Soft Computing for Greenhouse Climate Control

R. Caponetto, L. Fortuna, G. Nunnari, L. Occhipinti, and M. G. Xibilia

***Abstract*—The methodology proposed in the paper applies artificial intelligence (AI) techniques to the modeling and control of some climate variables within a greenhouse. The nonlinear physical phenomena governing the dynamics of temperature and humidity in such systems are, in fact, difficult to model and control using traditional techniques. The paper proposes a framework for the development of soft computing-based controllers in modern greenhouses.**

***Index Terms*—Fuzzy logic, genetic algorithms (GAs), greenhouse temperature control, proportional integrative derivative (PID) distributed control and system modeling.**

I. Introduction

THE popularity of computers for the management of greenhouses is still increasing even in those countries where the environmental conditions are not prohibitive for the development of plants. In The Netherlands, computers are used for different applications like the climate, the boiler, and the irrigation control, but the best known of them is the climate control (temperature, humidity, CO_2, artificial lighting). The main improvements in the computer-based climate control are found in data logging the determination of climate set-points, monitoring and alarm functions. A large amount of literature is available about the application of classical dynamic systems and control theory in the areas of greenhouse modeling and control (see for example [1]–[3]).

The approach proposed here is oriented in the direction of artificial intelligence (AI) techniques, intelligent control methodologies and soft computing for the analysis and synthesis of intelligent climate controllers. Soft computing [4] is an association of computing methodologies centered on fuzzy logic, neurocomputing, genetic algorithms (GAs), and probabilistic computing.

Soft computing methodologies are complementary and synergistic rather than competitive. The guiding principle of soft computing is to exploit the tolerance for imprecision, uncertainty and partial truth, and the approximation to achieve the tractability, the robustness, the low solution cost, and the better rapport with reality. The main advantages obtainable using, for example, fuzzy logic and control, neural networks, and expert systems can be summarized as follows.

- The modeling of some complex behavior can easily be achieved by an input–output (I/O) data learning using artificial neural networks (ANNs). This will avoid the analysis of physical phenomena involving complex dynamics [8].
- The use of fuzzy logic controllers (FLCs) for the regulation of climate variables like temperature and humidity in the artificially conditioned greenhouses represents a powerful way to minimize the energy cost for heating. These are important greenhouse climate control aspects.
- The expert systems, in particularly the expert systems including fuzzy rule-based systems, are essential for the implementation (and optimization) of the human experts abilities in the field of computerized greenhouses in order to avoid significant damage to plants.
- Finally, human experts have the intuitive capability to evaluate the potential economic return of the plants at every stage of their development, while experts in biology can establish the most appropriate actions that have to be carried out in order to optimize the growth-development rate of the plants [9].

Even if the fuzzy logic control is hard to use it can be considered as an alternative to the traditional nonlinear control system because it has been successfully applied in a lot of applications [10], [11].

The subject of this work is to give some results in order to demonstrate the validity of the use of the AI techniques described above in the field of greenhouse climate control. A lot of simulations, referring to different control techniques, have been done and reported in the paper as it follows: Section III—standard bang-bang control technique; Section IV—fuzzy controller designed on the basis of expert description; Section V—fuzzy controller optimized via GAs; and, finally, in Section VI—distributed proportional integrative derivative (PID) controller.

II. Modeling the Greenhouse

The first part of the work is based on the development of a computer simulator for the greenhouse based on physical considerations. The simulator has been developed using the SIMULINK tool within the MATLAB environment on the basis of the work described in [12], [13] (see Fig. 1).

For the sake of simplicity, all the physical parameters have been included in a data file referring to a fixed structure.

The environmental conditions have been simulated using a meteorstation considering average values for the external air temperature, wind speed, and solar radiation.

Modeling a greenhouse from a physical point of view requires a large computer effort due to the intrinsic complexity of the system and of the phenomena involved.

A greenhouse is a distributed parameter system whose effectiveness strongly depends on several nonlinear phenomena. The heat transferred inside the greenhouse depends, in fact, on the

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R. Caponetto and L. Occhipinti are with the Soft Computing Group, STMicroelectronics, 95121 Catania, Italy.

