Greenhouse Climate Control Enhancement by Using Genetic Algorithms

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Abstract: This paper develops a control system for greenhouse climate with PID controllers tuned based on genetic algorithms. The greenhouse climate nonlinear model with dead-time and measurable disturbances is decoupled by feedback-feedforward linearization method, tacking the feedback without delay from an internal model. The equivalent system consists in two integrator plus dead-time channels for temperature and humidity suitable for PID control. The genetic algorithms (GA) with fitting objective cost functions are developed for PID tuning, including in initial population the PID controllers from four conventional tuning methods. Simulation results in real scenarios show improved performances for PID tuning by GA in comparison with conventional methods, where Ziegler-Nichols method is the best.

Keywords: greenhouses, climate control, nonlinear systems, feedback linearization, feedforward decoupling, integrator plus time delay, PID controllers, genetic algorithms.

1. INTRODUCTION

Greenhouses are defined as structures which cover and protect the crop providing at least one way for changing the internal environment (van Straten *et al.*, 2011). This separation between the crop environment and the external environment protects the crop from strong winds, acid rain or pests and allows control over the main environmental factors affecting plant growth: temperature, humidity, CO_2 concentration, light intensity. All these variables should be maintained through control and managed automatically according to proper time programs. Due to their spatial distribution, the greenhouses are systems with distributed parameters, but currently, for the sake of simplicity, they are considered as MIMO systems with lumped parameters characterized by high coupling between the two main control variables: temperature and humidity.

As showed in (Gurban and Andreescu, 2012), the feedback linearization procedure (Slotine & Li, 1991); (Isidori, 1995), can lead to an efficient control. By employing this technique, an equivalent decoupled system is obtained with an integrator plus dead-time behavior, permitting the usage of PID controllers. In particular, conventional PID tuning methods, synthesized by (Visioli and Zhong, 2011), can be used. Because of their differentiated ways for treating the freedom degrees, these methods produce results that leave ways for improvement. The genetic algorithms prove to be a useful tool in PID tuning (Fleming and Purshouse); (Zalzala and Fleming, 1999). They offer so called suboptimal results. However, even if the case results by using genetic algorithms are not dramatically better comparing with the conventional methods, they offer at least another indicator on which one or other method needs to be favored.

This paper develops a study in the presented context. It completes the results previously presented in (Gurban and Andreescu, 2012). The paper is organized as following. Chapter 2 describes the greenhouse climate model. Chapter 3 presents the decoupling strategy, resulting in two decoupled control loops with an integrator plus dead-time behavior. Chapter 4 develops the control strategy and controller design. The control performances of four conventional tuned PID controllers are improved by using genetic algorithms, in a progressive manner for different scenarios.

2. GREENHOUSE CLIMATE MODEL

From the control engineering point of view, a greenhouse is a distributed parameter nonlinear system, based on energy and mass transfer processes (Fig. 1), with quit difficult modelling.

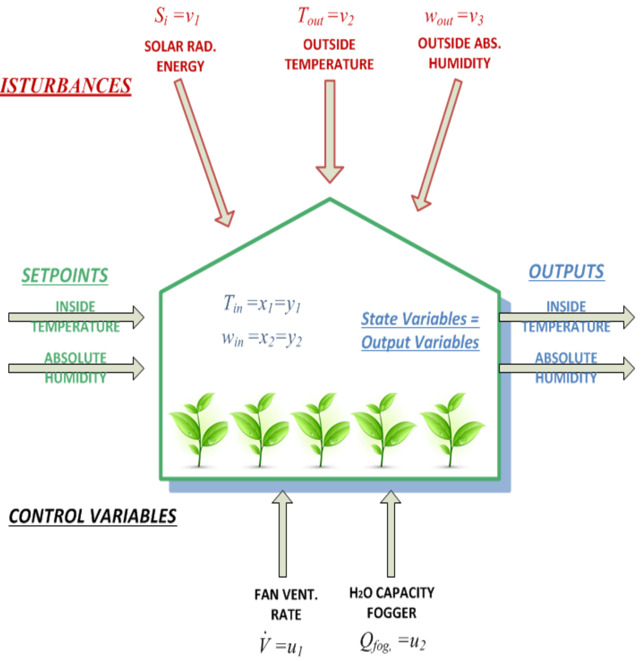

Fig. 1. Greenhouse climate - a schematic representation oriented on climate issues–suited for control approaches.

Furthermore, the models obtained on this way are not suitable for control system design. That is why, actually, simple models with lumped parameters are used, as those developed by Albright *et al.*, (2001), given by the equations:

$$\frac{dT_{in}}{dt}=\frac{1}{\rho C_C V}\left[Q_{heater}(t)+S_i(t)-\lambda Q_{fog}\right] \qquad \text{(1a)}$$
$$-\frac{\dot{V}(t)}{V}\left[T_{in}(t)-T_{out}(t)\right]-\frac{U_A}{\rho C_C V}[T_{in}(t)-T_{out}(t)]$$

$$\frac{dw_{in}}{dt}=\frac{1}{V}Q_{fog}(t)+\frac{1}{V}E(S_i(t),w_{in}(t)) \qquad \text{(1b)}$$
$$-\frac{\dot{V}(t)}{V}\left[w_{in}(t)-w_{out}(t)\right]$$

Inside the greenhouse, the first equation describes the temperature dynamics, while the second one describes the humidity dynamics under the hypothesis that only the main disturbances are considered: outside temperature, outside humidity, and the solar radiation. The meaning of the notations is given in Table 1.

Only summer operation regimes are considered, thus Q_{heater}=0. According to (Pasgianos *et al.*, 2003), the plant evapotranspiration rate $E(S_i(t),w_{in}(t))$ can be expressed as:

$$E(S_i(t),w_{in}(t))=\alpha\frac{S_i(t)}{\lambda}-\beta_T w_{in}(t), \qquad (2)$$

Finally, from (1) and (2) the second order nonlinear state model (3) is obtained.

Table 1. Variables of the greenhouse climate model

A	coefficient accounting for shading and leaf area index
C_p	specific heat of air (1006 J/(kgK))
$E(S_i, w_{in})$	plants evapotranspiration rate (kg/s)
P	air density (1.2 kg/m^3)
Q_{fog},, u_2	water capacity of the fog system (kg/s)
Q_{heater}	heat flow provided by the greenhouse heater
S_i, v_1	intercepted solar radiant energy (W)
T_{in} , x_1, y_1	air temperature inside the greenhouse (^{o}C)
T_{out}, v_2	air temperature outside the greenhouse (^{o}C)
u	control variable
U_A	heat transfer coefficient (W/K)
v	external disturbance variable
V	greenhouse volume (m^3)
$\dot{V}$, u_1	ventilation rate (m^3/s)
w_{in}, x_2, y_2	interior absolute humidity (kg/ m^3)
w_{out}, v_3	exterior absolute humidity (kg/ m^3)
x	state variable
y	output variable
β_T	coefficient to accounting for thermodynamic constants and other factors affecting evapotranspiration
Λ	latent heat of vaporization (2257 J/g)

$$\left\{\begin{aligned}
&\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\end{bmatrix}=\begin{bmatrix}\frac{-U_A}{\rho C_p V} & 0\\ 0 & -\frac{\beta_T}{V}\end{bmatrix}\cdot\underbrace{\begin{bmatrix}x_1\\ x_2\end{bmatrix}}_{x}+\begin{bmatrix}\frac{1}{\rho C_p V} & \frac{U_A}{\rho C_p V} & 0\\ \frac{\alpha}{\lambda V} & 0 & 0\end{bmatrix}\cdot\underbrace{\begin{bmatrix}v_1\\ v_2\\ v_3\end{bmatrix}}_{v}+\\
&\quad+\begin{bmatrix}\frac{1}{V}[v_2-x_1] & -\frac{\lambda}{\rho C_p V}\\ \frac{1}{V}[v_3-x_2] & \frac{1}{V}\end{bmatrix}\cdot\underbrace{\begin{bmatrix}u_1\\ u_2\end{bmatrix}}_{u}\\
&\underbrace{\begin{bmatrix}y_1\\ y_2\end{bmatrix}}_{y}=\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}\cdot\begin{bmatrix}x_1\\ x_2\end{bmatrix}
\end{aligned}\right. \qquad (3)$$

