INTELLIGENT CONTROL FOR A GREENHOUSE CLIMATE

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ABSTRACT

The greenhouse is designed to recreate an environment wherein the temperature, humidity and light are monitored and adjusted to optimize the conditions of plant cultivation.
The algorithms of control proposed in this paper are based on the use of three methods: optimal control, fuzzy control and fuzzy adaptive control. The advantage of fuzzy logic is its ability to process imprecise. It comes from the human ability to decide and act appropriately despite the uncertainty of available knowledge.
The synthesis of fuzzy controllers for controlling MIMO systems requires writing a lot of rules and setting an impressive number of parameters. The goal we have set is to reduce the complexity of the fuzzy controller through an optimization technique based on gradient descent algorithm.
This paper shows that it is possible to control the greenhouse by using a fuzzy adaptive algorithm. The study is illustrated with several representative numerical examples

KEYWORDS: *Intelligent control, Fuzzy control, MIMO system, greenhouse, optimal control, Fuzzy adaptive control.*

I. INTRODUCTION

The greenhouse sector has experienced considerable growth in the last two decades. In view of its importance, numerous studies have been conducted to control the greenhouse. To put the computers in an intelligent control of the greenhouses is more and more popular even in the developing countries due to the economical interest. Computer control technologies make use of computer systems and other hardware to monitor physical conditions of an environment, make decisions about actions required to modify the environment, and act on devices that will result in changes to the environment. Computer controls are particularly useful in Multi Input – Multi Output (MIMO) systems in which many variables are controlled. The integrated computer system can be used to improve the performance of a greenhouse for which temperature and humidity need to be controlled.
To design efficient environmental controllers for greenhouse it is necessary to develop models that adequately describe the system to be controlled. These models must be related to the external influences of the weather condition (such as solar radiation, outside air temperature, wind speed, etc.) and to the instruments used in the greenhouse (such as ventilators, cooling systems, heating systems, etc.).
Basically, there are two different methods for computing the models. One is based in terms o the physical laws involved in the process [1], [2], [3], and the other is based on an analysis of the Input / output of the process.
The model that we use to simulate the greenhouse in this work is a linear model whose coefficients are obtained by identification. The model describes with precision the internal state of the greenhouse and follows well the evolution of the real values, the outcome mistakes remains tolerable. The obtained of the simulation with files of measures recorded on an experimental greenhouse at the University of Toulon in France.
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 contribution, low solution cost and better rapport with reality. The use of fuzzy logic for the regulation of climate variables represents an excellent means for the minimization of the energy cost for commands like heating and moistening.

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.

In this paper, different algorithms to control a greenhouse are presented; first we presented the model of the greenhouse and the algorithm of control: optimal control, fuzzy control, and the fuzzy adaptive control. This paper shows that a fuzzy adaptive controller can be successfully applied to control the greenhouse environment.

II. MODEL OF GREENHOUSE

The greenhouses are designed to recreate an environment in which the temperature, humidity and light are controlled and modified to optimize the culture conditions as diverse as the orchids, cactus, tomatoes and citrus plant.

The role of greenhouses is to modify the plant environment and therefore improve their growth during periods when environmental conditions are not conducive to good productivity. Management and control of greenhouse climate are thus of great importance, and several studies have been developed in order to define and understand the phenomena characterizing the microclimate and affecting the growth and development of the plant.

The process is a MIMO system, nonlinear and non stationary in which intervene the energizing exchange 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], and [7]. In general, these models are taken from the physical models.

The process is a system that has two sorts of variety of entries, commands and disturbance Fig. 1.

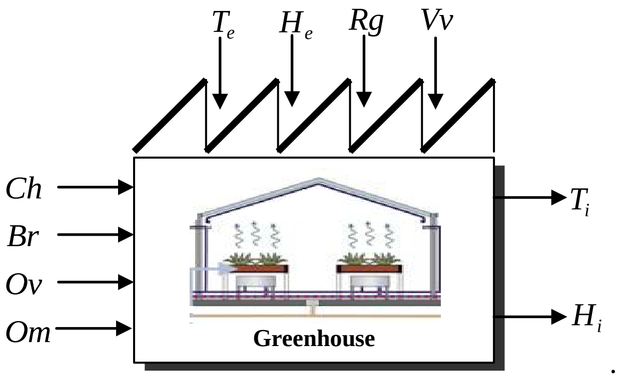

Figure 1. Model of the greenhouse control system

The Variables of command U are:

- Ch : Heating;
- Br : Moistening;
- Ov : Opening;
- Om : Shadiness.

The disturbances variable P are:

- T_e : External temperature;
- H_e : External humidity;
- Rg : Solar radiation;
- Vv : Wind speed.

The exits of this model are variables of intern greenhouse climate:

- T_i : Internal temperature;

- H_i : Internal Humidity.

To describe the different properties of the greenhouse, we took the model [8], this one is represented by a system of nonlinear equations, this one can be considered like linear and stationary around a particular operating point in which the parameter values are determined by dynamic identification.
The recurrent algebraic shape of the model is given by discrete form in space state

$$X_{k+1} = AX_k + BU_k + DP_k$$

$$Y_k \quad = CX_k$$

Where:

$X_k \in \Re^n$, $U_k \in \Re^m$ and $Y_k \in \Re^l$.

k is the time variable.

On the basis of this structure of the model, we are going to determine the numeric values of the coefficients that intervene in these equations by identification.

System identification deals with the problem of building mathematical models of dynamical systems based on observed data. We use the method of the least squares method [9], [10], it has the advantage to have a simple and explicit formulation. We have executed the simulation using the meteorological data file in the same day the plotting of the external, predicted and measured temperature and hygrometry are presented in Fig 2.

