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ORIGINAL ARTICLE

A GA-Based Adaptive Neuro-Fuzzy Controller for Greenhouse Climate Control System

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Abstract In this research paper, a new application of Adaptive Neuro-Fuzzy Inference System (ANFIS) to the control of greenhouse climate system is introduced. To cope with the large amount of uncertainties present in such systems and in order to improve the system performance, a Genetic Algorithm (GA) is used to adapt the controller parameters such as the number and shape of membership functions employed and scaling factors. Simulation results showed that the proposed control architecture is able to provide smooth control regardless of the continuously changing environmental conditions and the complexity of the plant. The performance of the proposed controller has been assessed against other traditional controllers and has been found to outperform its counterparts.

1. Introduction

The purpose of the greenhouse climate control (GCC) is to create a favorable environment for plant growth to maximize the yield and to minimize the cost of production in terms of input resources like energy consumption which can be correlated to minimizing the environmental impact. The creation of a favorable environment inside a GH requires the regulation of all relevant variables such as air temperature (°C) and humidity ratio [kg (water)/kg (air)]. In the last decade, the control design of the climatic conditions in GHs has been addressed by a number of researchers. GH modeling and identification have been studied by Bot [7], Nielsen and Madsen [22], Linker et al. [21], Ferreira et al. [10], Boaventura and Cunha, [6], and Bennis et al. [5], while intelligent GH climate control was developed by Arvantis et al. [2], Albright et al. [1], Lafont and Balmat [17], Sigrimis et al. [25], Pasgianos et al. [23], Koutb et al. [16], Fourati and Chtourou [11], Bennis et al. [4], Bennis et al. [5]. whereas fault detection and isolation in GHs was addressed by [3], Linke [18], Linker et al. [20], Linker et al. [19], and El-Rabaie and Hameed [9]. Recently, measurement and modeling uncertainties in greenhouses have been addressed and a solution based on using type-2 fuzzy logic controller has been proposed [13]. The use of Kalman filter (KF) and extended Kalman filter (EKF) in GCC problem has been investigated by a considerable number of researchers. A climate control ARAMAX model in combination with a Kalman Filter (KF) was described by Davis [8] and an online estimation and adaption of the greenhouse model was outlined by Pinon et al. [24] and Speetjens et al. [26]. The use of EKF

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and Unscented KF to improve the energy efficiency of the GCC problem has been studied [14,15].

In this paper, a GA-based ANFIS is used to control the climate instead a GH. The dynamics of the GH model are comparatively slow and therefore it is a reasonable application for the computationally extensive control algorithms such as the one introduced in this paper. For the purpose of simulation and comparison, a coupled nonlinear GH model is used [1,12]. The performance of the proposed control architecture is evaluated against a traditional Fuzzy Pseudo-Derivative Feedback (FPDF) controller [16] in maintaining the GH states, defined by the temperature and humidity ratio inside the GH, within suitable ranges.

1.1. Greenhouse model

A simple greenhouse heating, -cooling and -ventilation model for a mechanically ventilated greenhouse can be developed by considering a set of differential equations which governs sensible and latent heat as well as water balances on the interior volume [1,12]. These differential equations are as follows:

$$\frac{dT_{in}(t)}{dt} = \frac{1}{\rho\zeta V}[q_{heat}(t) + \xi AS(t) - \lambda q_{fog}(t)] - \frac{q_{vent}(t)}{V} \times [T_{in}(t) - T_{out}(t)] - \frac{\mu}{\rho\zeta V}[T_{in}(t) - T_{out}(t)] \quad (1a)$$

$$\frac{dH_{in}(t)}{dt} = \frac{1}{\rho V} q_{fog}(t) + \frac{1}{\rho V} ET - \frac{q_{vent}(t)}{V}[H_{in}(t) - H_{out}(t)] \quad (1b)$$