Note that: i) the system (3) is characterized by a high nonlinearity and coupling, ii) the input variable u_1 takes only positive values ($u_1 \geq 0$), and iii) the state variables x_1=T_{in} and x_2 = w_{in} are considered also as output variables. Because the matrix $\begin{bmatrix}-\left(\frac{U_A}{\rho C_p V}+\frac{u_1}{V}\right) & 0\\ 0 & -\left(\frac{\beta_T}{V}+\frac{u_1}{V}\right)\end{bmatrix}$ is negative definite, the MIMO system (3) is stable, hence for constant inputs u and v, a steady state regime is achieved.

3. DECOUPLING STRATEGY

Since (3) is stable, the control structure and design method proposed in (Pasgianos *et al.*, 2003) and (Albright *et al.*, 2001) based on the well-known feedback-linearization method (Slotine and Li, 1991); (Isidori, 1995) for plants with measurable external disturbances, will be further applied. To do that, plant system (3) is brought to the form:

$$\dot{y}=F(y,v)+G(y,v)\cdot u\ , \qquad (4)$$

where:

$$F(y,v)=\begin{bmatrix}f_1(y,v)\\ f_2(y,v)\end{bmatrix}=\begin{bmatrix}\frac{-U_A}{\rho C_p V}y_1+\frac{1}{\rho C_p V}v_1+\frac{U_A}{\rho C_p V}v_2\\ -\frac{\beta_T}{V}y_2+\frac{\alpha}{\lambda V}v_1\end{bmatrix},$$

$$G(y,v)=\frac{1}{V}\cdot\begin{bmatrix}v_2-y_1 & -\frac{\lambda}{\rho C_p}\\ v_3-y_2 & 1\end{bmatrix}\ .$$

Assuming that $G(y,v)$ is nonsingular, and also:

$$\Delta(t)=\rho C_p[v_2(t)-y_1(t)]+\lambda[v_3(t)-y_2(t)]\neq 0\ , \qquad (5)$$

a nonlinear control function of the form (6) is considered:

$$u=G^{-1}(y,v)\cdot[-F(y,v)+\hat{u}]\ . \qquad (6)$$

Here $\hat{u}=[\hat{u}_1\quad \hat{u}_2]^T$ is the new control input vector.

By substituting u from (6) in (4) is get:

$$\dot{y}=\hat{u}\ . \qquad (7)$$

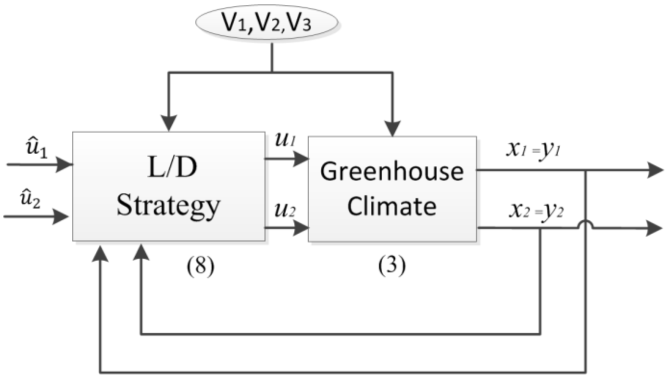

Fig. 2. Decoupling structure - ideal version.

This result illustrates a linear decoupled final interaction along the channels $\hat{u}_1 \to \dot{y}_1 \to y_1$ and $\hat{u}_2 \to \dot{y}_2 \to y_2$. A simple look inside the problem brings to the surface the significance of the new control variables: $\hat{u}_1$ is the rate of change for y_1 (rate of temperature), and $\hat{u}_2$ the rate of change for y_2 (rate of humidity).

Consequently, the linearization law, and in the same time, the decoupling law (6) that assures the behavior (7) is:

$$u_1 = [U_A y_1 + \lambda\beta_T y_2 - (1+\alpha)v_1 - U_A v_2 + \rho C_p V\hat{u}_1 + \lambda V\hat{u}_2]/\Delta \quad (8.1)$$

$$u_2 = (y_2 - v_3)(U_A y_1 - v_1 - U_A v_2 + \rho CpV\hat{u}_1)/\Delta + \\ + \rho Cp(-y_1 + v_2)(\beta_T x_2 - \frac{\alpha}{\lambda} v_1 + V\hat{u}_2)/\Delta \quad (8.2)$$

The whole linearization / decoupling (L/D) strategy is illustrated in Fig. 2.

The inside greenhouse variables, i.e., the temperature and absolute humidity, necessary to implement the decoupling algorithm, are measured with sensors, typically located at a certain distance from the moisturizing devices like wet-pads and foggers, and also from fans and window openers. The measurement and propagation processes are associated with time delays. Hence, two dead times d_1 and d_2, one for each system output y_1 and y_2 are considered. Consequently, based on the assumption that the disturbance variable v is measurable and the input variable u is available from control, the decoupling low (8) becomes:

$$u_1(t) = [U_A y_1(t-d_1) + \lambda\beta_T y_2(t-d_2) - (1+\alpha)v_1(t) - \\ - U_A v_2(t) + \rho C_p V\hat{u}_1(t) + \lambda V\hat{u}_2(t)]/\Delta(t, d_1, d_2) \quad (9.1)$$

$$u_2(t) = [(y_2(t-d_2) - v_3(t)) \cdot (U_A y_1(t-d_1) - v_1(t) - U_A v_2(t) + \\ + \rho CpV\hat{u}_1(t) + \rho Cp(-y_1(t-d_1) + v_2(t))(\beta_T y_2(t-d_2) \\ - \frac{\alpha}{\lambda} v_1(t) + V\hat{u}_2(t)]/\Delta(t, d_1, d_2) \quad (9.2)$$

with

$$\Delta(t) = \rho C_p(v_2(t) - y_1(t-d_1)) + \lambda(v_3(t) - y_2(t-d_2)). \quad (9.3)$$

Instead to obtain (7), rewritten here as $\dot{y}(t) = \hat{u}(t)$, the real input-output relationship is:

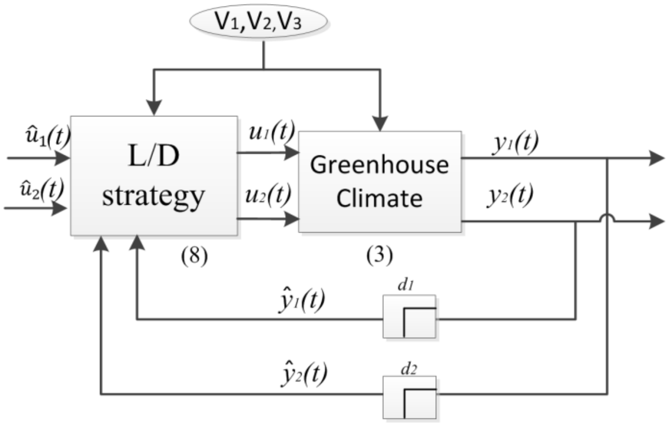

Fig. 3. Decoupling structure - real version.

$$\dot{y}(t) = F(y(t), v(t)) + G(y(t), v(t)) \cdot G^{-1}(y(t, d_1, d_2), v(t)) \cdot \\ \cdot [-F(y, d_1, d_2), v(t) + \hat{u}(t)] \quad (10)$$

Indubitable, the real decoupling strategy shown in Fig. 3, is no more effectively comparing with the ideal decoupling from Fig. 2.