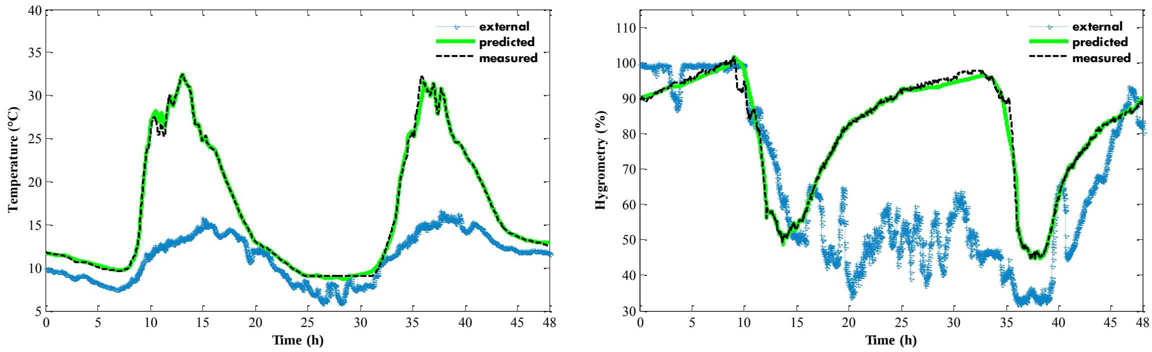

Figure 2. External, predicted and measured temperature and hygrometry for 2 consecutive days in the greenhouse

III. OPTIMAL CONTROL

The second part of this work deals with the development of a suitable methodology for the temperature and the humidity control. Nowadays, some greenhouses are equipped with an intelligent device of regulation. Many of them are still controlled manually and require the intervention of the grower.

However, there are installations with thermostatic systems and on–of commands (logical with low and high thresholds).This control is based on heater device, which is turned on and off by thermostat whenever the temperature error exceeds the fixed regulation band.

The humidity depends on the internal air temperature and on the ventilation rate this last variable is simply regulated by opening the windows of the greenhouse according to the measured wind speed (to note also there is some dangerous situations due to a high wind speed in the external environment).A such a system of regulation is often insufficient because it does not take into account the relationships between temperature and humidity.

Using the model of the greenhouse developed before, an initial experiment has been carried out using a classic control system based on an optimal control techniques [11], [12], [13], [14], [15].

This method is elaborated fig 3 in two stages:

▪ First, we identify the parameters of the model. Then following the criteria of performance fixed, we determine the parameters of the command. The quadratic criterion is constituted of terms that achieve a better dosage between performances and costs.

▪ Second, we fix the orders that the temperature and the humidity must follow. The computer determines the values of the other variables applied to the devices.

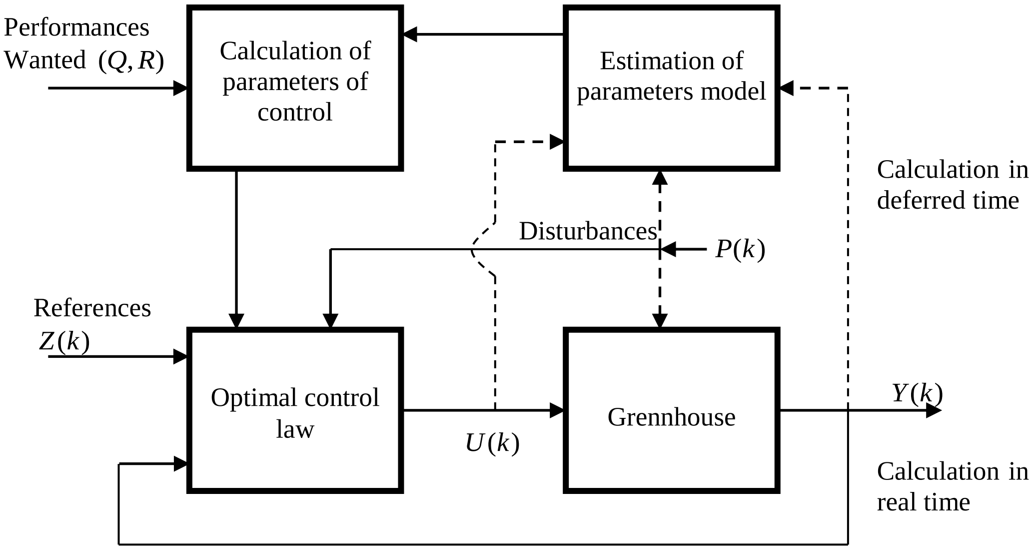

Figure 3. Principe of a greenhouse optimal control

2.1. Determination Of The Optimal Control Law

We wish to control the outputs $Y(k)$ (temperature and relative humidity) around the set-point $Z(k)$ on the interval $[0, N]$ acting on the inputs $U(k)$ ($Ch,\ Br,\ Ov,\ Om$).
The control law is obtained by minimizing the criterion equation (1) with respect to $U(k)$

$$J = \sum_{k=0}^{N-1}\{(U^{\mathrm{T}}(k)RU(k) + (Z(k)-Y(k))^{\mathrm{T}}Q(Z(k)-Y(k)))\} \quad (1)$$

These terms are weighted by two square matrices R and Q and symmetrical positive and respectively defined dimension (r, r) and defined nonnegative (m, m).
Diagonal form we choose below provides an easier physical interpretation:

$$R = \begin{bmatrix} r_{11} & & & 0 \\ & r_{22} & & \\ & & r_{33} & \\ 0 & & & r_{44} \end{bmatrix} \qquad Q = \begin{bmatrix} q_{11} & 0 \\ 0 & q_{22} \end{bmatrix}$$

These matrices are used to select a control strategy through a compromise between performance accuracy and energy costs.
These matrices are used to select a control strategy through a compromise between performance accuracy and energy costs. Whose development gives the equation (2)

$$J = \sum_{k=0}^{N-1}\{(U^{\mathrm{T}}(k)RU(k) + Z^{\mathrm{T}}(k)Q(Z(k) + Y^{\mathrm{T}}(k)QY(k) - 2Z^{\mathrm{T}}(k)QY(k)\} \quad (2)$$

