \tag{2}$$

This vector composed of m process inputs $U(k)$, q measurable disturbances $P(k)$ and n process outputs $Y(k)$.

The unknown function $f(.)$ is determined by identification and k is the discrete time; the identification is made from data taken in a greenhouse situated to the University of Toulon-Var.

We have used a least squares method [15], [16] as an algorithm of identification. This method presents the advantage to have a simple formulation.

The identification had several zones where the parameters converge locally [18], what corresponds to several points of working.

A first zone corresponds to the night; the second corresponds to the morning and the third to the afternoon. Then, for a same day we had 3 models to represent the greenhouse.

III. Structure of the Fuzzy Controller

The approach used in this work to control of the greenhouse is the implementation of a fuzzy control algorithm.

The block diagram of a fuzzy controller is shown in Fig. 2. It is composed of four principal modules:

- Definition of the entries and interface of fuzzification.
- Basis of rules.
- Mechanism of inference.
- Interface of défuzzification.

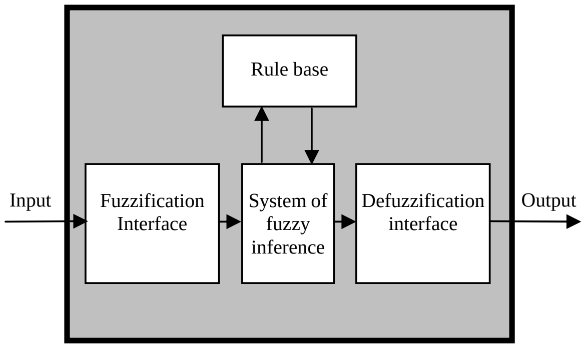

Fig. 2 Block diagram of fuzzy controller

The first module treats the entries of the system, which has four entries that we reduced with a reduction method based on mathematical fusion, and we associates him with Gaussian membership functions. We call fuzzification the stage that consists to partner to every real value of an entry variable, a function of adherence, therefore to transform the real entry in a fuzzy subset. The basis of rules is constituted of a set of 25 rules.

These rules, expressed in natural language, translate symbolically the knowledge in the process. The mechanism of inference permits, from the basis of rules and a vector of entry given, the calculation of the order of the system.

Because of the number important of parameters to identify, the global optimization of a fuzzy controller is delicate to achieve, it is why several techniques of optimization are considered often jointly, to optimize the controller's part [14], [19].

The system of fuzzy inference is initialized with Gaussians membership function, the used technique is based on the method of coming down of the gradient.

IV. Auto – Tuning of the Fuzzy Controller

The method described here is based on the fact that the parameters of the controller can be adjusted automatically. The proposed tuning method for automatic adjustment of parameters of a fuzzy controller is a learning algorithm based on gradient descent

The initialization of the fuzzy controller is achieved like follows:

The procedure of auto - regulating of the fuzzy controller (C.F) is based on an adaptive order structure [19]. Witch is presented by the Fig. 3.

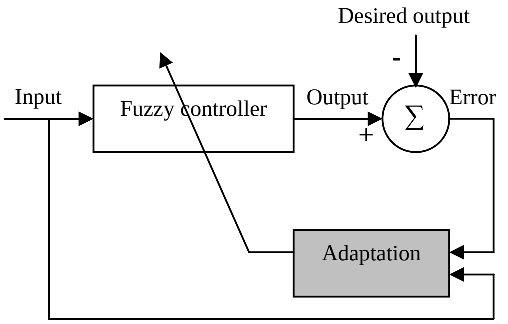

Fig 3 A learning scheme of the fuzzy controller

We distinguish in this diagram an intern of regulation and an external permitting to modify the parameters of the mad controller. Adaptation of parameters is achieved by presenting pairs of input and desired output vectors to the system and applying an adaptive algorithm which adjust the parameters, by minimising a measure of the actual output of the system.

The auto regulating of the fuzzy controller consists in minimizing a quadratic criteria.

$$V = \sum_{t=t_{début}}^{t=t_{fin}} e^T(t)Qe(t) = \sum_{t=t_{début}}^{t=t_{fin}} v(t) \qquad (3)$$

With $e(t) = y(t) - C(t)$ the difference of the real output and the desired one $C(t)$.

Q Is a diagonal matrix definite non negative.

The instantaneous gradient descent training rule updates the parameters vector Γ by:

$$\Gamma(t+1) = \Gamma(t) - \eta\left(\sum_{t=t_{start}}^{t=t_{end}} \frac{\partial V(t)}{\partial \Gamma}\right) \qquad (4)$$

With Γ the parameter to adjust and η is the predefined constant named learning rate.

The algorithm ends when the variation of the criteria has not significant value.

The variables of entries of the fuzzy controller are:

- The mistake of the temperature
- The variation of the mistake of the temperature
- The mistake of the hygrometry
- The variation of the mistake of the hygrometry

One of the difficulties, for the implementation of a fuzzy system, is the choice and the number of input variables. In our case the structure of the MIMO fuzzy controller has four variables of entries and outputs; we used the temperature and humidity variations compared to their references.