L. Fortuna and G. Nunnari are with the System and Control Group, University of Catania, 95121 Catania, Italy.

M. G. Xibilia is with the Dipartimento di Matematica, University of Messina, 88166 Messina, Italy.

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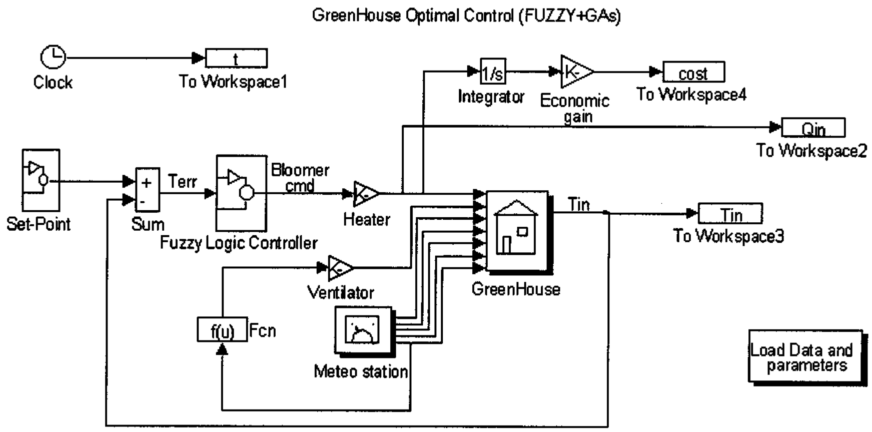

Fig. 1. The Simulink model of the greenhouse control system.

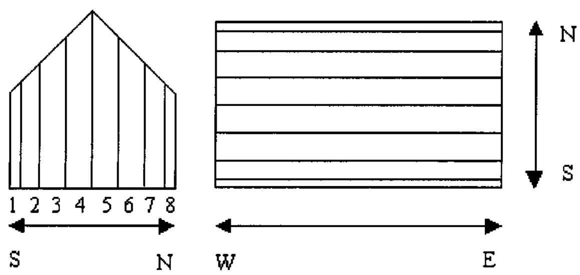

Fig. 2. Finite elements approximation of the greenhouse model.

radiative and convectional effects. Moreover, the presence of many uncontrollable signals which depend on the weather, the solar radiation, the crop transpiration, and so on, make validation of the model even difficult.

In order to take into account all these characteristics a multilayers model of the greenhouse has been considered: it represents a simple finite-element greenhouse approximation model. In Fig. 2 it is depicted the structure of the model that divides the internal volume of the greenhouse in eight sections whose thickness is proportional to the distance from the wall of the structure. Each layer represents a modeled subsystem which consider the interaction with the roofing, the ground external environment and/or the adjacent layers.

The motivations for the distribution of the internal adjacent layers, which constitute the elements in our finite-element method (FEM) analysis are, first of all, due to the natural distribution of thermal and humidity gradients in the north–south direction (front–rear side, which is also the short side of the greenhouse in usual position). It is in this direction, in fact, that the internal climate variables are quite varying from the side walls to the center area. The need to maintain uniform the distribution of the temperature and of the humidity, in the north–south direction is fundamental for the optimal growing of the plants. Therefore, eight internal layers have been obtained, so that the modeling of climate variables for each layer allow us to set up the control dynamics in order to maintain an internal uniform distribution of the climate variables.

According to that representation the heat balance equation system, referring to the ith layer, can be written as follows:

$$Q_{a1} = Q_{a2} + Q_{a3} + Q_{a4} - Q_{a5} + Q_{a6} + Q_{a7} + Q_{a8} \quad (1)$$

where

- Q_{a1} energy stored in the internal air volume as latency and sensitive heat;
- Q_{a2} input heat quantity (heating system);
- Q_{a3} convective heat exchange with the lateral wall;
- Q_{a4} transmission heat exchange with frontal walls (only for layer numbers one and eight);
- Q_{a5} fraction of heat exchanged with the external air as latent and sensitive heat;
- Q_{a6} conductive heat exchange with adjacent layer;
- Q_{a7} convective heat exchange with soil;
- Q_{a8} fraction of natural heat (solar radiation)

where each term is given by a set of dynamic equation systems. More detailed equation systems are reported in appendix.

Concerning with the heat quantity stored in the ith layer Q_{a1} it can be obtained from the following equation:

$$Q_{a1} = Q_{a11} + Q_{a12} + Q_{a13} + Q_{a14} \quad (2)$$

with

$$Q_{a11} = 0,5 * \rho * c * V_i * (3/4\dot{T}_i + 1/4\dot{T}_{i+1})$$
$$Q_{a12} = 0,5 * \rho * \lambda * V_i * (3/4\dot{U}_i + 1/4\dot{U}_{i+1})$$
$$Q_{a13} = 0,5 * \rho * c * V_i * (3/4\dot{T}_i + 1/4\dot{T}_{i-1})$$
$$Q_{a14} = 0,5 * \rho * \lambda * V_i * (3/4\dot{U}_i + 1/4\dot{U}_{i-1})$$

where

- V_i volume of the ith layer (m^3);
- ρ air density (Kg/m^3);
- c air specific heat (J/Kg $*$ K);
- λ heat latent energy (J/Kg);
- U specific humidity;
- T internal temperature (°C).