The principle of optimality Bellman [11] permits from the definition of the cost function at each iteration to consider a recursive form resulting in optimum cost: development gives the expression:

$$J(X(k)) = \min_{/U}\{(U^{\mathrm{T}}(k)RU(k) + Z^{\mathrm{T}}(k)Q(Z(k) + Y^{\mathrm{T}}(k)QY(k) - 2Z^{\mathrm{T}}(k)QY(k) + j(X(k+1))\} \tag{3}$$

The criterion can be expressed in the following quadratic form:

$$J(X(k+1)) = X(k+1)^{\mathrm{T}}K(k+1)X(k+1) + 2g(k+1)^{\mathrm{T}}X(k+1) + h(k+1) \tag{4}$$

Where $K(k+1)$ is a symmetric square matrix (n,n), $g(k+1)$ is a vector dimension n, and $h(k+1)$ is a scalar.

$J(X(k+1))$ can be expressed in terms of equations of state control model equation (5)

$$\begin{aligned} X(k+1) &= A\,X(k) + B\,U(k) + D\,P(k) \\ Y(k) &= C\,X(k) \end{aligned} \tag{5}$$

$$\begin{aligned} J(X(k+1)) = {} & (AX(k) + BU(k) + DP(k))^{\mathrm{T}}K(k+1)(AX(k) + BU(k) + DP(k)) \\ & + 2g(k+1)^{\mathrm{T}}(AX(k) + BU(k) + DP(k)) + h(k+1) \end{aligned} \tag{6}$$

Recurrent equation defined above, equation (3), is written:

$$\begin{aligned} J(X(k)) = {} & \min_{/U}\{(U^{\mathrm{T}}(k)RU(k) + (Z(k) - Y(k))^{\mathrm{T}}Q(Z(k) - Y(k))\} \\ & + \min_{/U}\{(AX(k) + BU(k) + DP(k))^{\mathrm{T}}K(k+1)(AX(k) + BU(k) + DP(k))\} \\ & + \min_{/U}\{2g(k+1)^{\mathrm{T}}(AX(k) + BU(k) + DP(k)) + h(k+1)\} \end{aligned} \tag{7}$$

To determine the optimal value of the order, we derive the equation (7)

Provided that the matrix of second partial derivatives $(R + B^{\mathrm{T}}K(k+1)B)$ is regular and positive definite, the control vector $U(k)$ that minimizes the quadratic criterion equation (1) can be written in the form:

$$U(k) = -L(k)X(k) + \mu(k) \tag{8}$$

Where $L(k)$ is a correction matrix state feedback dimension $(r \times n)$ and $\mu(k)$ is a function of anticipation vector R of disturbances $P(k)$ and set-point $Z(k)$

$$L(k) = (R + B^{\mathrm{T}}K(k+1)B)^{-1}B^{\mathrm{T}}K(k+1)A \tag{9}$$

$$\mu(k) = -(R + B^{\mathrm{T}}K(k+1)B)^{-1}B^{\mathrm{T}}(g(k+1) + K(k+1)DP(k)) \tag{10}$$

Where $K(k)$ is the Riccati equation in the discrete case matrix dimension $(n \times n)$:

$$K(k) = A^{\mathrm{T}}K(k+1)A - A^{\mathrm{T}}K(k+1)B(R + B^{\mathrm{T}}K(k+1)B)^{-1}B^{\mathrm{T}}K(k+1)A + C^{\mathrm{T}}QC \tag{11}$$

With the free end condition $(K(N) = 0)$ and vector $g(k)$ dimension n:

$$g(k) = (A - B(R + B^{\mathrm{T}}K(k+1)B)^{-1}K(k+1)A)^{\mathrm{T}}(g(k+1) + K(k+1)DP(k)) - C^{\mathrm{T}}QZ(k) \tag{12}$$

With the free end condition:

$$(g(N) = 0) \tag{13}$$

2.2. Results

For numerically solving the algebraic Riccati equation, we use method shown in [16].

Each of these methods has their own characteristics, defects or advantage depending on the size of the problem and packaging matrices. We chose the method of induction on for the numerical solution of the Riccati equation applied to our control model. This method is easily implemented on the computer and is iterated to construct a sequence of the form.

$$K(j+1) = A^{\mathrm{T}}K(j)A - A^{\mathrm{T}}K(j)B(R + B^{\mathrm{T}}K(j)B)^{-1}B^{\mathrm{T}}K(j)A + C^{\mathrm{T}}QC \quad (14)$$

Using the simulation model oh the greenhouse, we tested the optimal control algorithm. In fact, the simulation is an indispensable before testing the command on the actual process step. Particularly in the context of this command it will help us to determine the weighting matrix R and Q.

The choice of matrices R and Q and will allow us to adjust the performance of the closed loop system. The shape of the test indicates that more elements of the matrix R are large relative to the matrix elements Q, the lower are the amplitudes of action and are more we have errors.

We proceed as follows:

▪ First, we fix the weight of the matrix R and Q

▪ In a second step, we vary the weight of the matrix Q that come near the desired performance.

Several simulations were done, we have chosen for the matrix value:

$R = \begin{bmatrix} 1 & & & 0 \\ & 1 & & \\ & & 0.01 & \\ 0 & & & 1 \end{bmatrix}$ and for the choice of the matrix Q, we first selected a relatively low weight of the matrix R. $Q = \begin{bmatrix} 10^{-3} & 0 \\ 0 & 10^{-5} \end{bmatrix}$

The elements of the Riccati equation tend to finite limits and there is the slow convergence of the parameters of control law in Fig 4 and 5.

The simulation results of the regulated outputs and controls are shown in Fig 5 and 6.