where T_{in} and T_{out} are the indoor and outdoor air temperature (°C), respectively, H_{in} and H_{out} are the interior and exterior humidity ratios (g[H_2O]/kg[dry air]), respectively, μ is the heat transfer coefficient (W/K), ρ is the air density (1.2 kg[air]/m^3), λ is the latent heat of vaporization (2257 J/g), ζ is the specific heat of air (1006 J/kg/K), ξ is the solar heating efficiency (dimensionless), ξ varies from 0.8 in a clear day to 0 in a cloudy day, in this paper, ξ is set to 0.5, S is the intercepted net solar radiant energy (W/m^2), ET is the evapo-transpiration rate of the plants (g[H_2O]/s), q_{heat} is the heat provided by the greenhouse heater (W), q_{fog} is the water capacity of the fog system (g[H_2O]/s), q_{vent} is the ventilation rate (m^3[air]/s), A is the greenhouse floor area (m^2) and V is the greenhouse volume (m^3). ET is in most part related to the intercepted solar radiant energy through the following simplified relation:

$$ET = \alpha\frac{S(t)}{\lambda} - \beta H_{in}(t) \quad (2)$$

where α is an overall coefficient to account for shading and leaf area index, dimensionless, α is an empirical coefficient and needs to be tuned for different locations, climates and crops, in this study, α is set to 0.124887333. β is the overall coefficient to account for thermodynamic resistances and other factors affecting evapo-transpiration (i.e., stomata, air motion, etc.) in (kg/min/m^2).

In this climate model, two variables have to be controlled, namely the indoor air temperature and the humidity ratio, through the processes of heating, cooling, humidifying, and/or dehumidifying. Dehumidification is often expensive and therefore dehumidifiers will not be used and instead a combination of heating and ventilation will be used for the purpose of dehumidifying the greenhouse. Ventilation brings in fresh air, which is heated, allowing it to absorb some of the moist air from the inside before exhausting it to the outside. When the relative humidity of the outside air is low, ventilation alone can be used to dehumidify the greenhouse air by exchanging moist inside air with drier outside air. Raising humidity levels requires evaporative devices such as misters, fog units, evaporative cooling pads, all of which cool and add water vapor to the air. Evaporative cooling devices require good ventilation rates. Fresh air must be continually brought in for warmed and humidified air to be exhausted. When humidifying occurs under sunny conditions, ventilation is necessary to avoid steaming conditions.

The feedback-feedforward linearization and decoupling (FFLD) control method is applied [23]. Eq. (1) could be rewritten in the following form:

$$\frac{dT_{in}(t)}{dt} = -\frac{\mu}{\rho\zeta V}T_{in}(t) - \frac{1}{V}T_{in}(t)q_{vent}(t) - \frac{\lambda}{\rho\zeta V}q_{fog}(t) + \frac{1}{\rho\zeta V}q_{heat}(t) + \frac{\xi A}{\rho\zeta V}S(t) + \frac{\mu}{\rho\zeta V}T_{out}(t) + \frac{1}{V}q_{vent}(t)T_{out}(t) \quad (3a)$$

$$\frac{dH_{in}(t)}{dt} = -\frac{\beta}{\rho V}H_{in}(t) + \frac{1}{\rho V}q_{fog}(t) + \frac{\alpha\xi A}{\lambda\rho V}S(t) - \frac{1}{V}H_{in}(t)q_{vent}(t) + \frac{1}{V}q_{vent}(t)H_{out} \quad (3b)$$

Due to the complexity appearing as the cross-product terms between control and disturbance variables Eqs. (3a) and (3b) are obviously coupled nonlinear equations, which cannot be put into the rather familiar form of an affine analytic nonlinear system. Therefore, a combined scheme of feedback with simultaneous feedforward linearization is plausible. For the system to be input/output (I/O) linearized, decoupled, and disturbance isolated, the closed-loop system should take the form:

$$\frac{dT_{in}(t)}{dt} = -\frac{\mu}{\rho\zeta V}T_{in}(t) + \tilde{K}_T\tilde{u}_T(t) \quad (4a)$$

$$\frac{dH_{in}(t)}{dt} = -\frac{\beta}{\rho V}H_{in}(t) + \tilde{K}_H\tilde{u}_H(t) \quad (4b)$$