Using this model, a comparative analysis has been carried out for traditional *bang-bang*, *fuzzy logic*, and *distributed PID* controllers.

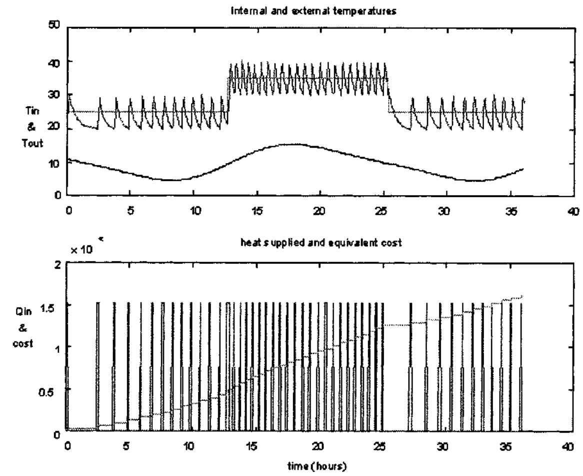

Fig. 3. Variables trend of traditional controller with a threshold of ± 5 °C temperature bandwidth. Internal temperature (UP Tin) and external temperature (Tout); supplied heat (DOWN Qin) and control cost (cost).

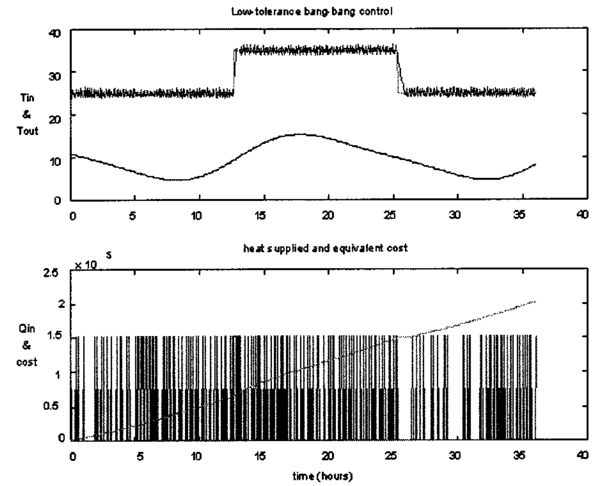

Fig. 4. Variables trend of traditional control with a threshold of ± 1 °C temperature bandwidth. UP Tin and Tout; DOWN Qin and cost.

III. Traditional Climate Control

The second part of the work deals with the development of a suitable methodology for the temperature and the humidity control.

The temperature is controlled by regulating the water temperature within an appropriate set of pipes uniformly distributed in the greenhouse, while the humidity is controlled indirectly by the ventilation rate regulation (which affects both temperature and humidity).

Using the physical model shown in Fig. 1 an initial experiment has been carried out using a traditional control system based on a *bang-bang* technique.

This control system is based on a heater actuator, which is turned on and off by a 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 (this can avoids also some dangerous situations due to a high wind speed in the external environment).

Figs. 3 and 4 show the obtained results. As it can be seen, the precision level depends on the thermostat thresholds, which affects the energy spent for the control.

It could be noted that the error bandwidth decreasing has an indirect effect on the energy consumption. So, intuitively, a bang-bang control technique is more expensive than a suitable soft control technique.

This is the main reason of FLC—based system, which is the subject of the next section.

IV. Fuzzy Logic Climate Control

The second approach implements a nonlinear MISO controller for the regulation of the temperature within the greenhouse, extending the concept of the PID fuzzy controller in the two-dimensional case [14].

As it is known from fuzzy logic principles, an FLC acts as a nonlinear system implementing human-based reasoning for computation of the control values.

TABLE I
Rules Set Obtained by Implementing the Human Expertise

r1	IF Error IS Pos THEN Blooming_control IS Mbf7
r2	IF Error IS Zero AND Change_in_error IS Pos THEN Blooming_control IS Mbf2
r3	IF Error IS Zero AND Change_in_error IS Zero THEN Blooming_control IS Mbf3
r4	IF Error IS Zero AND Change_in_error IS Neg THEN Blooming_control IS Mbf4
r5	IF Error IS Neg THEN Blooming_control IS Mbf0
r6	IF Error IS PosLow THEN Blooming_control IS Mbf6
r7	IF Error IS NegLow THEN Blooming_control IS Mbf1

More precisely, an FLC, which is defined by a set of linguistic rules and fuzzy sets, is able to compute appropriate values for the heater actuator by taking into account information data coming from the actual system.