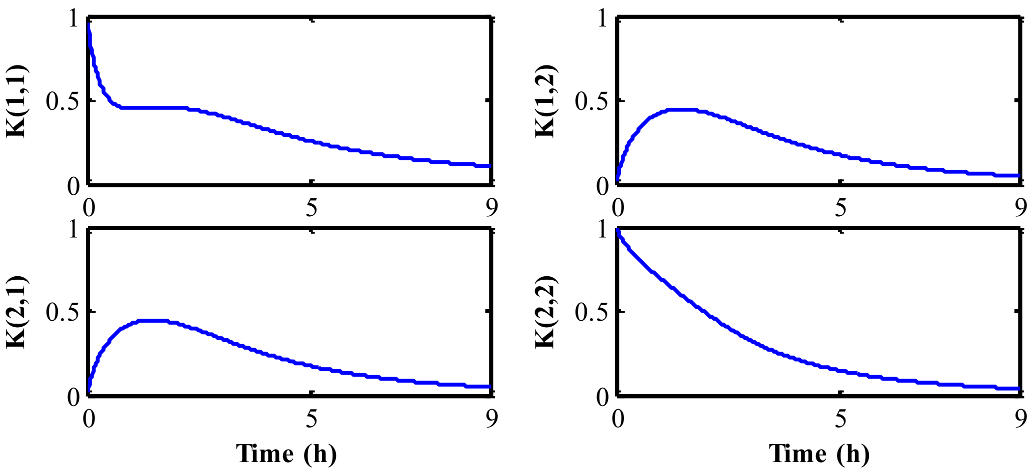

Figure 4. Principe of a greenhouse optimal control

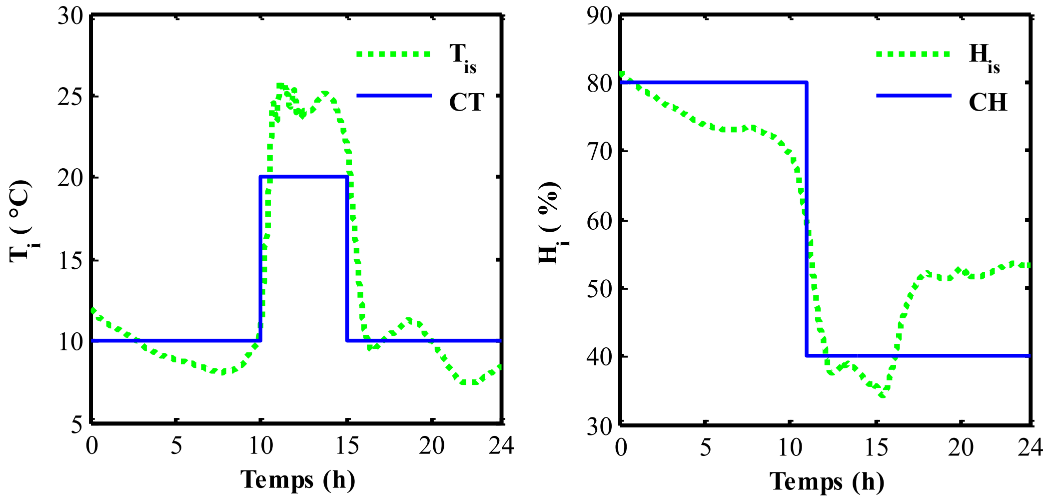

Figure 5. Principe of a greenhouse optimal control

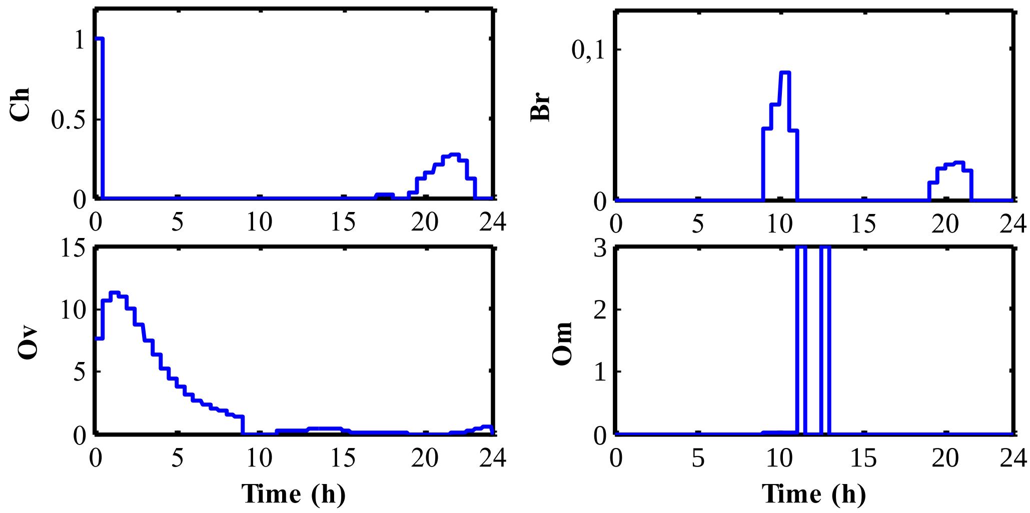

Figure 6. Principe of a greenhouse optimal control

IV. Fuzzy Control

In the last decade, the fuzzy logic gained interest in the scientific community, one of the reasons in the huge financial success of the industry in producing a considerable number of appliances using fuzzy controllers (FC).

The aim advantage of fuzzy control is the possibility of implementing human expert knowledge in the form of linguistic if – then rules [17], [18], [19], [20], and [21].

The design of a fuzzy controller begins with the choice of linguistic variables, the process state, the input and the output variables. The next step is the choice of the set of linguistic rules and the kind of fuzzy reasoning process.

Once the rules are setup, after the inference, the fuzzy set and the crisp output value have to be generated; a defuzzification strategy has to be established too.