where $\tilde{u}_T$, and $\tilde{u}_H$ are new external control signals and $\tilde{K}_T$, and $\tilde{K}_H$ are process gains. By comparing Eqs. (3) and (4) and solving for q_{vent}, q_{fog} and q_{heat}, the following relations are obtained:

$$q_{vent}(t) = L(t)^{-1}\left[\frac{1}{\rho\zeta V}(q_{heat}(t) + (\alpha+1)\xi AS(t)) + \frac{\mu}{\rho\zeta V}T_{out}(t) - \tilde{K}_T\tilde{u}_T(t) - \frac{\lambda}{\zeta}\tilde{K}_H\tilde{u}_H(t)\right] \quad (5a)$$

$$q_{fog}(t) = -\frac{\alpha}{\lambda}\xi AS(t) + \rho q_{vent}(t)(T_{in}(t) - T_{out}(t)) + \rho V\tilde{K}_H\tilde{u}_H(t) \quad (5b)$$

$$q_{heat}(t) = -\xi AS(t) + \lambda q_{fog}(t) + \rho\zeta q_{vent}(t)(T_{in}(t) - T_{out}(t)) - \mu T_{out}(t) + \rho\zeta V\tilde{K}_T\tilde{u}_T(t) \quad (5c)$$

where

$$L(t) = \frac{1}{V}(T_{in}(t) - T_{out}(t)) + \frac{\lambda}{\zeta V}(H_{in}(t) - H_{out}(t)) \quad (6)$$

By applying the above control law, the control system structure is depicted as in Fig. 1, where the heater control

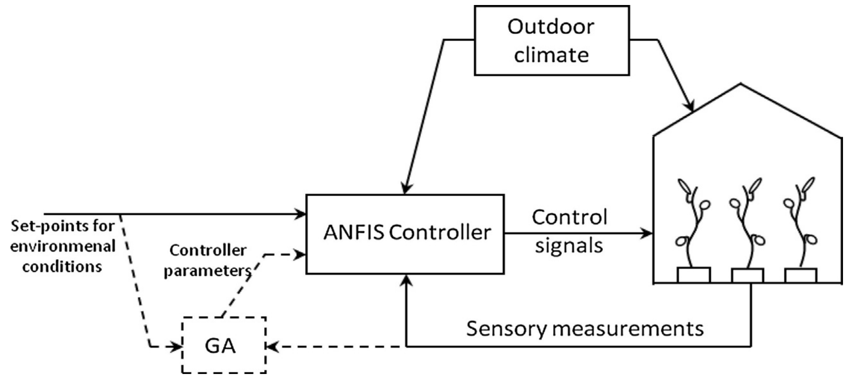

Figure 1 Using GA to tune ANFIS parameters.

signal will only be used when the desired indoor air temperature is higher than the outdoor temperature (i.e., under winter condition).

2. Controller architecture

2.1. Overview of ANFIS structure

The control process is divided into two distinct control loops, the first maintaining the temperature by adjusting the ventilation rate, and the second maintaining the humidity ratio by adjusting the moisturizing rate. These controllers, which are a set of MISO ANFIS controllers, control the two outputs of the greenhouse system in terms of the input set values and the continually changing outdoor climate conditions. For simplicity we explain the ANFIS controller for first loop only as described in Fig. 2., the second can be done as first. The fuzzification stage was performed for the MISO controller that has two inputs, temperature (T), and humidity (H) and one control output ventilation rate (v). The designing of a fuzzy logic involves the construction of control rules. In many cases, we can obtain control rules by writing down the operator's actions in the IF-THEN format. Therefore, there is no generic method of constructing control rules. In addition, we may construct IF-THEN rules not only from operator's actions but also from the response characteristic of the target system.

In this case, Gaussian MFs are only used as input MFs as described in Fig. 3, where it is often used to represent vague:

$$\mu_{A^i}(x) = exp\left(\frac{(c_i - x)^2}{2\sigma_i^2}\right)$$

where c_i an σ_i are the center and width of the ith fuzzy set A^i, respectively. The controller inputs are labeled with three linguistic variables Small (S), Medium (M) and Big (B), and output MF type is linear.