The construction of fuzzy controller is a complex task because many parameters are required for its design. To reduce the number of rules we decrease the number of entries of the fuzzy controller [22], by a mathematical fusion of entry variables. This fusion of variables of entries of the fuzzy controller gives the following variables:

$$E_{Ti} = K_2 \Delta\varepsilon_{Ti} + K_1 \varepsilon_{Ti} \quad (K_1 > 0, K_2 > 0)$$
$$E_{Hi} = K_4 \Delta\varepsilon_{Hi} + K_3 \varepsilon_{Hi} \quad (K_3 > 0, K_4 > 0) \qquad (5)$$

With E_{Ti} and E_{Hi} represent, respectively, the state of the temperature and the state of the hygrometry, CH and CT represent desired output of the internal humidity and temperature.

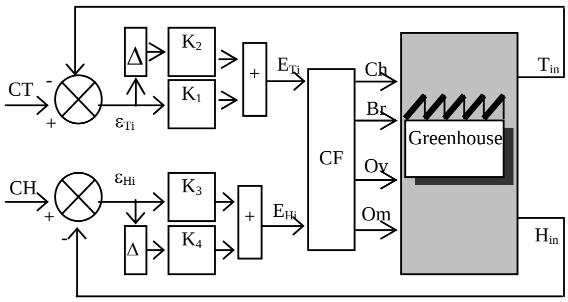

Fig. 4 Diagram of the regulation after reduction

The gains in entries K_1, K_2, K_3, K_4 are equivalent to factors of scale, they are initialized therefore a priori from a knowledge of the maximal value of their entries. The functions of adherence are spaced regularly on their universe of speech normalized and form a fuzzy partition. The basis of rules is initialized from a practiced knowledge on the process.

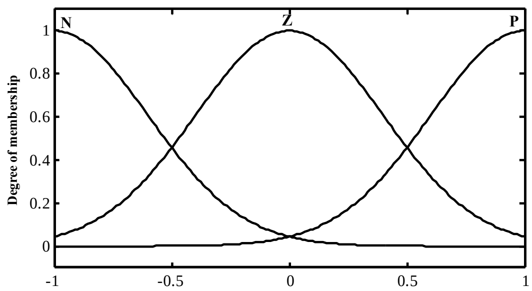

Fig. 5 An initial Gaussians membership functions

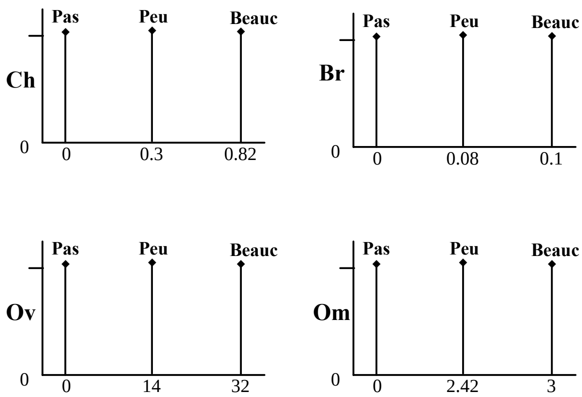

Fig. 6 Consequences values for the fuzzy logic controller

While taking account of the number of entries, the number of adherence functions and of the constraints of the process, the basis of rules contains 25 ones defined by an analysis of the greenhouse system. The considered rules are those of Takagi-Sugeno of order zero.

TABLE I
EXAMPLE OF RULE BASIS

E_{Ti}	E_{Hi}	CH	Br	Ov	Om
N	N	Beauc	Pas	Pas	Pas
Z	N	Pas	Beauc	Pas	Pas
P	N	Pas	Beauc	Pas	Pas
N	Z	Beauc	Pas	Pas	Pas
Z	Z	Pas	Pas	Pas	Pas
P	Z	Pas	Pas	Beauc	Pas

Pas : not to manipulate the order ;
Peu : to manipulate the order fairly;
Beauc : to manipulate the order to the maximum.