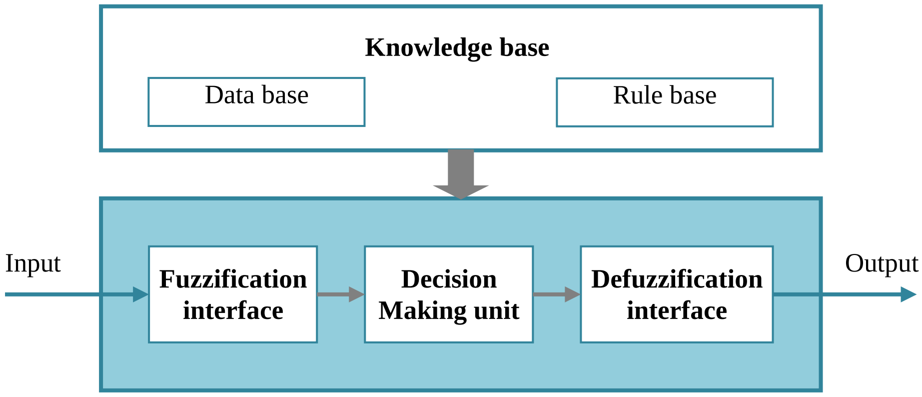

Figure 7. Block diagram of a fuzzy controller

The block diagram of a fuzzy controller is shown in fig 7. It is composed of four principal modules:

The fuzzification interface performs the transformation of crisp inputs into fuzzy sets.

The knowledge base supplies the fuzzification module, the interface engine, and the defuzzification interface with necessary information for their proper functioning.

The decision making unit or interface engine computes the meaning of the set linguistic rules.

The defuzzification interface transforms the union of fuzzy sets (individual contributions of each rule in the rule base) into a crisp output.

3.1. Determination Of The Fuzzy Control Law

Using the Model of the greenhouse control system fig 1, the structure of the fuzzy controller for our process will have the following diagram fig 8.

The output variables are commands and the Variables of entries of the fuzzy controller are:

ε_{Ti} Error of the temperature

$\Delta\varepsilon_{Ti}$ Variation of the error of the temperature

ε_{Hi} Error of the hygrometry

$\Delta\varepsilon_{Hi}$ Variation of the error 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 fuzzy controller should have the structure shown in Fig 8 that means a MIMO fuzzy controller with four variables of entries and exits. We have used the temperature and hygrometry 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:

$$X_{Ti} = K_2\Delta\varepsilon_{Ti} + K_1\varepsilon_{Ti} \quad (K_1 > 0, K_2 > 0)$$

$$X_{Hi} = K_4\Delta\varepsilon_{Hi} + K_3\varepsilon_{Hi} \quad (K_3 > 0, K_4 > 0) \tag{15}$$

Where X_{Ti} and X_{Hi} represent respectively, the state of the internal temperature and the hygrometry and K_1, K_2 , K_3 , K_4 represent dynamic factor and they are initialised from the maximal values of their entrances. The fig 9 shows the diagram control after reduction.

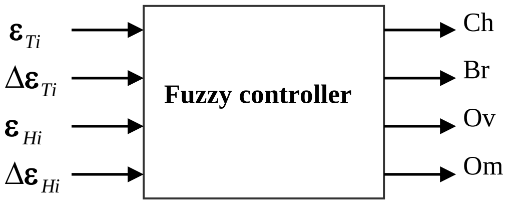

Figure 8. Block diagram of a fuzzy controller

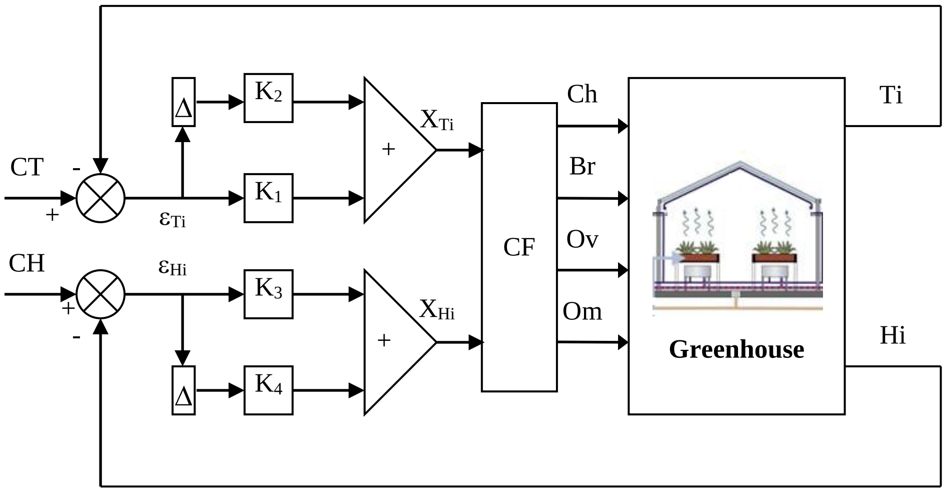

Figure 9. Block diagram of a fuzzy controller

3.2. Result

The fuzzy logic controller obtained has two input variables and four output variables, the variables of inputs are characterised by five fuzzy sets in the universe of discourse.
By taking into account the number of inputs, the membership functions, the fuzzy base contains 25 rules; we give an example as shown in table 1.

Table 1. Sample of rules obtained by implementing the human expertise.

X_{H_i}		**N**	**NZ**	**Z**	**ZP**	**P**
X_{T_i}	**N**	Pas	Pas	Pas	Pas	Pas
	NZ	Pas	Pas	Pas	Pas	Pas
	Z	Pas	Pas	Pas	Peu	Beauc
	ZP	Peu	Peu	Peu	Peu	Beauc
	P	Peu	Peu	Peu	Peu	Beauc

As it's known a fuzzy logic controller acts as a nonlinear system implementing human-based reasoning for computation of the control values. In our case, the adopted fuzzy rules are in Takagi-Sugeno (order zero). The set of chosen membership functions is presented in fig 10 and the consequences are shown in the fig 11.