The problem lies in finding the values of the parameters of the membership functions in the rule antecedents and the coefficients in the rule consequents of the TSK-type fuzzy systems, The knowledge rules of the fuzzy system have the following form:

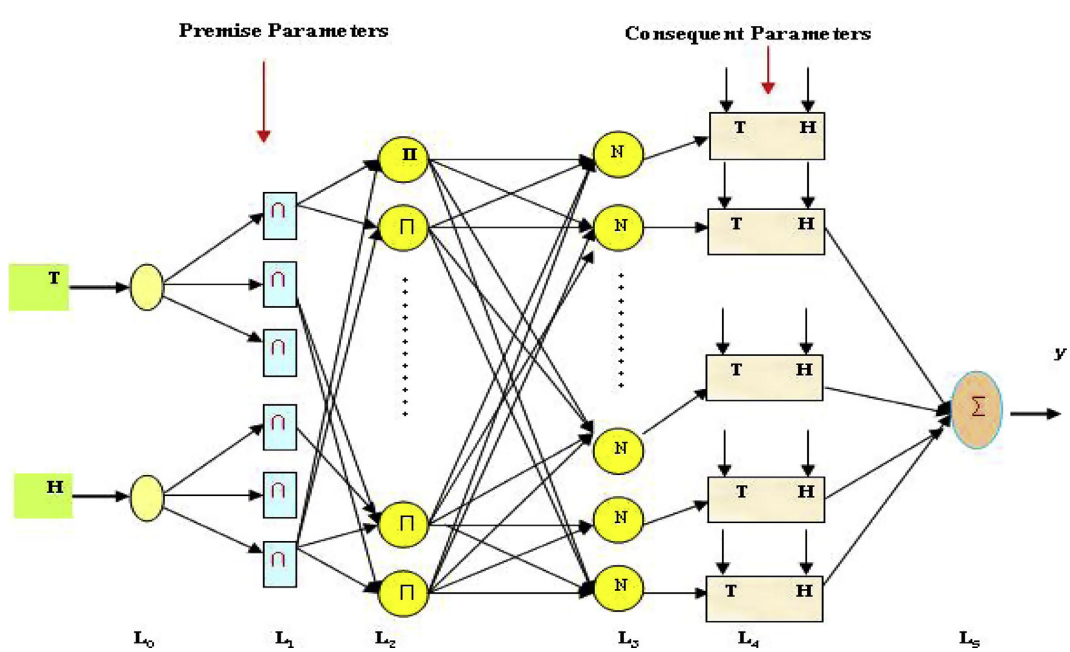

Figure 2 ANFIS Architecture with nine rules.

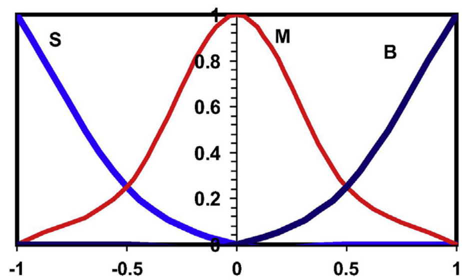

Figure 3 Gaussian membership function.

$$IF: T \text{ is } LT^r \text{ and } H \text{ is } LH^r \quad THEN: u^r = c_o^r + c_T^r T + c_H^r H \tag{7}$$

where $r = 1,2,\ldots, R$ is the rule number, LT^r and LH^r are the linguistic terms of the input signals T and H,respectively, in the r-th rule, u^r is the contribution of the r-th rule to the total output of the fuzzy system, and c_o^r, c_T^r, and c_H^r are the consequent coefficients, the output of the fuzzy system is given by:

$$u = \frac{\sum_{r=1}^{R} w^r u^r}{\sum_{r=1}^{R} w^r} \tag{8}$$

where w^r, for $r = 1,2,\ldots, R$, are the rule fulfillment weights. For each rule, its weight is calculated as the product of the input membership values as:

$$w_r = \mu_{Lr^r}(T) \cdot \mu_{LH^r}(H) \tag{9}$$

where $\mu_{LT^r}(\cdot)$ *and* $\mu_{LH^r}(\cdot)$ are the membership functions corresponding to the linguistic terms $LT^r andLH^r$ respectively, in the r-th rule. In addition, note that (8) can be written as:

$$u = \sum_{r=1}^{R}\left(\frac{w^r}{\sum_{r=1}^{R} w^r}\right)u^r = \sum_{r=1}^{R}\bar{w}^r u^r = \sum_{r=1}^{R}\bar{u}^r \tag{10}$$

where $\bar{w}^r$ for $r = 1,2,\ldots, R$ can be equivalently called the normalized rule consequents:

$$\bar{w}^r \cong \left(\frac{w^r}{\sum_{r=1}^{R} w^r}\right) \tag{11}$$

In our case the complete knowledge base will have $3 \times 3 = 9$ rules of the form given in (7), also, the network will have 2 distribution units in layer L0, 6 neurons in L1, 9 neurons in L2, L3, and L4, and 1 neuron in L5.

So the determined parameters using 3 fuzzy sets as described bellow:

Inputs	Fuzzy sets	Total no of rules	Premise parameters	Consequent parameters	Total number of parameters
2	3	9	18	27	45

The consequent parameters are estimated using a least square estimation (LSE) procedure. Using 3 fuzzy set, and 9 rules, each input–output training pattern can be written as:

$$\bar{V} = \sum_{r=1}^{9}\bar{\tau}_r(c_0^r + c_1^r \mathrm{T} + c_1^r H) \tag{12}$$

$$\bar{V} = [\bar{\tau}_1 \quad \bar{\tau}_1 T_{11} \quad \bar{\tau}_1 H_{11} \cdots \bar{\tau}_2 \quad \bar{\tau}_2 T_{12} \quad \bar{\tau}_2 H_{12} \cdots \bar{\tau}_9 \quad \bar{\tau}_9 T_{19} \cdots \bar{\tau}_9 H_{19}] * \left[c_{01}^1 \quad c_{11}^1 \cdots c_{12}^1 \quad \cdots c_{02}^2 \quad c_{12}^2 \quad c_{12}^2 \quad \cdots c_{09}^9 \quad c_{19}^9 \quad c_{19}^{9T}\right]^T \tag{13}$$

Considering all M input–output training patterns together:

$$\begin{bmatrix} V_1 \\ \vdots \\ V_M \end{bmatrix} = \begin{bmatrix} (\tau_1 & \tau_1 T_1 & \tau_1 H_1 \cdots & \bar{w}_9 & \bar{w}_9 T_9 & \bar{w}_9 H_9)1 \\ (\tau_1 & \tau_1 T_1 & \tau_1 H_1 \cdots & \bar{w}_9 & \bar{w}_9 T_9 & \bar{w}_9 H_9)2 \\ (\tau_1 & \tau_1 T_1 & \tau_1 H_1 \cdots & \bar{w}_9 & \bar{w}_9 T_9 & \bar{w}_9 H_9)M \end{bmatrix} \begin{bmatrix} c_{01} \\ c_{T1} \\ c_{H1} \\ \vdots \\ c_{09} \\ c_{T9} \\ c_{H9} \end{bmatrix} \tag{14}$$

$$V = XC \tag{15}$$

Through appropriate definitions, (14) can be written as where V is $M \times 1$, X is $M \times (2 + 1)N$, and C is $(2 + 1)9 \times 1$, that can be detailed as:

V is $M \times 1$, X is $M \times (3)(9) = \mathrm{M} \times 27$, and C is 27×1. In general the problem is

overdetermined, that is $M > 108$.

An LSE solution for C can be computed recursively.

$$C_{i+1} = C_i + \psi_{i+1} x_{i+1}\left(V_{i+1}^T - x_{i+1}^T C_i\right) \tag{16}$$

$$\psi_{i+1} = \psi_i - \frac{\psi_i x_{i+1} x_{i+1}^T \psi_i}{1 + x_{i+1}^T \psi_i x_{i+1}} \tag{17}$$

where $\bar{x}_i^T$ is the ith row vector of matrix X and Vi the ith element of vector V, for $i = 0, 1,2,\ldots, M-1$, and Ψ is the covariance matrix, then Clse = CM, where Ψ is called the covariance matrix. The initial conditions are $C_0 = 0$ and $\Psi_0 = \gamma I$, where I is a size $(2 + 1)N$ identity matrix and γ is a large positive number. At the end of iterations: C = CM.