In the case considered here, we are taking into account the temperature error and the change in error. The set of fuzzy rules have been obtained by a human expert by reducing and adjusting the start-up configuration to a suitable number of fuzzy sets for each input variable.

The adopted fuzzy rules are in the Mamdani [5] form, with singleton output fuzzy set. The generic i rule assumes the following form:

$$\text{if } x_1 \text{ is } G_1^i \text{ and } x_2 \text{ is } G_2^i, \cdots, \text{and } x_m \text{ is } G_m^i \text{ then } y \text{ is } h^i \qquad i = 1, 2, \cdots, n \tag{3}$$

where

x_k input variables;
G^i input fuzzy sets;
h^i consequent singletons.

The FLC obtained has two input variables and one output variable characterized by five fuzzy sets in the universe of discourse of the error variable and three fuzzy sets for the change-in-error input variable. As dictated by experience, the fuzzy rule base is composed of seven rules, as shown in Table I.

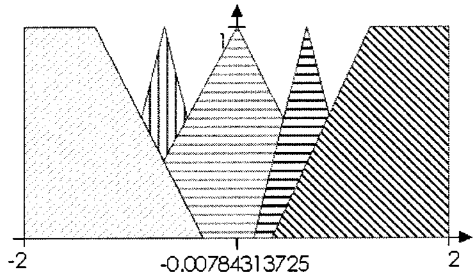

Fig. 5. Error membership functions drawn by expert.

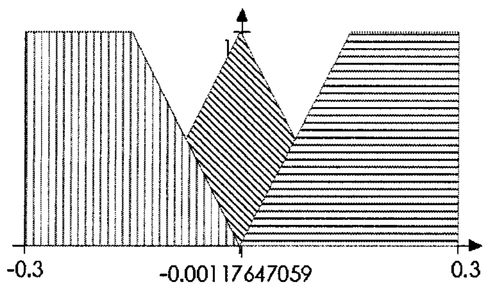

Fig. 6. Change in error membership functions drawn by expert.

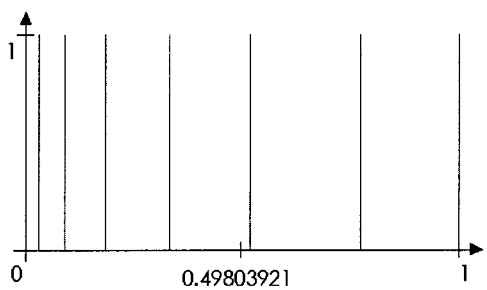

Fig. 7. Crisp consequences values fixed by expert.

The set of chosen membership functions and appropriately modified following a trial and error strategy are shown in Figs. 5–7, while the obtained internal temperature (average values) and the supplied control energy to the greenhouse are described in Fig. 8, showing the good performance obtainable through quite simple tuning operations. Simulation results have been achieved using the FS2 SW development tool [15], with the MATLAB exporter of the FLC.

V. Fuzzy Logic Controller Optimization through Genetic Algorithms

In order to increase the degree of automation of the fuzzy control system, a "near-optimal" controller synthesis strategy has been developed using GAs. This will allow comparative evaluation of the human-based approach described above.

GAs are general-purpose global optimization techniques based on randomized search and incorporating some aspects of iterative algorithms [6], [7]. These algorithms have been inspired by Darwin's evolution theory and they study the growth of population in a particular environment. The fittest individual only will be able to reproduce handing down his chromosomes. The descendants of the original population

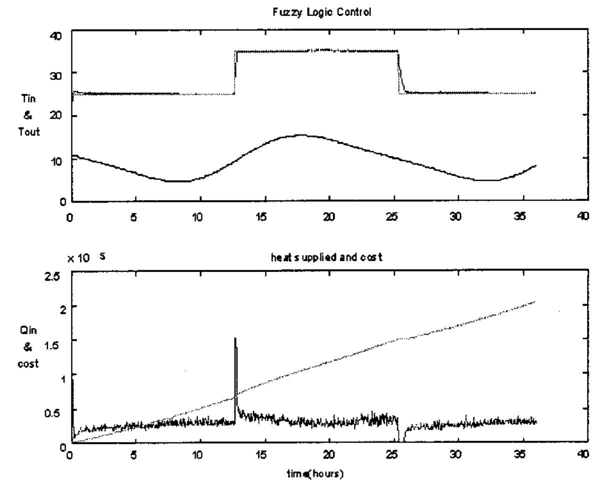

Fig. 8. Variable trend of fuzzy logic control obtained by expert description. UP Tin and Tout; DOWN Qin and cost.

will inherit the qualities that better fit the environment. GAs implement optimization strategies based on the simulation of these natural laws in order to obtain the fittest individual in the evolutionistic sense. Adopting this analogy, the optimal solution corresponds to the fittest individual.