A rigorous analysis of this real structure is difficult to follow and thus a qualitative inspection may be helpful. Fig. 4 shows the comparative behavior of the ideal and real decoupling structures for a greenhouse with parameters listed in Table 2.

Table 2. Greenhouse variables and parameter values

A	0.1249
d_1, d_2	30 s
S_i, v_1	300 W/m^2
T_{out}, v_2	22 °C
$\hat{u}_1$	Step change: 0.1 to 0 at t = 300 s
$\hat{u}_2$	Step change: 0.001 to 0 at t = 600 s
V	2800 m^3
w_{out}, v_3	0.004 kg/ m^3
x_1 *init. cond.*	25 °C
x_2 *init. cond.*	0.018 kg/ m^3
Λ	2257 J/g

Two experiments are summarized in Fig. 4, employing the ideal and real decoupling structure, for stepwise increase in rate of the inside greenhouse temperature and humidity (Fig. 4a and eq. (11) with σ(t) unit step signal):

$$\hat{u}_1(t) = 0.1 \cdot [\sigma(t) - \sigma(t-d_1)] \\ \hat{u}_2(t) = 0.001 \cdot [\sigma(t) - \sigma(t-d_2)], \quad (11)$$

The time variations of y_1 and y_2 appear in Fig. 4b and Fig. 4c, while the corresponding control signals in Fig. 4d and Fig.4e. It is clear that the delayed feedback signals $\hat{y}_1(t) = y_1(t-d_1)$ and $\hat{y}_2(t) = y_2(t-d_2)$ induce a different behavior of the real structure, but equally important is the maintaining of the decoupled behavior at the level of output variables even if there is a high cross interactions in the driving signals $u_1(t)$ and $u_2(t)$.

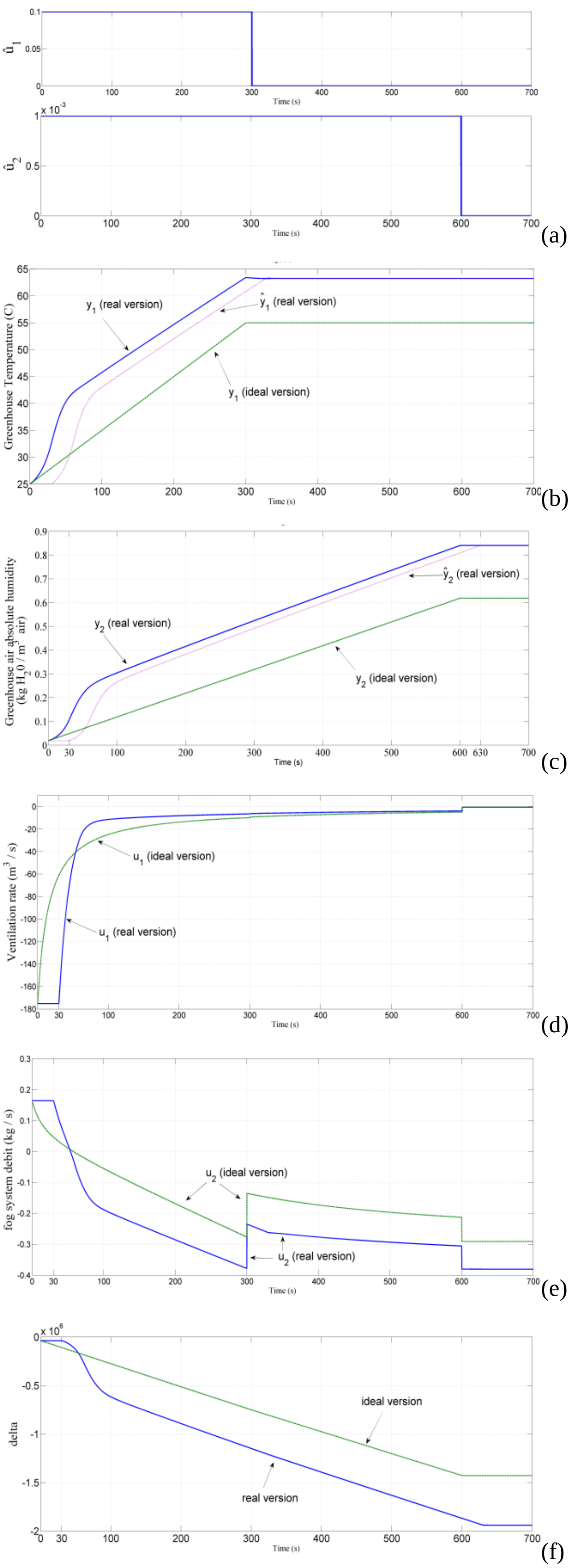

Fig. 4. Comparative behavior of ideal (Fig. 2) vs. real decoupling structure (Fig. 3). Finally, Fig. 4f illustrates how quantity $\Delta(t)$ behaves.

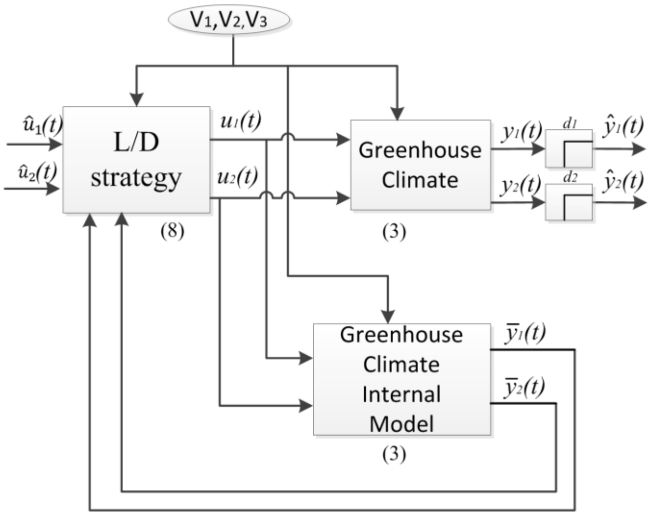

Fig. 5. Decoupling structure using internal model.

The fact that the steady state regime does not differ, allow to use the control structure from Fig. 3. The out way from this situation is to employ the internal model of the process in order to carry out the decoupling reaction without delays (Fig. 5). The internal model output variables used for feedback in L/D strategy are marked with $\bar{y}_1$ and $\bar{y}_2$.

In practical terms, the control can be further developed by using the quasi-equivalent structure in Fig. 6a. Finally, by taking into account eq. (7), the decoupled structure is clarified in Fig. 6b.