2.2. Overview of GA

A Genetic Algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems. GAs were first introduced by John Holland in 1975. A GA will be used to evolve the proposed simplified architecture of T1FLS to test the hypothesis that the simplified architecture retains the ability to handle measurement and modeling uncertainties. It is not mandatory to use a GA to adjust the controller parameters and instead the controller parameters could be set manually. GA will not only be used as an optimization algorithm but rather it will be used as an uncertainty sensor to detect the level of uncertainty which exist in the controlled system. The so called scale factors (SF), have to be tuned. SFs are real constants which multiply the values of the variables (input or output variables), modifying the limits of their variation range, and therefore have a significant impact on the performance of the resulting fuzzy control system, and hence they are often a convenient parameter for tuning. The modification of the input scale factors has a general effect on the behavior of the system: increasing input gains implies reducing their universes of discourse, having a direct consequence on control: the response is faster and more oscillatory, reducing the stationary error. It thus improves the transient response by reducing rise time and set-up time, but it does increase the risk of instability with the overshoot increment. On the other side, reducing input gains produces the opposite effects; the wider the membership functions the rougher control can be achieved, which produces a slower response with less overshoot. However, the variation of the output gain has a complex relation with the behavior of the controller and has not been analyzed in depth.

The fitness function used to quantify the optimality of a solution (i.e., chromosome) is the reciprocal of the Integral of Square Error (ISE), given in Eq. (13) where the error e is the difference between the desired set point and the actual system output. Chromosomes in a population are ranked according to their fitness value. Optimal or near optimal chromosomes (i.e., solutions) are allowed to reproduce through new generations that will (hopefully) be even better. In this paper, the maximum number of generations is set to 30. The number of chromosomes or solutions in a population is set to 20. The mutation and crossover probability are set to 0.2 and 0.25 respectively. The roulette wheel selection method is used to select the fittest chromosomes, the generational process is repeated until a termination condition has been reached; a solution is found that satisfies minimum criteria or a fixed number of generations reached.

$$ISE = \int_0^\infty (e(t))^2 dt \tag{13}$$

where the error $e(t)$ is the difference between the desired output and the actual output of the plant.

2.3. GA-based ANFIS

Application of the GA to the optimization of the scaling factors of inputs to control signal controller parameters was done by converting the scaling factor parameters associated for difference errors between set-points and actual values for temperature, and humidity, which are Scalf-T, and Scalf-H, for simplicity consider the unsigned binary code with a length of 12 bits using the relationship:

$$b = \frac{2^{10} - 1}{v_{up} - v_{lo}}(v - v_{lo})$$

where b is the rounded binary value of the decimal V (phenotype) in the range $[V_{lo}, V_{up}]$. The binary string (chromosome) can be taken the form

$$s : \underbrace{1001010101}_{scalf-T}\ \underbrace{1010010010}_{scalf-H}$$

The implementation of the GA proceeds as follows:

(1) Produce an initial population of randomly generated sets of parameters (Scalf-T, Scalf-H).
(2) Simulate the step response of the closed-loop system and evaluate the fitness function of each set of parameters.
(3) Select by the roulette wheel method the sets of parameters to be reproduced.
(4) Recombine by pairs the selected sets of parameters with a randomly generated point of crossover.
(5) Mutate the selected sets of parameters according to the probability of mutation.
(6) Repeat steps (2) through (5) iteratively until the fittest set of parameters provides and acceptable closed loop response.

Note that steps (1) and (2) are carried out with the decimal representation of the controller parameters (phenotype), while steps (3), (4) and (5) are carried out with the binary representation in a binary string (chromosome).

The values of scaling factors for temperature and humidity before tuning are 0.9883 and .987189, where the values after tuning are 4.9445 and 11.0195.