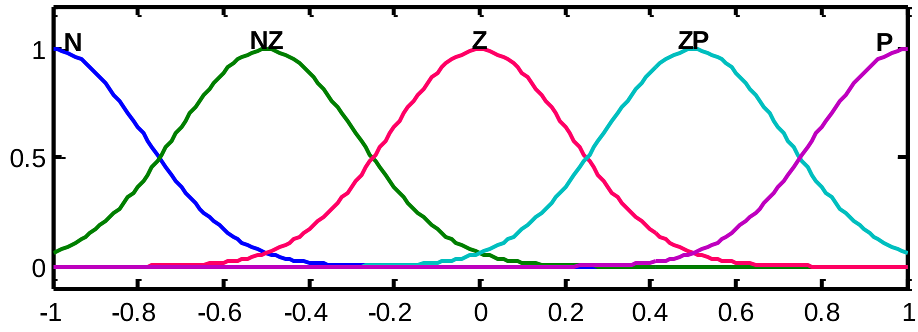

Figure 10. Membership functions for inputs X_{Ti} and X_{Hi}.

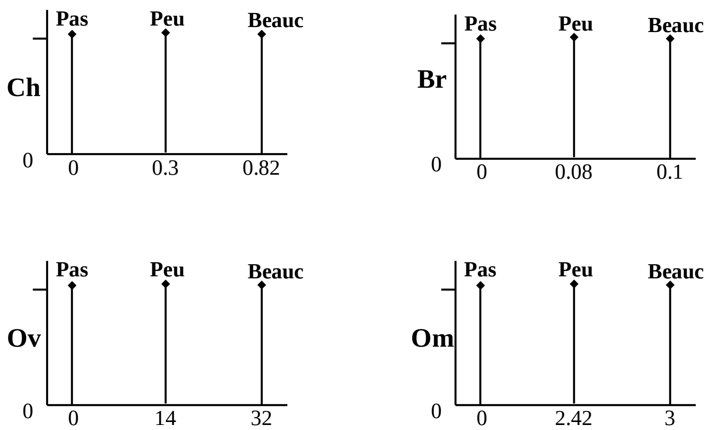

Figure 11. Consequences values for the fuzzy logic controller

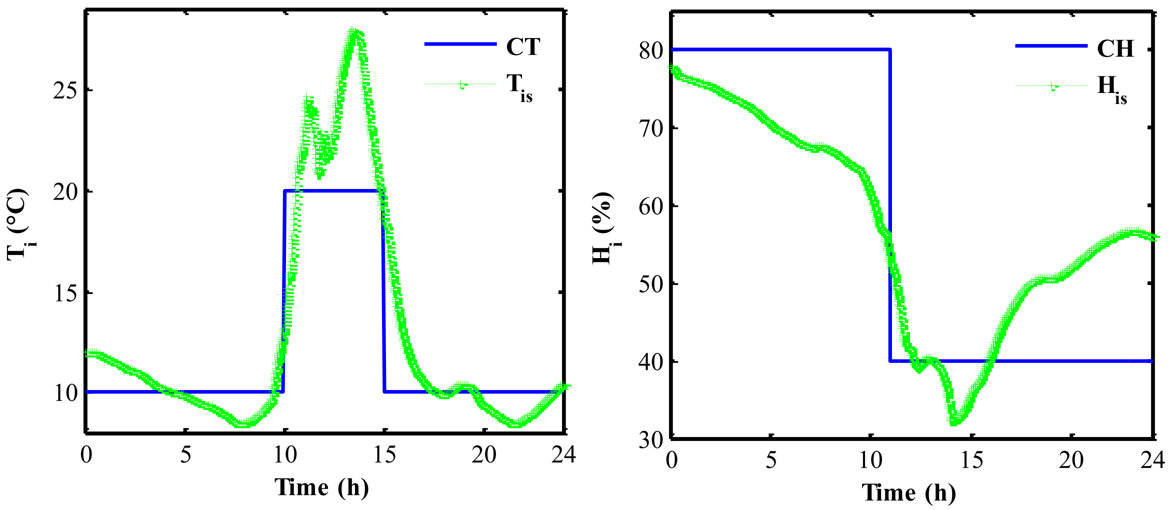

Figure 12. Simulation of internal temperature and hygrometry compared to set points CT and CH

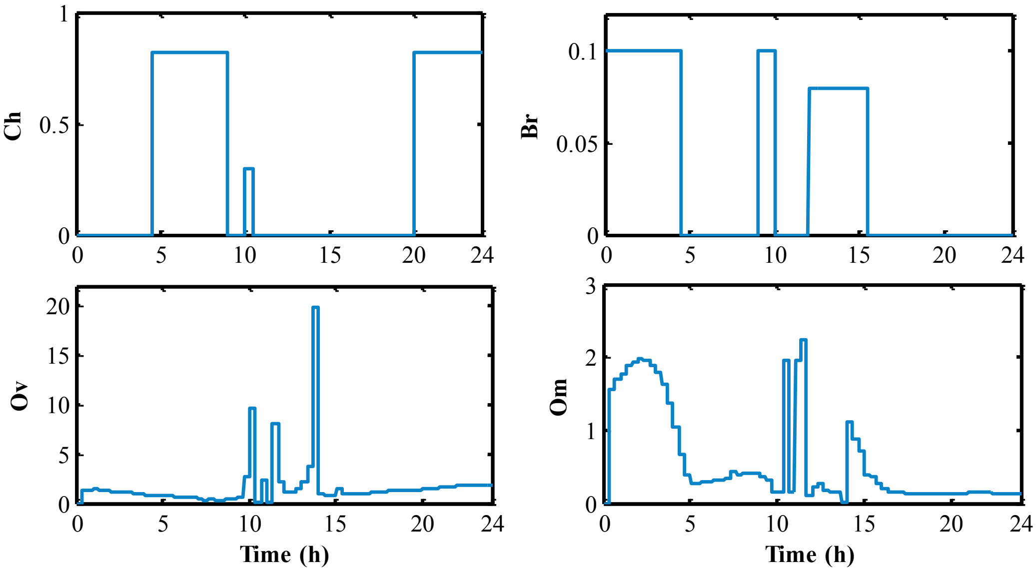

Figure 13. Simulation of command in the greenhouse

The temperature reference CT changed from 10 °C to 20°C at 10h and changed to 10 °C at 15h. The hygrometry reference CH changed from 80% to 40% at 11h. The Follow-up of the trajectory represented in the fig 12, 13 is satisfactory and the interactions are compensated extensively; it is necessary to note that it is impossible to glue to the references. Considering the numerous parameters in a fuzzy controller the elaboration by a procedure of type tests – errors are revealed to be long and tiresome.