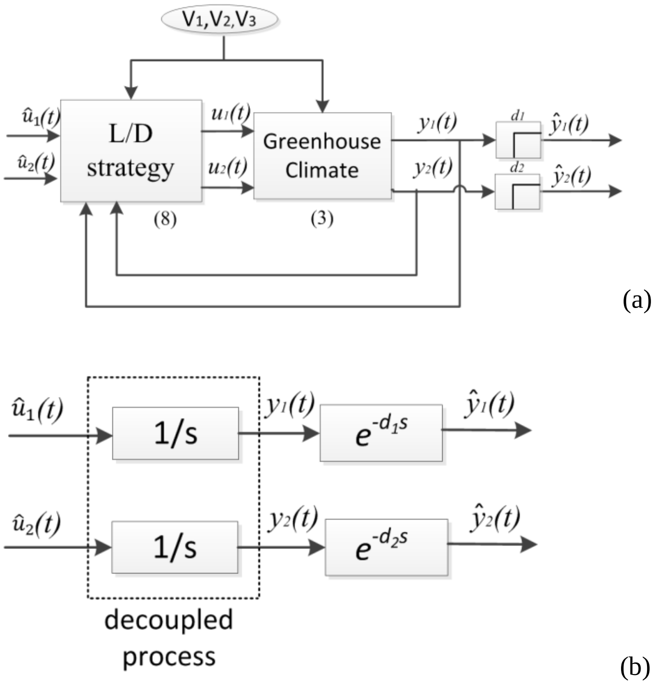

Fig. 6. (a) Equivalent decoupled structure with time delay, and (b) equivalent decoupled processes, i.e., integrator plus dead-time, used in controller design.

4. CONTROL STRATEGY AND CONTROLER DESIGNS

4.1 Control System Structure for Greenhouse Climate

The control system structure chosen for the entire greenhouse climate system, based on the final results of chapter 3, is illustrated in Fig. 7a, and it behaves as two decoupled conventional control loops like in Fig. 7b.

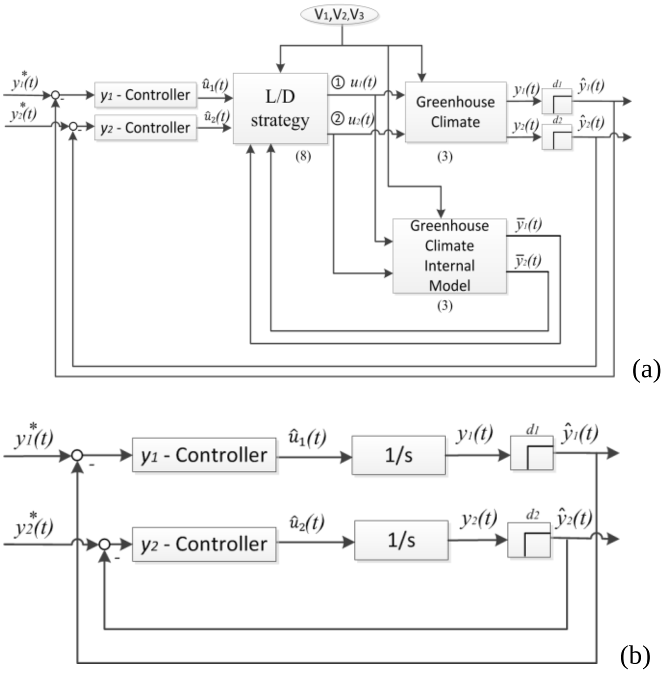

Fig. 7. (a) Greenhouse climate system for temperature and humidity control, and (b) equivalent decoupled control structure with time delay.

The controlled process in each control loop consists of an integrator plus dead-time element, with the transfer function:

$$P(s)=\frac{1}{s}e^{-d_i\cdot s}\ , \quad i=1\,or\;2\ . \tag{12}$$

In our particular case, in (12): $d_i=d_1=d_2=30$ s.

According to (Visioli and Zhong, 2011), PID controllers with the transfer function

$$C_i(s)=K_{Pi}(1+\frac{1}{T_{Ii}s}+T_{Di}s)\ , \quad i=1\,or\;2 \tag{13}$$

are used to achieve rational performances. In (13) K_P, T_I, T_D are the PID controller parameters. To prove the closed-loop stability, the phase margin criterion is applied (Appendix I).

4.2 Some Conventional Tuning Methods for PID Controllers - A Case Study (Part 1)

A wide range of tuning methods for PID (and PI) controllers, based on empirical formulae, analytical methods and frequency-domain approaches, focused on integral plus dead-time processes, are available (Ziegler and Nichols, 1942); (Morari and Zafiriou, 1989); (Arbogast and Cooper, 2007); (Chidambaram and Sree, 2003); (Rao and Sree, 2010); (Wang and Cluett, 1997); (Visioli and Zhong, 2011); (Vilanova and Visioli, 2012).

Four of these methods, applied in (Gurban and Andreescu, 2012) for a greenhouse climate system described at the top of Table 3, led to the results given in the same table. The control system design was done under the assumption that $C_1(s) = C_2(s)$. The following aspects were taken into account:

- The empirical tuning rules of Ziegler-Nichols are providing good load disturbance rejection performances, but not very good set-point following performance, and therefore, the obtained results should be considered as a starting point for further improvements.
- The analytical methods as Internal Model Control and Closed-loop Transfer Function Coefficients Matching, based on exploiting of the transfer function of the closed-loop system, are control design approaches characterized by an acceptable trade-off between nominal performance and robustness. But, this is done with the price of using Padé approximants for the exponential e^{-ds}, and thus, by transforming of an infinite dimensional system into a finite dimensional one of second order.
- The approach based on the specification of the desired control signal, that is a technique consisting in the selecting the transfer function between the set-point and the control variable in a given canonical form, has the disadvantage of using just a canonical form that is not physically realizable (a proper transfer function and not a strictly proper one).

Table 3. PID parameter values determined in (Gurban and Andreescu, 2012)

Greenhouse climate system description: · Floor area: 500 m^2; · Height: 4 m; · Volume: 2800 m^3; ·Solar radiation reduced inside the greenhouse by 50% (with a shading screen); · Control constraints: upper and lower bounds for the ventilation rate: u_{1max} = 22.2 m^3/s and 0 m^3/s, and for the fog system: u_{2max} = 1.2 kg H_2O/s and 0 kg H_2O/s; · α = 0.1249; and λ = 2257 J/g.					
No.	PID tuning method	K_P	T_I [s]	T_D [s]	Design parameter
1	Ziegler-Nichols (M_1)	0.04	60	15	-
2	Specification of desired control signal (M_2)	0.03	78.3	0.01	ξ = 0.707 *α* = 1
3	Closed-loop transfer function coefficients matching (M_3)	0.02	135	13.5	α = 1.25
4	Internal model control (M_4)	0.016	249	26.4	IAE, λ = $d_i\sqrt{10}$

λ, α and ξ are specific design parameters (Visioli and Zhong, 2011).

An overview on the control system performances reached with these controllers offer the step responses in Fig. 8. First, y^*_1 is increased at t = 2000 s (Fig. 8b), than y^*_2 is decreased at t = 4000 s (Fig. 8a).