3. Results

The effectiveness of the proposed control schemes is demonstrated by a case study. For this example consider a greenhouse of surface area 1000 m^2 and a height of 4 m. The greenhouse has a shading screen that reduces the incident solar radiation energy by 60%. The maximum water capacity of the fog system is 26 g[H_2O] min^{-1} m^{-3}. Maximum ventilation rate corresponds to 20 air changes per hour (22.2 m^3 s^{-1}). Parameter α takes the value 0.129524267 and β_T = 0.015 kg min^{-1} m^{-2}. The heat transfer coefficient is UA = 25 kW K^{-1}. Finally, we assume that unknown system and sensor dynamics contribute an overall dead time of 0.5 min in both temperature and humidity measurements (i.e., $d_T = d_w = 0.5$ min). Also, we assume that no crop was present in the greenhouse at the time of experiment, but the concrete floor was continuously wetted to simulate a greenhouse with a wet soil surface. Therefore, the results presented here are supposed to apply to a greenhouse with small seedlings, which do not influence the greenhouse climate. The greenhouse climate control variables consisted of humidification and forced ventilation. Suppose this study focuses on daytime control under summer conditions, heating was not considered. A first simulation experiment has been conducted to demonstrate the ability of the proposed control schemes to provide interacting control and smooth closed-loop response to set point step changes. For the proposed G-ANFIS controller, the dual parameters for each controller are obtained using GA through 50 generations by minimizing the mean square errors,

In the first simulation, the outside weather conditions are T_{out} = 35 °C and w_{out} = 4 g/kg (RH = 10%), while Si = 300 W/m^2. The humidity ratio set point was raised from 18 to 24 g/kg (which corresponds to a relative humidity change from 60% to 80%) at t = 100 min, with the temperature set point 30 °C; then the temperature set point was decreased from 30 to 28 °C at t = 200 min (humidity ratio set point 24 g/kg), the responses for set point step changes in humidity ratio and temperature are in Fig. 4. As we see the response under proposed G-ANFIS controller is very smooth and nearly close to set point than that given by ANFIS without tuning .The ventilation rate and water capacity of fog system as a control signals are shown in Fig. 5. The simulation results clearly demonstrate the interacting control was attained and the closed-loop system response is very acceptable. Moreover, the response of the G-ANFIS controller is much faster than AFISN.

In the second simulation experiment, the desired set point for the temperature is set to $T_{in,sp}$ = 30 °C and then decreased to 20 °C at t = 200 min, and the desired set point for the humidity ratio was raised from 18 to 24 g/kg t = 300 min g. The system step response in humidity ratio and temperature is close to the set point in a wide range of operation as

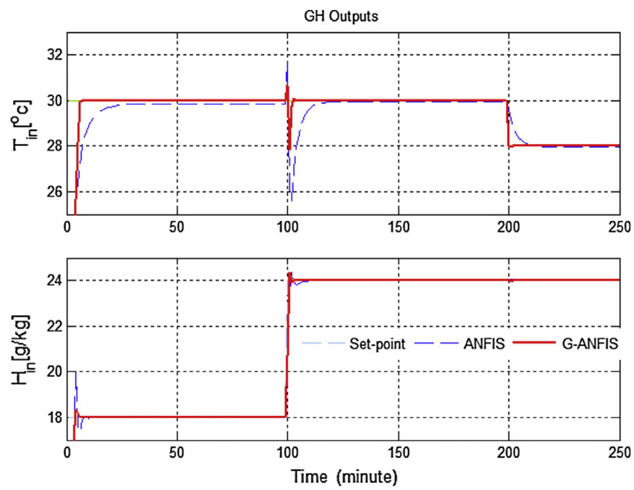

Figure 4 Greenhouse outputs: indoor air temperature (upper) and indoor air humidity ratio (bottom).