V. RESULTS

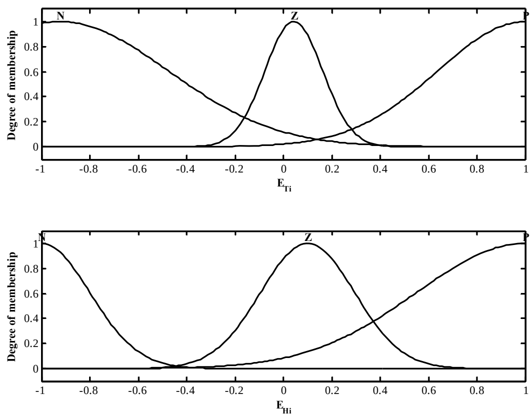

Fig. 7 The membership function to one random moment in the simulation

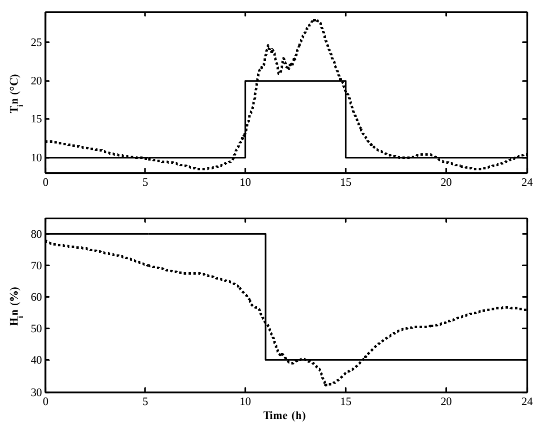

Fig. 8 Simulation of internal temperature and humidity basic on the fuzzy controller

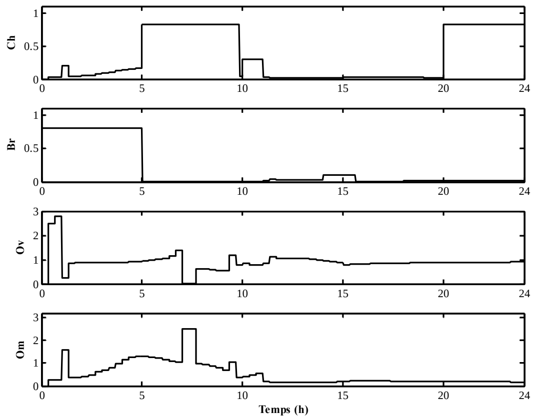

Fig. 9 Simulation of command in the greenhouse basic on the fuzzy controller

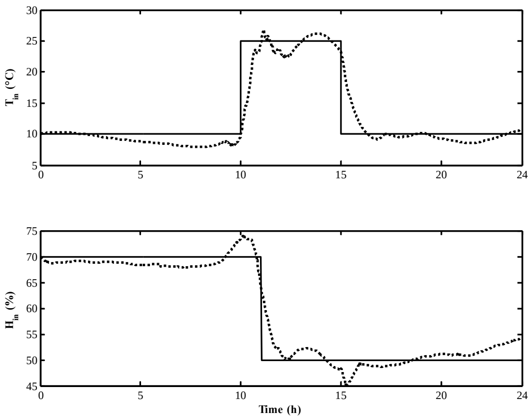

Fig. 10 Simulation of internal temperature and humidity basic on optimised fuzzy controller

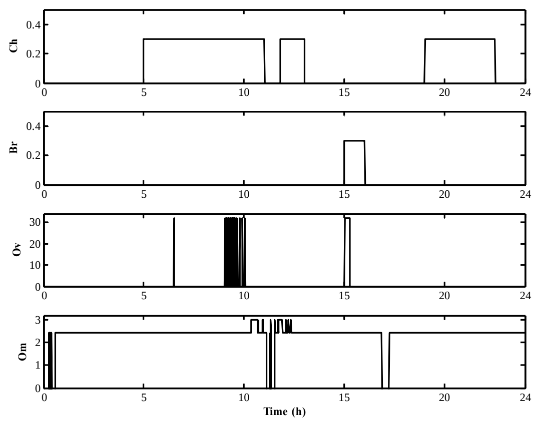

Fig. 11 Simulation of command in the greenhouse basic on the optimised fuzzy controller

The goal searched for in this work is the regulation of the temperature and the humidity inside the greenhouse.

The fuzzy controller is initialized with tree Gaussians membership functions.

The Fig. 7, shows the membership function in a random moment of the simulation because the Gaussians membership functions move in the same time that the simulation.

The internal temperature T_{in} and humidity H_{in} react correctly with the variation of the references Figs. 8, 10.

After the transient periods at the time of changes of references the temperature and the humidity follow the desired profiles correctly. Error of regulation and tracking remain in the acceptable limits. Signals applied to the greenhouse present the non agitated behaviour.

The choice of the references is fixed in relation to the external climate because we haven't a strong air-conditioning installed in the greenhouse.

The behaviour of T_{in} and H_{in} in Fig. 10 is more perfect to the one without optimization represented in Fig. 8. This is due to the adaptation of the membership functions in the universe of work.

The command of the heating CH is not activated at 5h to 11h between 12h to 13h and 19 to 22h00 when the temperature is lower to the desired order Fig. 11.
We note the same thing for Br it only intervenes when the humidity is lower to the order and when the command of heating is not activated, it is normal seen the basis of rules table 3 their actions are opposed.

The roofing is activated when the internal temperature is high in comparison with the reference and when the moistening is activated; the goal is to reduce the internal temperature.

The follow-up of the reference for the optimization fuzzy control is very satisfactory compared to a fuzzy control without tuning of the membership functions

VI. Conclusion

This paper shows that we can applied the control of the agricultural greenhouse with the help of the fuzzy logic associated to an algorithm of optimization. We have shown that a fuzzy control associated to a tuning of the membership functions is an efficient approach for the control of such MIMO system.

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