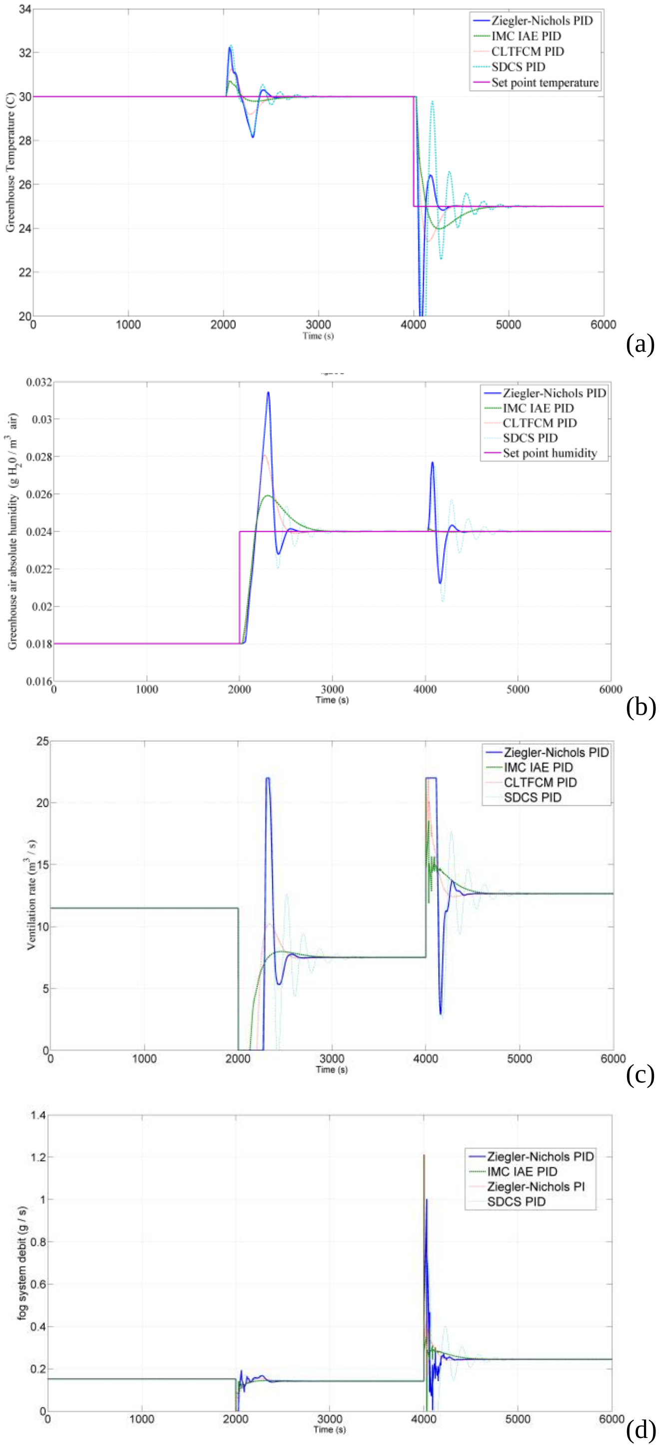

Fig. 8. Step responses of the control system from Fig. 7 with PID controllers tuned according to Table 3.

Some relevant aspects should be notice: i) Due to the limitations of u_1 (Fig. 8c) the decoupling is lost several times, so that both control loops react after every step (Figs. 8a, b). ii) The limitations of u_2 act in the same manner, but for a shorter time interval (Fig. 8d). iii) The most "nervous" system, but also the system with the shortest transient regime, is the control system tuned according to Ziegler-Nichols method (M_1).

From Table 3, it is also obvious the scattering of controller parameter values. The explanation must be sought in relation with the realistic design assumptions and methodological peculiarities.

Except the requirement for stability, the design assumptions of the PID tuning methods M_1,..., M_4 are different. Therefore, it is useful to evaluate the behaviors of the four solutions by the same criteria, and to try to improve the solution by using genetic algorithms.

4.3 Genetic Algorithms for PID Controller Tuning - Methodological Remarks

The genetic algorithms (GA) are heuristic searches, inspired by the evolutionary species concept, used to determine a global suboptimal solution (Fleming and Purshouse), (Zalzala and Fleming, 1999). The parameter values from Table 3 are considered as a proper basis for further investigations by using genetic algorithms to determine the parameters K_P, T_I, T_D of the PID controllers $C_1(s)$ and $C_2(s)$ according to a minimum cost function.

For the controller tunings using genetic algorithms, two milestones are necessary (m = 1, 2) with different scenarios for each stage. In the first stage $C_1(s)$ and $C_2(s)$ are considered identical, and then different in the second stage.

Every time, the tuning process by applying the GA approach follows the steps from Fig. 9. The explanations refer only to the first stage, in the second stage the things are similarly.

- *Gathering of the initial population*

The evolutionary process starts from an initial population, i.e., generation $\ell = 0$, composed by n individuals:

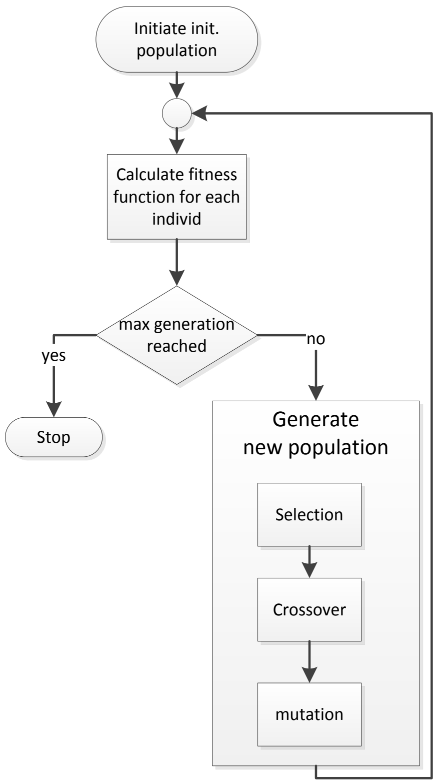

Fig. 9. Genetic algorithm flowchart.

$\{(K_{Pij\ell}, T_{Iij,\ell}, T_{D,j,\ell})\}_{j=\overline{1,n},\ell=0}$ defined by the controller parameters represented in Fig. 7b. Each parameter plays the role of a chromosome that has three genes.

The initial population individual chromosomes can be generated automatically, can be defined by the user, or can combine the previous two situations. A set of n=10 individuals for each population are considered. Four of them are taken from Table 3. The rest of 6 individuals are randomly generated by the Matlab Optimization tool, where the initial interval, defined by the 4 parameter sets based on PID tuning techniques, is extended with ± 30%.

• *Evaluation of the current generation (ℓ) individuals*

Each individual from each generation, i.e., each controller, is evaluated through its effect on the corresponding control system. Due to the large manifold of possible effects in a control system, a relevant operating regime is chosen. For the evaluation of the system behavior in adopted regime, fitness functions J_m, $m=l$, are defined and a fitness value is computed for each individual. As evaluation criteria, the ascending order in respect to the computed values of J_m is considered: i.e., the individual with the lowest fitness value is viewed as the best and has the rank 1.

• *Inspection of stopping criteria*

As GA stopping criteria, the reaching of maximum number of generations is chosen. Hence, if $\ell < \ell_{max}$, where ℓ_{max} is the maximum of generations, a new generation of n individuals is built. Otherwise, the GA is stopped.

• *Building of a new generation,* $\ell+1$

A new generation is created using 3 basic evolution mechanisms: selection, crossover and mutation. The *selection mechanism*, based on the principle of elitism, decides to survive the best two individuals (rank 1 and rank 2) from each generation to the next generation. For obtaining the rest of 8 individuals of generation $\ell+1$, the individuals of generation ℓ are playing the role of parents. For every new individual, a pair of parents, or only one parent is selected by roulette wheel selection method. In the first case, with a crossover fraction of 0.8, the *crossover mechanism* combines the characteristics of the selected pair of parents and generates new values for K_P, T_I and T_D. In the second case, the *mutation mechanism* changes randomly the value of one of the parameters T_I and T_D.