GAs search for the best value of the function to be optimized starting from a "population" of points belonging to the function domain (not from a single one). This reduces the probability of finding local minima. Moreover, GAs do not require the first derivative knowledge of the objective function or of other auxiliary information. Finally, GAs use probabilistic transition rules during iteration. Adopting a natural analogy, the variables involved in the optimization, are codified in a particular structure similar to a chromosomal one. For example, a parameter can be translated into a string of l elements (l-bit digits) which will be manipulated by appropriate operators during the evolution of the algorithm. The basic string operators that will be applied are as follows.

- Reproduction: consists of duplicating a string.
- Crossover: given two different strings, the operator consists of exchanging substrings defined by some randomly chosen markers.
- Mutation: a variation of a randomly chosen bit belonging to a selected string.

The reproduction operator is used to improve the number of fittest individuals in the population, the crossover operator to recombine genetic information between different parents, and the mutation operator to introduce new information into the knowledge base.

Each string is characterized by a real value named "fitness," strictly connected to the function that has to be optimized and used to select the more promising elements of the population. The strings applied by the operators are chosen according to their fitness. The more the fitness function is high, the more that point belonging to the considered domain will be close to the optimal minimum/maximum. Therefore, the fitness value is fundamental to single out the more promising individuals of the population. From an evolutionistic point of view, we refer to those people who are properly fit and who, reproducing, have more opportunities to hand down their genetic patrimony.

The selection procedure can be implemented by adopting different approaches. The most common is the roulette wheel algorithm [6]. This procedure allows to assign a selection probability linear proportional to the fitness rank of each individual in the population.

A basic step-by-step GA is as follows.

1) Choose at random a fixed number of elements representing the initial population.
2) Evaluate their fitness.
3) Choose the elements of the population according to their actual probabilities.
4) With the respective probabilities, apply the operators onto the chosen elements in order to obtain new ones called offspring.
5) Evaluate the fitness of the string obtained.
6) Create a new population using offspring.
7) Go to step 3) until a stop criterion is verified.

In this paper, GAs have been used to choose the most appropriate parameter values characterizing the fuzzy membership functions and crisp consequence values. More precisely, two fuzzy controllers have been taken into account; the first one with three membership functions for both error and change in error variables (in the following, named CASE I) and the second one with five membership functions on error and three on change in error labeled CASE II.

During GAs optimization, Gaussian membership functions instead of triangular have been adopted.

Each membership function, characterized by two parameters (center and variance of the Gaussian function) is tuned with a discretization step of 8 bit. The same number of bits has been adopted for the crisp consequence values as well. This means that each chromosome has a fixed length of 248 bit. By fixing the population size to 80 elements, the optimization is carried out up to 30 generations. Many simulations with different number of generations have been done but, due to the fact that the SIMULINK greenhouse simulation time is very high, it has been noted that keeping this number close to 30 (20 min for one optimization on a Pentium 400 MHz), a good tradeoff between time and accuracy can be obtained.

We have started reducing membership function numbers with respect to the case reported in the previous section, hypothesizing that the reduced number of memberships could be balanced by the goodness of Gaussian shape versus triangular (*CASE I*). In fact, we expected to achieve good results due to the smothness of the bell-shaped membership function that could also saturate the universe of the discourse if the center of the membership function is on the extreme of the universe.

Figs. 9–11 show the near optimal fuzzy logic membership functions for the error and for the change-in-error variables and the obtained results in terms of temperature control and of energy spent for the control.

CASE I results do not confirm our hypothesis. In fact, while the error in temperature is acceptable, the cost of the control is not satisfying.

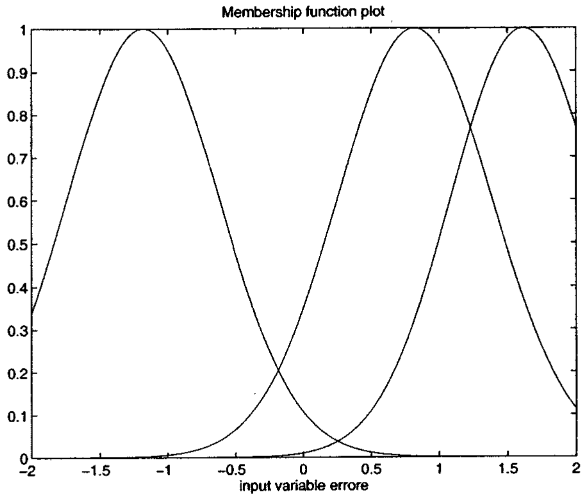

Fig. 9. Error membership functions obtained by using GAs; CASE I.

