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Adaptive PI control of temperature with natural ventilation in greenhouses using a bat algorithm variant ⋆

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Abstract: This paper presents a self-tuning PI controller to control the temperature of a greenhouse using natural ventilation. The PI controller parameters are adapted according to the changing dynamics of the process, identified with a simplified greenhouse temperature model based on first principles. The time-varying model parameters are estimated online using the random scaling-based bat algorithm. The model is linearized to obtain a first-order transfer function which facilitates the design of the PI controller using well-known tuning methods. Simulated results with real greenhouse data show that the proposed solution could be applied to keep controllers tuned throughout different agri-seasons.

Keywords: Agriculture, PID control, adaptive control, self-tuning control, parameter estimation, linearization, metaheuristic optimization

1. INTRODUCTION

Temperature control in greenhouses is essential for optimal crop growth as air temperature affects the physiological processes of plants. In Mediterranean greenhouses, natural ventilation is the main method to control the temperature during the day, due to the climate of the region and the fact that it is an inexpensive method (Rodríguez et al., 2015). Natural ventilation allows warm air from inside the greenhouse to be exchanged with cooler air from outside. It can be an effective passive cooling system to control temperature if proper regulation of the opening of the greenhouse vents is performed.

In this context, different control techniques based on proportional-integral-derivative (PID) control have been widely used with good results to control the temperature and other climate variables in greenhouses (Iddio et al., 2020; Rodríguez et al., 2015). However, the climate inside a greenhouse depends mainly on the external weather conditions, the crop transpiration, the greenhouse structure, and the soil material. These factors change over time, for example, depending on the seasons, the crop variety, or the plastic cover deterioration. Therefore, it is indispensable to periodically tune the controllers according to the short-term and long-term time-varying dynamics of the greenhouse climate. In addition, it may be necessary to have controllers tuned to operate at different setpoint values, depending on the temperature range to be controlled, due to the nonlinear behavior of the dynamics relating temperature and natural ventilation (and other effects).

Adaptive control is often used to address the above problems by continuously adjusting the parameters of a controller to account for changes in process dynamics and disturbances (Åström and Wittenmark, 2008). Several adaptive control techniques have been applied to greenhouses, including self-tuning PID control (Gouadria et al., 2017; Su et al., 2020), adaptive feedback linearization (Berenguel et al., 2003; Lijun et al., 2018), model reference adaptive control (Wang and Wang, 2020), multirate adaptive control (Arvanitis et al., 2000), adaptive generalized predictive control (Ramezani et al., 2023), adaptive robust control (Luan et al., 2011), and adaptive control using neural networks (Zeng et al., 2012).

This paper presents a self-tuning PI controller whose parameters are adapted indirectly by online estimation of a greenhouse temperature model based on first principles. The main contribution of this work consists of the combination of the following elements:

- As explained in Section 3, a simplified model for temperature is used to consider the effect of natural ventilation through an exponential expression, which reduces the complexity to linearize it and thus obtaining a first-order transfer function to relate the temperature (controlled variable) to the vents opening (manipulated variable). The parameters of the PI controller can be calculated from the resulting linear model using well-known design methods.
- As explained in Section 4, the time-varying parameters of the simplified temperature model are esti-

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mated using an online estimator based on the random scaling-based bat algorithm (RSBA), successfully tested by Guesbaya et al. (2022) for a temperature model in a real greenhouse. This fact motivated the selection of the RSBA for this work over other estimation methods.

The aforementioned control methods exhibit common limitations including sensitivity to modeling errors and uncertainties, complex analytical calculations, and computational expense. In comparison, the control approach proposed in this paper stands out for the design simplicity. Also, by utilizing first principles-based model estimation, the controller can better adapt to system dynamics, mitigating the effects of model mismatch and uncertainties.

Results are presented in Section 5 and confirm the good performance of the adaptive PI controller in different climatic conditions (summer and winter), and at different operating points (with changing setpoints).

2. DESCRIPTION OF THE GREENHOUSE

A traditional Almería-type greenhouse with an area of 877 m^2 was used in this work (see Fig. 1). It is located at “Las Palmerillas” Experimental Station of the Cajamar Foundation, in El Ejido, Almería, Spain.

The greenhouse has five roof vents (8.36 m $\times$ 0.73 m) and two side vents (32.75 m $\times$ 1.90 m) on the north and south walls. As shown in Figure 1a, the roof vents have an angled opening while the side vents are opened by rolling up the plastic cover. The vents can be opened from 0% to 100% of their ventilation area to control the temperature. All the vents actuate simultaneously by receiving the same control signal (i.e., percentage of open area of the vents).