V. OPTIMIZATION OF THE FUZZY CONTROL

The application of the reduction methods presented previously permits to define a fuzzy controller of reduced complexity; of the optimization skill can be put in work in order to facilitate the phase of elaboration of the fuzzy controller. The procedure of auto - regulating is based on an adaptive order structure [26], [27], [28], [29], [30], [31] and [32].

The adjustment of the controller's parameters is achieved by minimization of the error between the exit of the process and the references. The tuning of the fuzzy controller consists in minimizing quadratic criteria [23], [24] and [25].

$$J = \sum_{t=t_{start}}^{t=t_{end}} \left(\frac{1}{2} e^T(t).Q.e(t) \right) \tag{16}$$

Where $e(t) = y(t) - C(t)$ is the difference between the real y(t) and the reference C(t), Q a matrix, definite non negative and diagonal of dimension (2, 2) in our case.

Parameters of the fuzzy controller are optimized by the method of the gradient each k iteration, according to the formula.

$$X(k+1) = X(k) - \eta\left(\sum_{t=t_{start}}^{t=t_{end}} \frac{\partial J(t)}{\partial X}\right) \tag{17}$$

With X is the parameter to adjust and η the factor of descent. The algorithm ends when the variation of the criteria has not significant value.

In other stage, we will keep the same structure of the fuzzy controller described previously and also the references.

4.1. Results

The obtained results are represented in the fig 14 and 15.

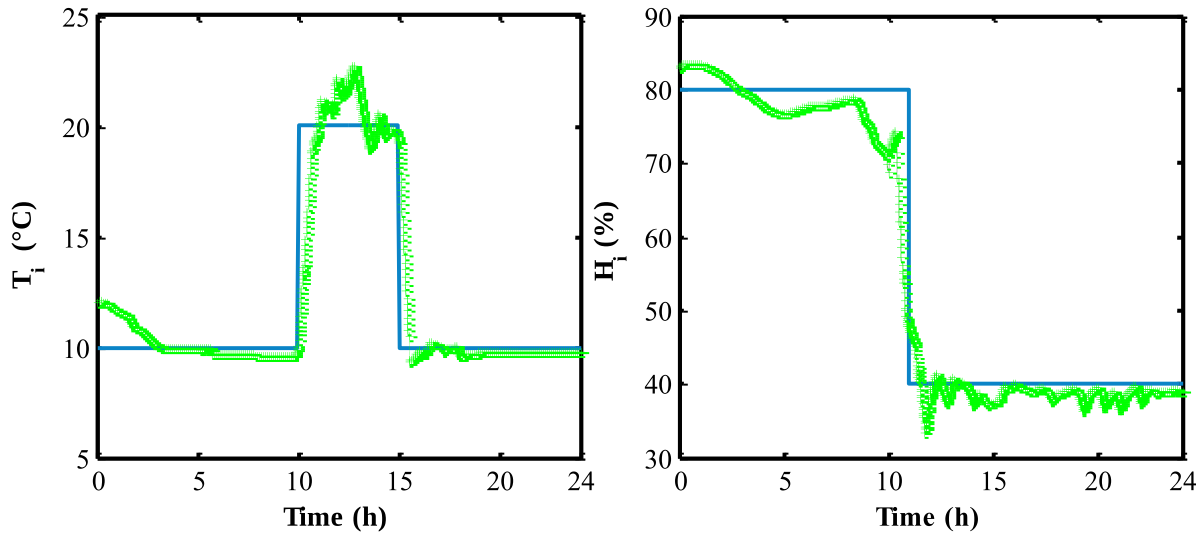

Figure 14. Simulation of command in the greenhouse compared to set points

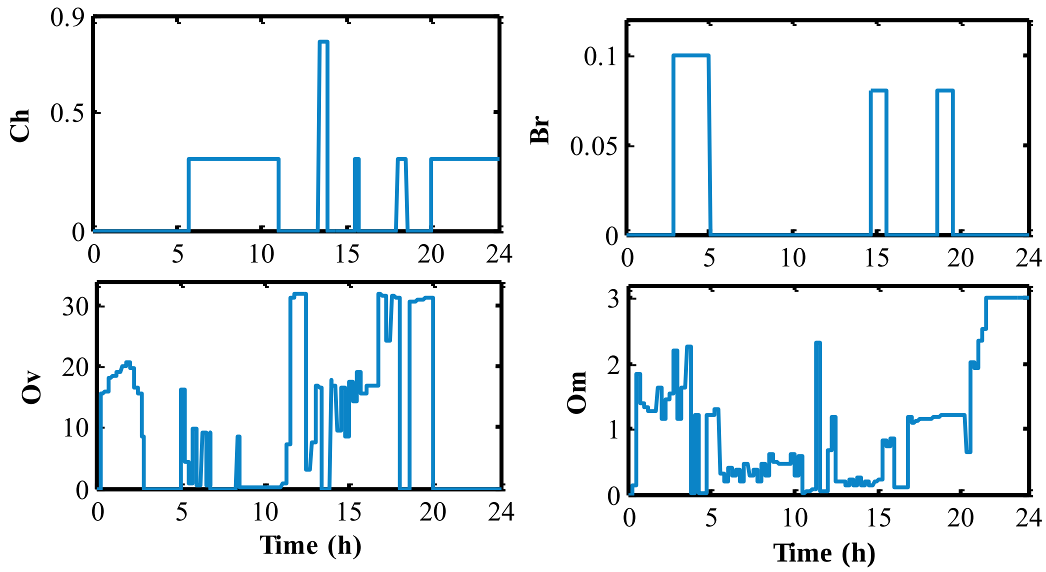

Figure 15. Simulation of command in the greenhouse

The internal temperature T_i and hygrometry H_i react correctly with the variation of the references fig 14. Around 3h the temperature comes closer to the order fixed by the expert, at 10h and at 15h there is a change of the internal temperature T_i behaviour, this change intervenes at the time of the change of the reference. The change of H_i intervened at 11h when there is a change of the reference.