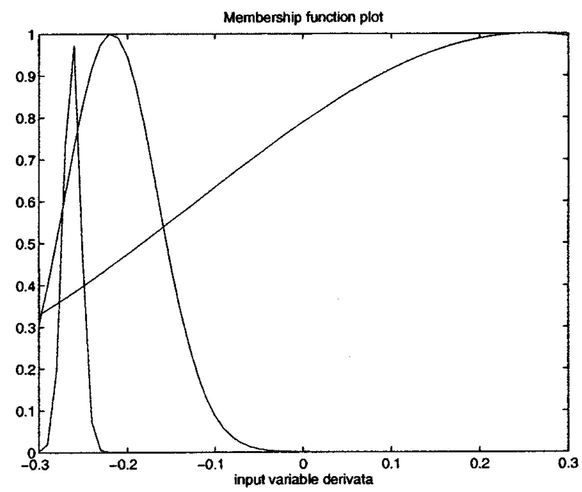

Fig. 10. Change in error membership functions obtained by using GAs; CASE I.

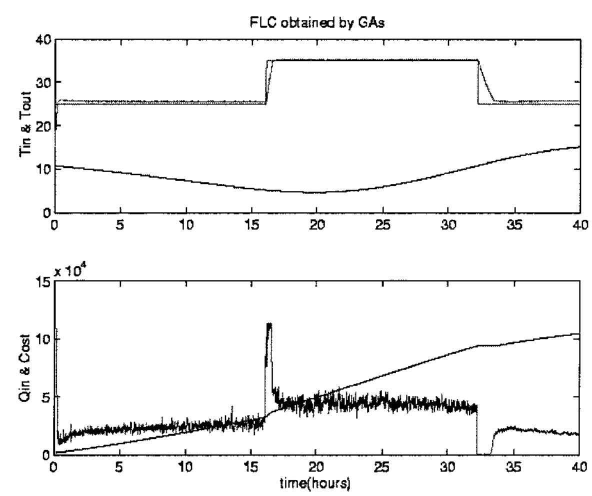

Fig. 11. Variable trend of fuzzy logic control obtained by using GAs; CASE I. UP Tin and Tout ; DOWN Qin and cost.

So it has been decided to start again GAs optimization assigning five membership functions on error and three on change

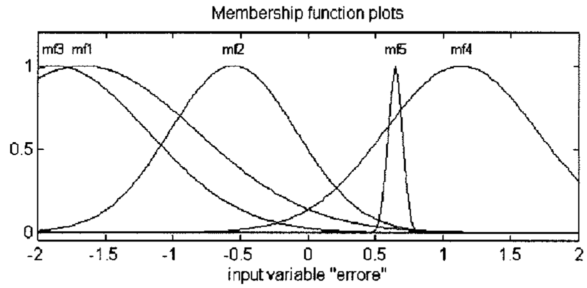

Fig. 12. Error membership functions obtained by using GAs; CASE II.

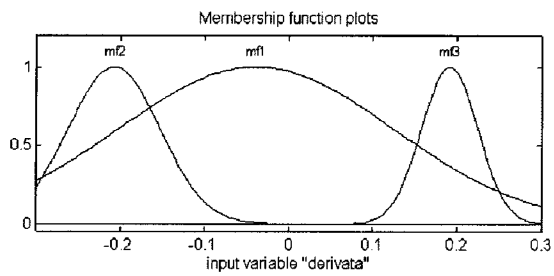

Fig. 13. Change in error membership functions obtained by using GAs; CASE II.

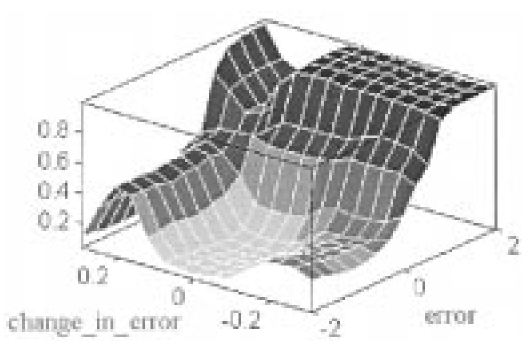

Fig. 14. Control surface; CASE II.