3. GREENHOUSE AIR TEMPERATURE MODEL

The dynamics of the greenhouse air temperature $x_{\mathrm{T,a}}$ is commonly modeled by the scientific community with a nonlinear differential equation (Rodríguez et al., 2015) which represents an energy balance as follows:

$$\begin{aligned} c_{\mathrm{thr}}\,\frac{\mathrm{d}x_{\mathrm{T,a}}}{\mathrm{d}t} &= Q_{\mathrm{sol,a}} + Q_{\mathrm{cnv,ss\text{-}a}} - Q_{\mathrm{cnv\text{-}cnd,a\text{-}e}} \\ &\quad - Q_{\mathrm{ven}} - Q_{\mathrm{loss}} - Q_{\mathrm{trp}} \end{aligned} \tag{1}$$

where $c_{\mathrm{thr}} = c_{\mathrm{sph,a}}\, c_{\mathrm{den,a}}\,(c_{\mathrm{vol,g}}/c_{\mathrm{area,ss}})$, being $c_{\mathrm{sph,a}}$ the specific heat of air, $c_{\mathrm{den,a}}$ the air density, $c_{\mathrm{vol,g}}$ the volume of air inside the greenhouse, $c_{\mathrm{area,ss}}$ the soil surface of the greenhouse, and Q denotes the different heat exchanges occurring in the greenhouse: $Q_{\mathrm{sol,a}}$ is the solar radiation flux assumed to be absorbed by the air in the greenhouse, $Q_{\mathrm{cnv,ss\text{-}a}}$ is the convective flux between the soil surface and the greenhouse air, $Q_{\mathrm{cnv\text{-}cnd,a\text{-}e}}$ is the convective and conductive flux through the cover, Q_{ven} is the heat lost by natural ventilation, Q_{loss} is the heat lost due to infiltration losses (e.g., holes in the cover), and Q_{trp} is the latent heat effect due to crop transpiration.

Note that natural ventilation is the only actuator considered in (1) by means of Q_{ven}. The calculation of the heat lost by natural ventilation depends on the volumetric flow rate of ventilation. This ventilation rate is calculated using highly nonlinear expressions that relate different factors

(a) (b)

Fig. 1. Greenhouse: (a) Exterior view with the roof and side vents, (b) Interior view

such as the vents opening percentage, the total ventilation area of the greenhouse, the wind speed outside, the temperature difference between inside and outside, and time-varying coefficients that depend on the weather conditions (Pérez-Parra et al., 2004). Therefore, it is complicated to use the model in (1) for the design of control strategies.

The following subsections present the steps taken to obtain a simplified temperature model (especially for Q_{ven}) and the corresponding linearized model for control purposes.

3.1 Simplified air temperature model

The model in (1) results in the following expression, taking into account that $Q_{\mathrm{ven}} + Q_{\mathrm{loss}}$ are both considered through the ventilation rate term $V_{\mathrm{ven,flux}}$:

$$\begin{aligned} c_{\mathrm{thr}}\,\frac{\mathrm{d}x_{\mathrm{T,a}}}{\mathrm{d}t} &= c_{\mathrm{asw,a}}\, c_{\mathrm{tsw,g}}\, \mathrm{e}^{\left(-c_{\mathrm{esw}}\, x_{\mathrm{LAI}}\right)}\, d_{\mathrm{sr,e}} \\ &\quad + c_{\mathrm{cvs}}\,(x_{\mathrm{T,ss}} - x_{\mathrm{T,a}}) \\ &\quad - c_{\mathrm{cvd}}\,(x_{\mathrm{T,a}} - d_{\mathrm{T,e}}) \\ &\quad - \frac{c_{\mathrm{thr}}}{c_{\mathrm{vol,g}}}\, V_{\mathrm{ven,flux}}\,(x_{\mathrm{T,a}} - d_{\mathrm{T,e}}) \end{aligned} \tag{2}$$

where $c_{\mathrm{asw,a}}$ is the shortwave absorption coefficient of the greenhouse air, $c_{\mathrm{tsw,g}}$ is the shortwave transmission coefficient of the cover, $d_{\mathrm{sr,e}}$ is the solar radiation outside the greenhouse, c_{cvs} is a convection coefficient for the difference between the soil surface temperature $x_{\mathrm{T,ss}}$ and the air temperature inside the greenhouse, and c_{cvd} is a coefficient of heat loss through the plastic cover due to the difference between the temperature inside and the temperature outside $d_{\mathrm{T,e}}$.