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_i and H_i in this simulation is more perfect for the one without optimization represented in fig 14. This is due to the adaptation of the membership functions in the universe to work. The fig 16, shows the membership function in a random moment of the simulation.

The command of the heating CH is not activated at 6h to 11h between 13h to 14h, 15h30 to 16h00 and 20h to 24h when the temperature is lower to the order fig 15.

We note the same thing for Br it only intervenes when the hygrometry is lower to the order and when the command of heating is not activated, it is normally seen the basis of rules table 1 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 satisfied compared to a fuzzy control without tuning of the membership functions even if compared to a classic one as the optimal control this is largely due to their potential of transfer of expert knowledge on the process.

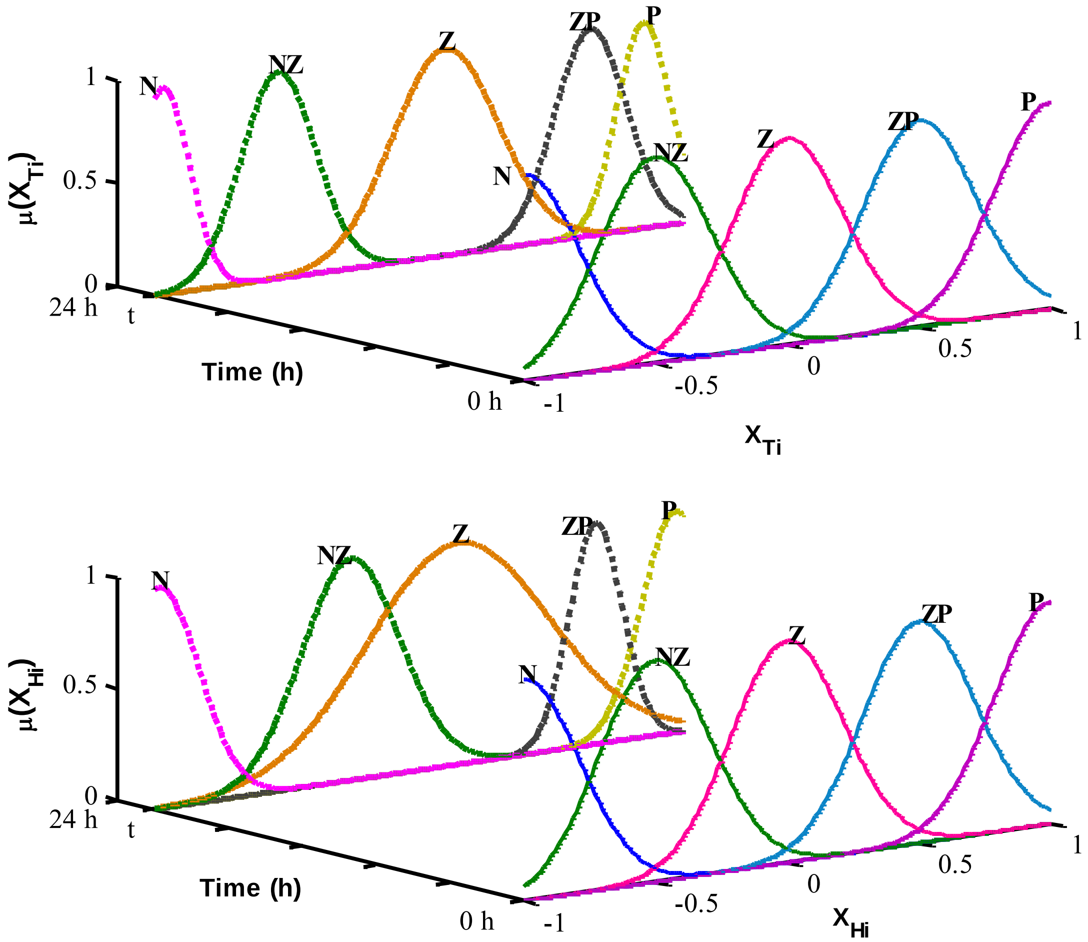

Figure 16. the membership function to one random moment in the simulation

VI. CONCLUSION

This paper proposes a contribution for the soft control of a MIMO system like a greenhouse.

In the first stage we elaborated a model of simulation for the need of the control based on algorithm of identification. In the second part we tested an optimal control and a fuzzy control and a fuzzy control based on an algorithm of optimization of the membership functions.

The optimal control is used to control the greenhouse climate taking into account the interactions between the internal components of the greenhouse temperature and humidity and those that are external, weather disturbances. One problem with this command is the choice of the matrices R and Q. These affect the dynamics of the system and can improve system performance.

Comparison of this command with the fuzzy control shows that the fuzzy controller is successful in continuing with its self-adaptation and use of dynamic functions affiliations.

Use of the fuzzy control based on the gradient descent allows a better control of the value compared to that obtained by optimal control, takes into account the coupling between the temperature and humidity and skips backward limitations practices encountered in optimal control, which is why they are so popular craze in the field of automation.

As perspective, it will attempt to apply this adaptive fuzzy control algorithm to a fuzzy PID controller whose parameters are automatically optimized for an intelligent control to the greenhouse

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