Finally, the new generation replaces the old generation of parents and the whole process restarts.

4.4 PID Controller Tuning for Dusk Regime (Diurnal to Nocturnal Transient Regime) - A Case Study (Part 2)

The 1st relevant operating regime for the control system from Fig. 7 consists on a 6 minutes ramp set-point decrease for both greenhouse temperature (with $\Delta y_1 = \Delta\theta = 5^oC$) and absolute humidity (with $\Delta y_2 = \Delta h = 0.006$ kg H_2O/m^3). This scenario corresponds to diurnal to nocturnal transient regime.

$$y_1^*(t) = 25 - \frac{1}{72}\cdot\left[r(t-2000) - r(t-2360)\right]$$
$$y_2^*(t) = 0.019 - \frac{0.001}{60}\cdot\left[r(t-2000) - r(t-2360)\right] \qquad (14)$$
$$with$$
$$r(t) = t\cdot\sigma(t) = \begin{cases} 0, & t<0 \\ t, & t\ge 0 \end{cases}$$

In (14) the temperature reference signal unit is 1^oC ($y_1^*(t)$) and the humidity reference signal unit is 1 kg H_2O/m^3 ($y_2^*(t)$). Its final value of 0.013 kg H_2O/m^3 corresponds to a 74% relative humidity level.

For $t\in[0, 2000]$, the system is considered to be in steady state regime defined by: $y_1(0) = 25^oC$ (greenhouse air temperature), $y_2(0) = 0.019$ kg H_2O/m^3 (greenhouse air absolute humidity), $v_1 = 300 W/m^2$ (intercepted solar radiant energy), $v_2 = 20^oC$ (outside greenhouse temperature), and $v_3 = 0.004$ kg H_2O/m^3 (outside greenhouse absolute humidity).

The objective cost functions associated as fitness function for above scenario is:

$$J_1 = f_\theta(\tau) + \alpha\cdot g_\theta(\tau) + p_\theta(2000,\tau), \qquad (15)$$

where:

$$f_\theta(\tau) = \int_{2000}^{\tau}\left|\frac{y_1^*(t)-\theta(t)}{\Delta\theta}\right|dt,$$

is the penalty component for temperature, on the time horizon [2000, τ], with τ = 2650 s;

$$g_\theta(\tau) = \frac{1}{\tau-2000}\int_{2000}^{\tau}(u_1(t))^2\,dt, \quad \alpha = 0.1$$

give the penalty component for command variable;

$$p_\theta(2000,\tau) = \begin{cases} 0, & \textit{if no saturation occurs} \\ & \textit{during the time interval } [2000,\tau] \\ 15, & \textit{if saturation occurs} \\ & \textit{during the time interval } [2000,\tau] \end{cases}$$

is the penalty component for saturation of actuator output (the saturations act in the points ① and ② from Fig. 7a).

Table 4 reveals the results obtained after a number of $\ell_{max} = 20$ generations. The notation M_5 is introduced for genetic algorithm method, σ_{max} for the maximum overshoot and t_s for the settling time.

Fig. 9 provides a narrow view on the behavior of genetic algorithms approach. The final solution is reached in practice since the 11th generation. In the abscissa is given ℓ, the rank of the generation, and in ordinate - the best individual in the corresponding generation.

Table 4. Cost functions, PID parameters and performance indicators in Dusk Regime

No	Tuning method	J_1; (f_θ, g_θ)	K_P T_I [s] T_D [s]	σ_{max} [%]	t_s [s]
1	M_1	42.84; (10.7, 171.5)	0.04 60 15	2.27	411
2	M_2	47.83; (29.78, 180.5)	0.0302 78.29 0.0107	2.80	444
3	M_3	72.47 (39, 184.7)	0.0203 135 13.5	3.05	509
4	M_4	108; (73.7, 193)	0.016 249.7 26.40	2.83	642
5	M_5	41.94; (9.77, 171.8)	0.0427 60.05 14.37	2.25	410

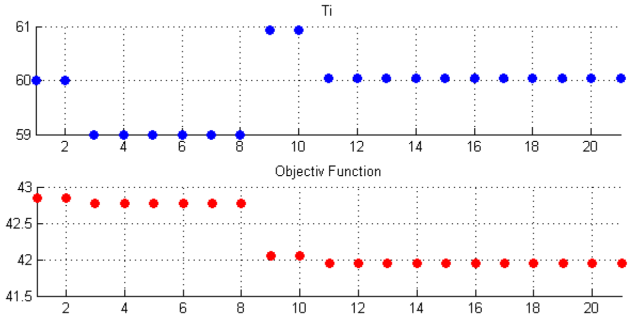

Fig. 9. Relating to the tuning process by GA in dusk regime.

Table 4 shows that the best solution for the initial PID controllers is obtained by the Ziegler-Nichols tuning method (J_1 = 42.84) with the parameters from Table 3. The solution determined by genetic algorithms seems to be better because in this case the obtained values of objective function (J_1 = 41.94), overshoot (2.25 %) and settling time (410 s) have the lowest values. The worst behavior appears for methods M_3 (Closed-loop transfer function coefficients matching) and M_4 (Internal model control - IAE optimal). Fig. 10 reveals comparatively the behavior in the cases M_4 and M_5.

In the cases M_1, M_2 and M_5 the solutions are very close. For the evaluation of differences, the Cartesian distance of relative values is used:

$$D_\zeta = \sqrt{\left(1-\frac{K_{P,M_\zeta}}{K_{P,M_5}}\right)^2+\left(1-\frac{T_{D,M_\zeta}}{T_{D,M_5}}\right)^2+\left(1-\frac{T_{I,M_\zeta}}{T_{D,M_5}}\right)^2}\ ,\ \zeta=\overline{1,4}$$

The results are given in the Table 5 in the column D-DR_1.

Because D_1 = 0.076, the idea to use the M_1 controller in the initial population having a role of attractor is plausible. Therefore, *a 2nd attempt* is made with an initial population that doesn't include Ziegler-Nichols controller.