Regarding the simplifications made to the model in (1), on the one hand, note in (2) that it was assumed that the crop transpiration can be considered as a gain reduction factor affecting the solar radiation flux by means of a canopy shortwave extinction coefficient c_{esw} and depending on the leaf area index of the crop X_{LAI}, as presented by Berenguel et al. (2003). The leaf area index is considered with a constant value for each day because it varies slowly, on a long-term time scale corresponding to crop growth. On the other hand, the ventilation rate can be calculated with the following exponential equation that was demonstrated by Pérez-Parra et al. (2006); Berenguel et al. (2006) to be accurate and valid for an Almería-type greenhouse with roof and side vents:

$$V_{\mathrm{ven,flux}} = d_{\mathrm{ws,e}}\, a\,(u_{\mathrm{ven}})^{b} + c_{\mathrm{loss}} \tag{3}$$

where $d_{\mathrm{ws,e}}$ is the wind speed, u_{ven} is the vents opening percentage, a and b are empirical parameters that depend on weather conditions and need to be estimated for each particular greenhouse, and c_{loss} are the infiltration losses.

Expression (3) is substituted in (2), and some parameters are grouped and renamed so that a straightforward model can be obtained for a linearization procedure, as follows:

$$\begin{aligned} c_{\mathrm{thr}} \frac{\mathrm{d}x_{\mathrm{T,a}}}{\mathrm{d}t} &= c_{\mathrm{rad}}\, d_{\mathrm{sr,e}} + c_{\mathrm{cvs}}\,(x_{\mathrm{T,ss}} - x_{\mathrm{T,a}}) \\ &\quad - c_{\mathrm{cvd}}\,(x_{\mathrm{T,a}} - d_{\mathrm{T,e}}) \\ &\quad - (c_{\mathrm{v1}}\, d_{\mathrm{ws,e}}\,(u_{\mathrm{ven}})^{b} + c_{\mathrm{v2}})\,(x_{\mathrm{T,a}} - d_{\mathrm{T,e}}) \end{aligned} \tag{4}$$

where $c_{\mathrm{rad}} = c_{\mathrm{asw,a}}\, c_{\mathrm{tsw,g}}\, \mathrm{e}^{\left(-c_{\mathrm{esw}}\, x_{\mathrm{LAI}}\right)}$, $c_{\mathrm{v1}} = a\,(c_{\mathrm{thr}}/c_{\mathrm{vol,g}})$, and $c_{\mathrm{v2}} = c_{\mathrm{loss}}\,(c_{\mathrm{thr}}/c_{\mathrm{vol,g}})$.

3.2 Model linearization

A linearization procedure was applied to (4), which can be expressed as a function in (5) that depends on the greenhouse air temperature, the soil surface temperature, the external weather, and the vents opening percentage.

$$c_{\mathrm{thr}} \frac{\mathrm{d}x_{\mathrm{T,a}}}{\mathrm{d}t} = f(x_{\mathrm{T,a}}, x_{\mathrm{T,ss}}, u_{\mathrm{ven}}, d_{\mathrm{sr,e}}, d_{\mathrm{T,e}}, d_{\mathrm{ws,e}}) \tag{5}$$

Note that the non-linearity of (4) remains in the ventilation rate term. Nonetheless, thanks to the aforementioned simplifications, it is easier to linearize the resulting function compared to the well-known complex ventilation rate expressions in the literature (Pérez-Parra et al., 2004).

The Taylor series first-order approximation was applied to linearize the function in (5). The operating point is expressed by the variables with notation such as $\bar{v}$, and the deviation variables are expressed such as $\tilde{v}$. Note that $f(\bar{v}) = 0$ when evaluated in the operating point (i.e., equilibrium point). Only the terms corresponding to the greenhouse air temperature and the vents opening are shown below in (6)-(8), but the linearization was applied to the complete function. The omitted terms, for reasons of limited space, consist of the effects of the external weather and the soil surface temperature on the greenhouse air temperature, considered as disturbances.