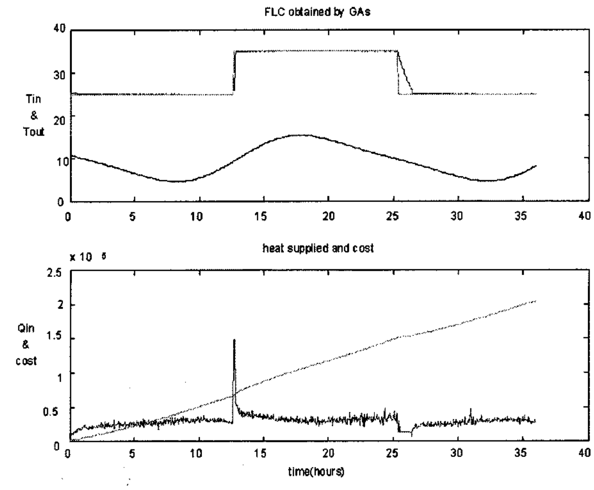

Fig. 15. Variable trend of fuzzy logic control obtained by using GAs; CASE II. UP Tin and Tout; DOWN Qin and cost.

TABLE II
RULES SET OBTAINED BY IMPLEMENTING THE HUMAN EXPERTISE

Generations number	400
Population size	300
Number of subpopulation	10
Mutation probability	0.001
Crossover probability	0.9
Convergence percentage	0.99
Replacement percentage	0.25
Replacement number	5

in error, CASE II. Regarding GAs parameter again 8 b have been used for each variable-phenotype representation while the number of generation has increased up to 50.

The results obtained are given in Figs. 12–14 concerning the near optimal fuzzy logic membership functions for the error and for the change-in-error variables and the nonlinear control map obtained, while Fig. 15 shows the results in terms of temperature control and of energy spent for the control.

As it is evident from these figures, there are only less improvements compared to the "human-based" fuzzy logic controller, justifying the robustness of fuzzy logic in directly transferring human expertise into automatic control laws.

VI. PID DISTRIBUTED CONTROL

Another approach usually adopted for temperature and humidity control in greenhouses is based on a PID controller. This type of control can be applied in a distributed way or not. In the case of the distributed controller the gain of the PID have been optimized by using GAs. The parameters adopted for the optimization are reported in Table II.

As it is showed in Table II, the number of generations has increased if compared to GAs optimization described in the previous section. In this case, in fact, fitness function computational time is reduced so we have decided to perform more generations in the same time.

Further simulations and comparison have been carried out. The genetic optimized distributed PID control (Fig. 16) is compared with a common bang-bang controller (Fig. 17) and with a nondistributed PID (Fig. 18). In Table III are reported the root mean square (rms) error and the required energy in four case with different values for the external temperature and plants eighth.

VII. CONCLUSION

The work represents an approach to apply an AI technique in a greenhouse climate control. Due to the physical dynamics involved in a greenhouse the synthesis of a climate controller becomes a complicated task using traditional control techniques. Fuzzy logic and distributed PID control represent useful tools for solving this problem.

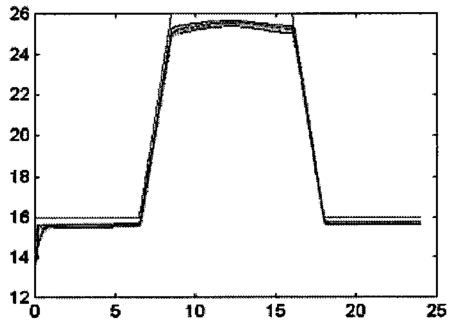

Fig. 16. Internal temperature with distributed PID control versus time (hours).

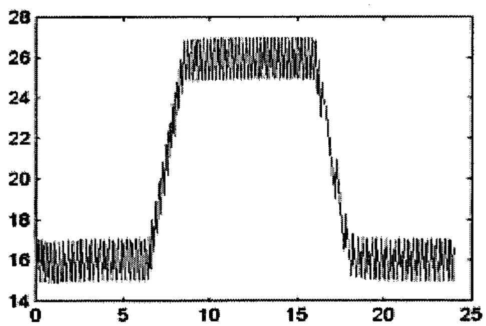

Fig. 17. Internal temperature with bang-bang control versus time (hours).

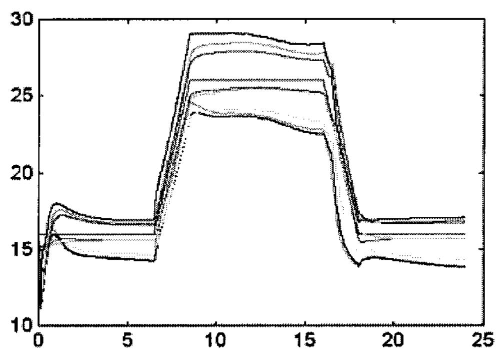

Fig. 18. Internal temperature with not distributed PID control versus time (hours).