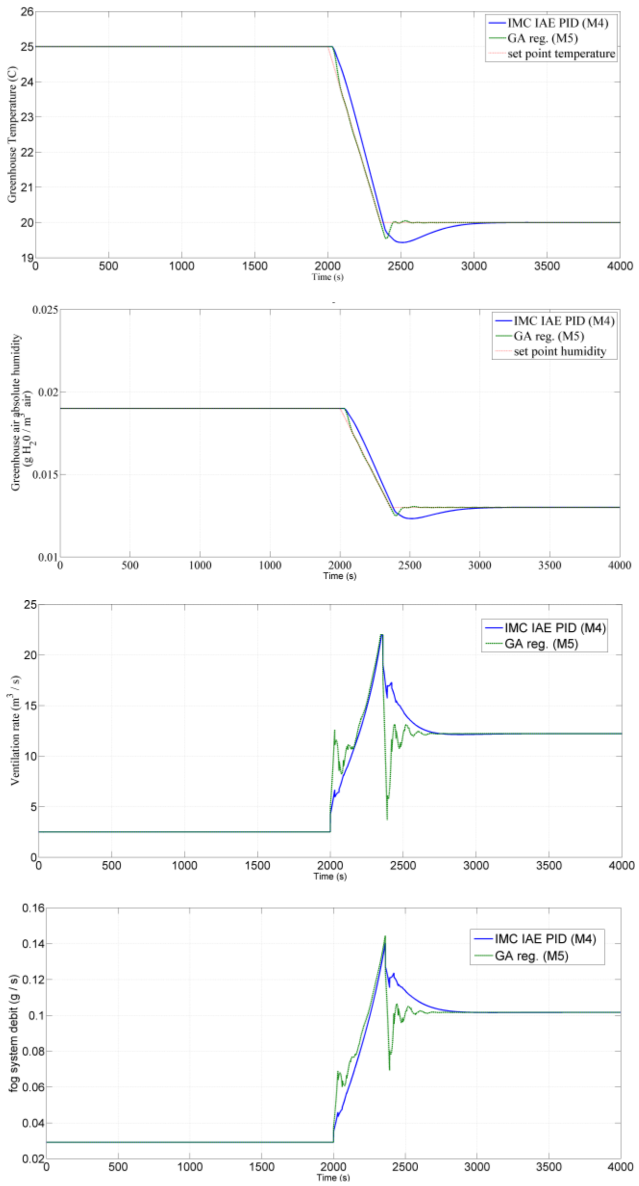

Fig. 10. System responses for diurnal to nocturnal transient (dusk regime) using M_4 and M_5 PID tuning methods.

The new results are given in the Table 5 in the column D-DR_2. For each generation a population of 10 individuals is set, and maximum number of generations is 20. By using genetic algorithms, the minimum cost function is J_1 = 43.48 and the PID parameters are: K_P=0.038, T_I= 47.5s, T_D=17.9s.

Table 5 shows that the new obtained PID parameters by genetic algorithm is closer to the Ziegler-Nichols PID, even if it was not included in the initial population.

Table 5. Distances from the PID parameter set in M1-M4 cases relative to the set given by genetic algorithms

No.	Tuning methods	D-DR_1	D-DR_2
1	M_1	0.076	0.31
2	M_2	1.084	1.212
3	M_3	1.355	1.919
4	M_4	3.327	4.325

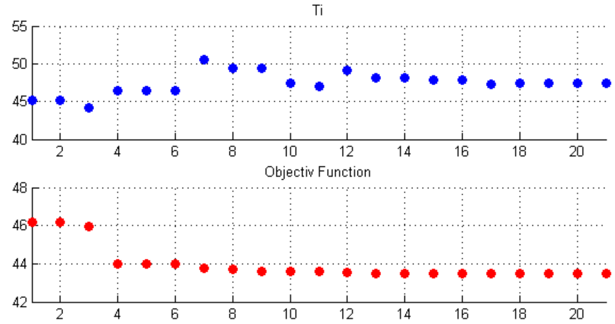

Fig. 11. Relating to the tuning process by GA in dusk regime, without Ziegler-Nichols controller in initial population.

A narrow view on the behavior of genetic algorithm approach for this second tuning case is provided in Fig. 11. Also in this case, the final solution is reached in the 11th generation.

To strengthen the conclusion that de GA PID tuning is better, a validation scenario of the first stage is considered, namely: the study of control systems behavior for diurnal normal regime by taking into account *the uncertainties of solar radiant energy estimation*.

The decoupling strategy adopted in chapter 3 is based on the assumption that the disturbances v_1, v_2 and v_3 are measurable. Particularly, the intercepted solar radiant energy v_1 is obtained every 10 minutes (600 seconds) and used like staircase function (see Fig. 12) from the nearest meteorological station, and not from sensors placed in the greenhouse close vicinity. If the real value of the solar radiant energy in greenhouse is v_{1r}, by considering a multiplicative modeling manner, the value used in the decoupling strategy is $v_{1r} = \rho\ v_1$. For example, supposing that the estimation error does not exceed $\pm$ 30 %, if v_1 takes the string of values:

$v_1 \in$ {300, 290, 240, 220, 350, 240, 340, 500, 700, 300, 710}

and for ρ the corresponding string of values is:

$\rho \in$ {1, 1.1717, 0.9684, 0.8732, 1.2179, 1.0937, 0.8708, 1.0867, 0.8581, 0.8049, 0.9212},

then the time variations of v_{1r} and v_1 is like in Fig. 12. The deviation vector has been generated using the Matlab random number generator. The first element of the deviation vector takes the value of 1 as initial condition, i.e., the same solar radiation at the greenhouse location and at the meteorological station.

In these circumstances, *the 2nd relevant operating regime* of the control system for diurnal normal regime is defined as:

- $y_1^*(t) = 30\,(^oC),\ y_2^*(t) = 0.018\,(\mathrm{kg\,H_2O/m^3})$
- $v_1(t)$ has the shape shown in Fig. 12, v_2 = 35 ^{o}C, v_3 = 0.004 kg H_2O/m^3,
- The initial state/output variable values are: x_1 = 30 ^{o}C, x_2 = 0.018 kg H_2O/m^3, representing a 59% relative humidity.
- The PID regulators have the parameters from Table 4.

The scenario validation did not lead to significant differences from previous results (see Table 6), i.e., the control system is robust to uncertainties in disturbance measurements.

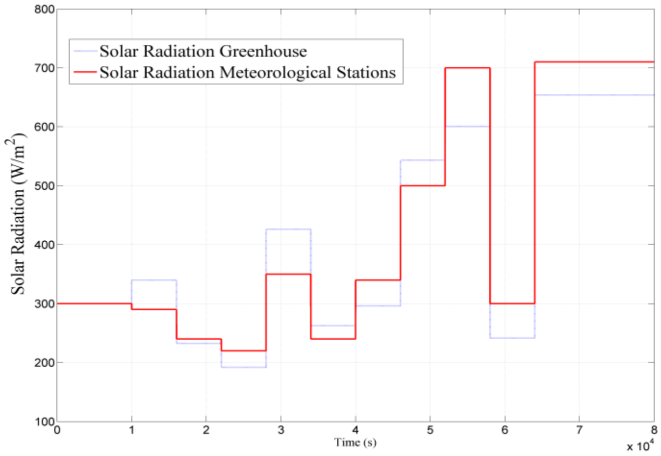

Fig. 12. Solar radiation energy trend in diurnal regime.

Table 6. Control performances for solar radiation uncertainties

No.	Tuning method	Maximum overshoot (%)	Settling time (s)
1	M_1	2.267%; (19.5466)	411
2	M_2	2.8%; (19.44)	444
3	M_3	3.05% (19.39)	509
4	M_4	2.83%; (19.43)	642
5	M_5	2.246% (19.5508)	410

4.5 PID Controller Tuning for Morning Transient Regime - A Case Study (Part 3)

The 3rd relevant operating regime for the control system consists on a 7 minutes ramp set-point increase for both greenhouse temperature (with $\Delta y_1 = \Delta\theta$ = 6 ^{0}C) and absolute humidity (with $\Delta y_2 = \Delta h$ = 0.006 kg H_2O/m^3). This scenario corresponds to the morning transient regime.

$$y_1^*(t) = 15 + \frac{1}{70}\cdot\left[r(t-2000) - r(t-2420)\right]$$
$$y_2^*(t) = 0.013 + \frac{0.001}{70}\cdot\left[r(t-2000) - r(t-2420)\right] \quad (16)$$

For $t \in [0, 2000]$, the system is considered to be in steady state regime defined by: $y_1(0)$ = 15 ^{o}C, $y_2(0)$ = 0.013 kg H_2O/m^3, and on whole time interval holds: v_1 = 300 W/m^2 (intercepted solar radiant energy), v_2 = 20 ^{o}C, and v_3 = 0.004 kg H_2O/m^3.