$$f(x_{\mathrm{T,a}}, u_{\mathrm{ven}}) \approx f(\bar{v}) + \left.\frac{\partial f}{\partial x_{\mathrm{T,a}}}\right|_{\bar{v}} \tilde{x}_{\mathrm{T,a}} + \left.\frac{\partial f}{\partial u_{\mathrm{ven}}}\right|_{\bar{v}} \tilde{u}_{\mathrm{ven}} \tag{6}$$

$$\left.\frac{\partial f}{\partial x_{\mathrm{T,a}}}\right|_{\bar{v}} = -c_{\mathrm{cvs}} - c_{\mathrm{cvd}} - c_{\mathrm{v1}}\, \bar{d}_{\mathrm{ws,e}}\,(\bar{u}_{\mathrm{ven}})^{b} - c_{\mathrm{v2}} = p_1 \tag{7}$$

$$\left.\frac{\partial f}{\partial u_{\mathrm{ven}}}\right|_{\bar{v}} = -c_{\mathrm{v1}}\, \bar{d}_{\mathrm{ws,e}}\, b\,(\bar{u}_{\mathrm{ven}})^{b-1}\,(\bar{x}_{\mathrm{T,a}} - \bar{d}_{\mathrm{T,e}}) = p_2 \tag{8}$$

The resulting linear model for the relationship between the greenhouse temperature and the effect of natural ventilation is calculated by applying the Laplace transform with null initial conditions to (6) to obtain a first-order transfer function:

$$G_u(s) = \frac{X_{\mathrm{T,a}}(s)}{U_{\mathrm{ven}}(s)} = \frac{k}{\tau\, s + 1} \tag{9}$$

$$k = -\frac{p_2}{p_1}\left(\frac{\mathrm{K}}{\%}\right) \qquad \tau = -\frac{c_{\mathrm{thr}}}{p_1}\,(\mathrm{s}) \tag{10}$$

4. ADAPTIVE CONTROL APPROACH

Fig. 2 presents the adaptive control scheme that has been implemented. The online adaptation of the model described in (2) is performed with the RSBA, the algorithm in charge of estimating the time-varying parameters. The model parameter estimation block is fed with the current and past values of the process input (i.e., vents opening), disturbances (i.e., outside weather), and outputs (i.e., greenhouse temperature and other state variables). The external wind speed and solar radiation are filtered before being used in the estimation block, due to the noise observed in the measurements.

From the estimated parameters of the model in (2), the parameters of the linear model in (9)-(10) are finally obtained, which are calculated depending on the operating point defined by $(\bar{x}_{\mathrm{T,a}}, \bar{u}_{\mathrm{ven}}, \bar{d}_{\mathrm{T,e}}, \bar{d}_{\mathrm{ws,e}})$, according to the values measured in the greenhouse at each instant in which the controller parameters are going to be updated.

The parameters estimated by the RSBA-based online estimator are provided to the controller design block to subsequently calculate the PI controller parameters according to the desired specifications for the closed loop and the chosen tuning method. It is important to note that the controller parameters should vary more slowly than the control loop sampling time (Åström and Wittenmark, 2008). Therefore, the model and PI parameter adaptation is performed every one minute and the control loop sampling time is 30 seconds, selected according to the dynamics commonly exhibited by the greenhouse climate and external weather, especially to account for fast variations of wind speed (Rodríguez et al., 2015). As demonstrated by Guesbaya et al. (2022), the computational cost of the RSBA is very low and can be used for real-time model adaptation.

4.1 Model parameter estimation using the RSBA

The random scaled-based bat algorithm is a metaheuristic optimization algorithm, inspired in nature as it imitates the bats' searching on prey (i.e., an optimal solution) using their echolocation skill when they fly with a random walk technique. The complete description of the RSBA-based online estimator can be found in Guesbaya et al. (2022), including its sensitivity and robustness analyses when used with a model like (2).

In this work, every one minute, the RSBA changes the temperature model parameters in a cost function that is evaluated with each possible solution (i.e., set of parameters) for a maximum of 100 iterations, tested to be sufficient to ensure that the best solution is found in much less than 1 min. The RSBA selects the solution that minimizes

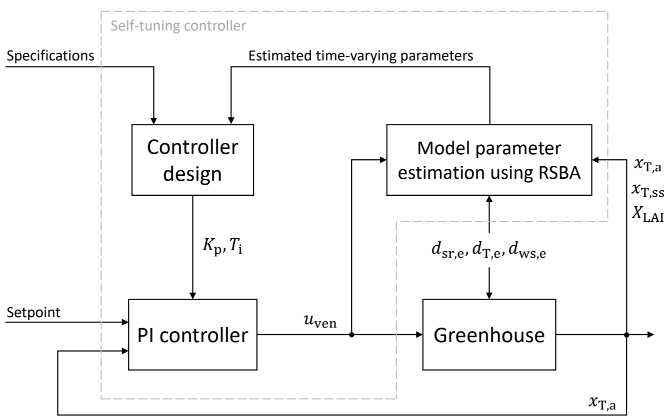

Fig. 2. Adaptive control scheme

the mean square error (MSE) between the temperature given by the model and the temperature measured in the greenhouse during the last three minutes (i.e., last three samples in a recursive manner). According to Guesbaya et al. (2022), undesirable fluctuations could appear in the estimation when using more than the last three samples.