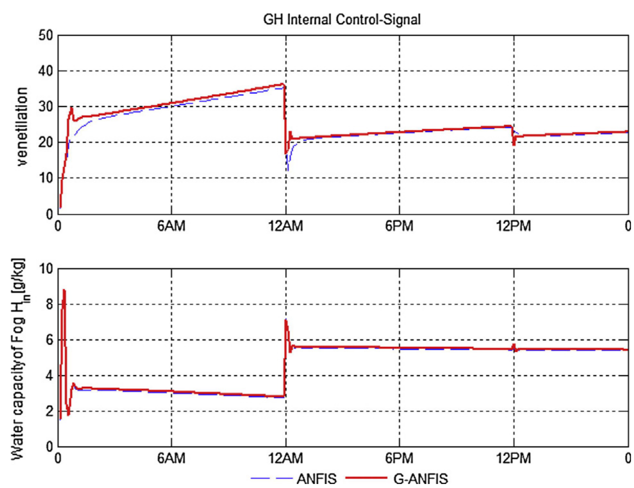

Figure 5 Greenhouse control signals: Ventilation (upper) and water capacity ratio (bottom).

described in Fig. 6. Step changes in disturbances were applied at t = 100 min (for *Si*), 150 min (for T_{out}), and 200 min (for w_{out}). The step changes were as follows: *Si* from 250 to 300 W/m^2, T_{out} from 35 to 32 °C, and wout from 4 to 8 g/kg. With no uncertainty in the model parameters, weather conditions do not affect T_{in} and w_{in}. The root mean square error (RMSE) as defined in equation (7) was computed for the outputs of the process for each individual controller in the two experiments, as shown in Table 1.

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{k=1}^{T}(Y_d[k] - Y[k])^2} \tag{7}$$

where *Yd*[*k*] and *Y*[*k*] are the desired and actual outputs respectively, and T is the number of samples used. Fig. 5, shows the change of set point for temperature with changing in humidity also. We can see that the proposed controller able to track set point with less time and overshoot than the other one. The

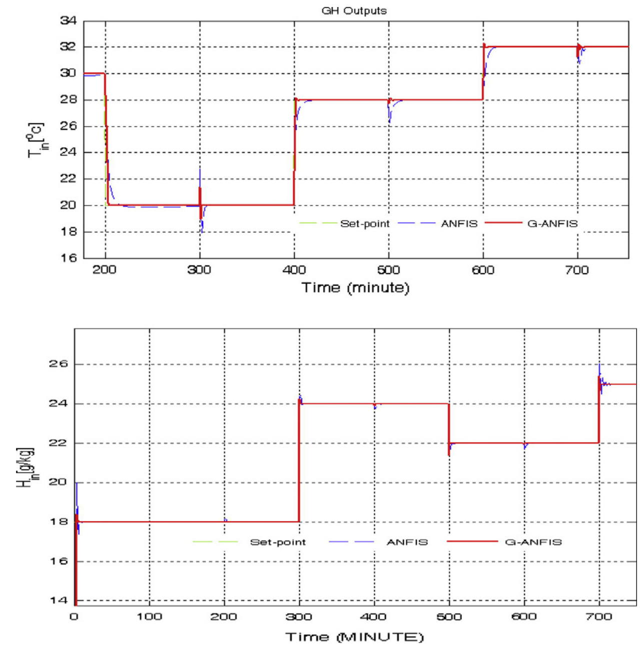

Figure 6 Greenhouse outputs using ANFIS and G-ANFIS: indoor air temperature (upper) and indoor air humidity ratio for (bottom) example2.

Table 1 RMSE values for different controller types for temperature and humidity loop calculated for the first 300 min of operation.

Controller type	RMSE	
	Temperature loop	Humidity loop
PDF	8.278E−02	9.818E−02
FUZZY	3.332E−01	2.390E−04
ANFIS	6.605E−02	6.556E−02
GA-based ANFIS	1.048E−02	6.305E−02

RMSE of the proposed controller at different ranges of operation is very smaller than given by the other controller, Table 1 includes the RMSE calculated in the first 300 min of operation.

4. Conclusions

In this paper, an adaptive neuro-fuzzy control system combined with a Genetic Algorithm tool for adapting the controller for the continually changing conditions influencing on the climate inside a greenhouse is presented. The proposed control method reduced the errors between the current situation and the set-point desired values. Step change test which is considered as the hardest to follow was used to test the robustness and reliability of the proposed control structure. Simulation results showed a significant improvement in the system response when the ANFIA system was equipped with GA in terms of following desired values and smoother controller signals which could result in significant increase in actuators' life time.

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