In this case, the parameters of the temperature and humidity controllers are considered as independent variables, in contrast to the previous scenarios. Now, every parameter plays the role of a chromosome that has six genes. The objective function, associated as fitness function, contents a distinguish component for each control loop:

$$J_2 = J_\theta + J_H\,, \quad (17)$$

$$J_\theta = f_\theta(\tau) + 10\cdot g_\theta(\tau) + 3\cdot p_\theta(2000,\tau)\,,$$

$$J_H = f_H(\tau) + 10\cdot g_H(\tau) + 3\cdot p_H(2000,\tau)$$

where: $$f_\theta(\tau) = \int_{2000}^{\tau} \left| \frac{y_1^*(t) - \theta(t)}{\Delta\theta} \right| dt,$$

$$f_H(\tau) = \int_{2000}^{\tau} \left| \frac{y_2^*(t) - h(t)}{\Delta h} \right| dt$$

are the penalty components for the temperature and humidity outputs, on the time horizon [2000, τ] with τ = 2650 s;

$$g_\theta(\tau) = \frac{1}{\tau - 2000} \int_{2000}^{\tau} \left(\frac{u_1(t)}{u_{1\_final}} \right)^2 dt, \quad u_{1\_final} = 4.1,$$

$$g_H(\tau) = \frac{1}{\tau - 2000} \int_{2000}^{\tau} \left(\frac{u_2(t)}{u_{2\_final}} \right)^2 dt, \quad u_{2\_final} = 0.0532$$

are the penalty components of the command variables and

$$p_\theta(t) = \int_{2000}^{\tau} s_\theta(t)\,dt,$$

$$p_H(t) = \int_{2000}^{\tau} s_H(t)\,dt,$$

$$s_\theta(t), s_H(t) = \begin{cases} 0, \ if \ \ no \ saturation \ occurs \\ 1, \ if \ \ saturation \ occurs \end{cases}$$

are the cost function penalty components for the saturation of actuator outputs (the saturations act in the points ① and ② from Fig. 7a).

After an evolutionary tuning process stabilized during 20 generations, the components of the fitness function achieve the values given by the last row from Table 7 (case M_6). In the same table are given also the values of the components for the previous five cases already discussed (M_1, …, M_5).

Table 7. Cost functions and penalty component values in morning transient regime

Tuning method	J_θ; (f_θ, g_θ, p_θ)	J_H; (f_H, g_H, p_H)	J_2
M_1	34.10; (8.88, 1.0121, 15.09)	23.72 (8.85; 1.488, 0)	57.83
M_2	227.1895 (25.021; 1.526; 186.9)	39.32 (23.21; 1.611, 0)	266.5
M_3	56.64; (31.91; 1.423; 10.5)	48.39 (31.78; 1.661,0)	105
M_4	150.5 (54.86; 1.575; 79.8)	72.33 (54.54; 1.779,0)	222.85
M_5	37.7 (8.063; 1.023; 19.41)	22.89 (8.037; 1.486,0)	60.59
M_6	19.88 (9.52; 1.035; 0)	27.58 (12.61; 1.49; 0)	47.46

The parameters obtained for the temperature PID controller are: $K_{P\theta}$ = 0.0385, $T_{I\theta}$ = 63.14 s, $T_{D\theta}$ = 13.03 s, and for the humidity PID controller are: K_{PH} = 0.0407, T_{IH} = 105 s, T_{DH} = 18.44 s.

The new parameter values for the temperature PID controller are not significantly different from those in cases M_5 and M_1, but for the humidity PID controller the difference is obvious.

5. CONCLUSIONS

The greenhouses are processes that, due to the lack of standards, allow the usage of more tuning methods for PID controllers. The solutions obtained by conventional methods can be improved by using genetic algorithms (GA). In this context, first of all, the methodological value of the paper, especially regarding the usage of GA for controller tuning should be emphasized.

A decoupled greenhouse climate control system is developed based on feedback linearization, resulting an equivalent simplified structure with integrator plus dead-time processes for each temperature and humidity control loop.

Comparative simulation results in real scenarios shows enhanced performances for PID tuning by GA in comparison with four conventional methods, where Ziegler-Nichols method is proved to be the best.

ACKNOWLEDGMENT

This work was partially supported by the strategic grant POSDRU 107/1.5/S/77265 (2010) within the Sectoral Operational Program for Human Resources Development 2007-2013, Romania, co-financed by the European Social Fund - Investing in people.

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APPENDIX

The transfer function of each loop from Fig. 7 (b) is

$$\tilde{H}_i(s) = K_{Pi}(1 + \frac{1}{T_{Ii}s} + T_{Di}s) \cdot \frac{1}{s} \cdot e^{-d_i \cdot s}, \quad i = 1 \text{ or } 2$$

Due to the presence of dead time, the phase margin stability criterion is applied (Föllinger, 2013). Hence, considering the Bode plots of the open-loop system $\left|\tilde{H}_i\right|_{dB} = 20\,lg\left|\tilde{H}_i(j\omega)\right|$ and $\varphi_{\tilde{H}_i} = arg\,\tilde{H}_i(j\omega)$, the crossover frequency $\omega_c = max\{\omega \in R_+ \,|\, \left|\tilde{H}_i\right|_{dB} = 0\}$ and the phase margin $\varphi_M = \pi + arg\,\tilde{H}_i(j\omega_c)$, the phase margin stability criterion shows that the closed-loop system is (theoretically) stable if $\varphi_M > 0$ (practically if $\varphi_M > \frac{\pi}{9}$.).

Table A presents the results for phase margin and crossover frequency obtained with the controllers considered in this paper. The Bode plots, the crossover frequencies and phase margins for two of the studied cases are illustrated in Fig. A.

Table A. Phase margin and crossover freq.

Tuning method	Phase margin φ_{res} (^{0})	Crossover freq. ω_c (rad/s)
M_1	31	$4.07 * 10^{-2}$
M_2	13	$3.24*10^{-2}$
M_3	50	$2.03*10^{-2}$
M_4	72	$1.63*10^{-2}$
M_5	29	$4.41*10^{-2}$
$M_{6\ temp}$	29	$3.9*10^{-2}$
$M_{6\ hum}$	40	$5.09*10^{-2}$

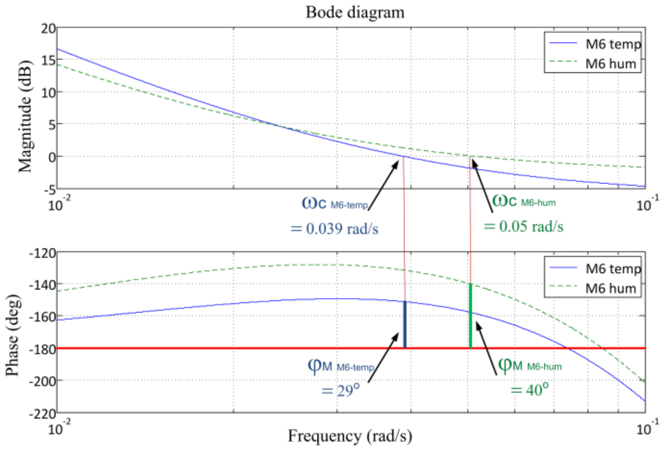

Fig. A. Bode plots for the system with M6 temperature and humidity controllers

Note that every time $\omega_c \in (0.01,\ 0.1)\,s^{-1}$.