GAs have been applied as global optimization procedure to improve the performance of both applied controllers.

FLC parameters setting, in particular, membership functions shape and position, has been performed applying GAs to smartly face the nonlinear plant control problem. Even if the procedure is time expensive, it is performed off line and, at the end, it provides a fuzzy controller hardware downloadable. Further improvements can surely be obtained by adjusting the fitness function appropriately including both the rms error and the global control energy with different weights.

Work is still in progress in order to implement a biological model of plant growth depending on environmental parameters so that it will be possible to establish automatically the best control policy and to compute the optimal values for the set points.

TABLE III
RMS AND ENERGY CONSUMPTION FOR DISTRIBUTED OPTIMAL PID CONTROLLER, BANG-BANG CONTROLLER AND NON DISTRIBUTED PID CONTROLLER

PID dist.		Bang-Bang		PID not dist.	
RMS	Energy	RMS	Energy	RMS	Energy
$T_{ext}0-6°C$			$HP=0.8m$		
1.97%	300,42	9.01%	311,76	5.58%	297,92
$T_{ext}0-6°C$			$HP=2m$		
2.35%	393,75	7.65%	420,29	5.45%	391,29
$T_{ext}3-9°C$			$HP=0.8m$		
1.72%	256,57	8.11%	266,9	5.05%	254,61
$T_{ext}3-9°C$			$HP=2m$		
2.33%	335,76	7.05%	360,14	4.97%	337,54

APPENDIX

In the following, the equations used to define the greenhouse model will be introduced [12].

The convective heat exchange with the lateral wall Q_{a3} is modeled with the following equation:

$$Q_{a3}=f_{c,i}A_{c,i}(T_{ci}-T_i) \tag{4}$$

where

- T_{ci} temperature of the wall in contact with the layer;
- $f_{c,i}$ (W/m$^2 * °$C) is the convective heat transfer coefficient;
- $A_{c,i}$ (m^2) is the surface of the wall through which convenction heat takes place.

The transmission heat exchange with frontal walls Q_{a4} is given by

$$Q_{a4}=2Ka_{ci}(T_e-T_i) \tag{5}$$

where K is the total heat transfer coefficient (W/m$^2 * °$C), a_{ci} is the surface of the external walls and T_e and T_i are respectively the external and internal temperature. This equation is used only for layer numbers one and eight.

The fraction of heat exchanged with the external air as latency and sensitive heat Q_{a5} can be obtained by using the following relation:

$$Q_{a5}=\rho_a c_a \phi_i (T_i-T_e)+\rho_a \lambda \phi_i (U_i-U_e). \tag{6}$$

This term takes into account the energy loose for forced or natural ventilation. The term ϕ_i (m^3/s) represents the air flow from the internal to the external part of the green house.Q_{a6} is the conductive heat exchange with adjacent layer and is given by

$$Q_{a6} = 2\,\frac{\lambda_a}{\Delta s_i - \Delta s_{i-1}}\,S_{c,J+1}(T_{i+1} - T_i) + 2\,\frac{\lambda_a}{\Delta s_i - \Delta s_{i-1}}\,S_{c,J}(T_{i+1} - T_i) \qquad (7)$$

where

Δs (m) is the thickness of the layer;
λ_a (W/m $*$ °C) is the thermal conductivity of the air;
S_c (m^2) is the surface contact between layers.

Also, in this case layers one and eight must be taken into account.

The convective heat exchange with soil is given by the simple formula

$$Q_{a7} = f_{si} A_{si}(T_s - T_i) \qquad (8)$$

where f_{si} (W/m^{2}C) is the convective heat transfer coefficient and A_{si} (m^2) is area of the soil in contact with the layer.

The last term Q_{a8} is the fraction of natural heat or solar radiation. This term can be modeled with

$$Q_{a8} = \delta_v a_a (I_{NS} * A_{c1} + I_{EW} * A_{c6} + I_V * A_b)\,\frac{V_i}{V} \qquad (9)$$

where

δ_v trasmittivity coefficient;
a_a area absorptivity coefficient;
A_{c1} and A_{c6} respectively, south and east layer;
A_b base surface of the greenhouse;
I_{NS} and I_{EW} respectively, fraction of the solar radiation in the north–south and east–west direction;
I_v radiation perpendicular to the soil.

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