In particular for exploitation, the RSBA generates a local solution around the best selected solution. Each new i-th set of parameters is generated with $C_i^{t+1} = C_*^t + \sigma^t \epsilon^t \bar{A}^t$, where t are the time instants when the model estimation is executed, C contains the sets of parameters, C_* is the current best solution, σ is a scaling factor to regulate the step size of the local random walk, $\epsilon \in [-1, 1]$ is a random number, and $\bar{A}$ is the mean bats' loudness. The scaling factor increases the chance to reach optimality by $\sigma^t = \sigma_{\min} + (\sigma_{\max} - \sigma_{\min})\, \beta^t$, where $\beta^t \in [0, 1]$ has a random value from a uniform distribution. $\bar{A}$, $\sigma_{\min}$, and $\sigma_{\max}$ can be set by trial and error to adjust the RSBA behavior, among other setting features (Guesbaya et al., 2019).

Table 1 lists the parameters of the model to be estimated with their respective search limits, which are imposed to ensure that the physical sense of the model is respected, based on previous experience or values reported in the literature (Rodríguez et al., 2015). Each parameter is estimated by the RSBA-based online estimator only when their related dynamics is changing or exciting the process. For instance, $c_{\mathrm{asw,a}}$ and $c_{\mathrm{tsw,g}}$ are estimated when solar radiation is greater than 5 W/m^2, c_{esw} is estimated when the leaf area index of the crop is greater that 0.1, and the ventilation parameters a and b are estimated when the vents are open. Otherwise, the parameters keep their previous optimal values.

The RSBA-based online estimator uses adaptive search ranges for each parameter. Instead of searching solutions in the total space given by the physical limits shown in Table 1, the computational burden is reduced by randomly generating the population of possible solutions in the neighborhood of the last best parameter value, depending on the variation rate R_j of each parameter (also shown in Table 1). Thus, the adaptive search ranges for each c_j parameter are $LB_j^{t+1} = c_j^t(1 - R_j)$ and $UB_j^{t+1} = c_j^t(1 + R_j)$, where LB are the lower bounds and UB are the upper bounds of the adaptive search ranges. In any case, the algorithm is prepared to keep the values of the adaptive search ranges inside the search space delimited by the physical limits.

4.2 Calculation of the PI controller parameters

For setpoint changes and to compensate for weather and non-measurable disturbances, the parameters K_{p} and T_{i} of the PI controller can be calculated with the SIMC tuning rules (Skogestad, 2003) applied to the transfer function presented in (9)-(10) and imposing a closed-loop time constant of $\tau_{\mathrm{cl}} = 0.3\,\tau$. In addition, the PI controller includes an anti-windup mechanism (Åström and Hägglund, 2006) based on the back-calculation technique to deal with the saturation of the vents opening and for bumpless transfers, with a tracking constant of $T_{\mathrm{t}} = T_{\mathrm{i}}$.

The resulting values of K_{p} and T_{i} are continuously supervised, and minimum and maximum limits are imposed to

Table 1. The time-varying parameters of the model to be estimated

Parameter	**Lower limit**	**Upper limit**	**Variation rate**	**Units**
$c_{\mathrm{asw,a}}$	0.1	0.9	1%	–
$c_{\mathrm{tsw,g}}$	0.1	0.9	3%	–
c_{esw}	0.4	0.8	0.1%	–
c_{cvs}	1	20	1%	W/(m^2 K)
c_{cvd}	2	30	1%	W/(m^2 K)
a	0.01	1	1%	–
b	1	2	1%	–
c_{loss}	0.1	0.9	1%	m^3/s

avoid values that may cause overly aggressive controller behavior or instability issues. Also, when the vents remain closed at any instant, the PI parameters are not updated and keep their last calculated value.

5. CONTROL RESULTS

The adaptive control was tested in simulation using a complete model for the greenhouse climate, which consists of a system of three nonlinear differential equations to simulate the greenhouse air temperature, relative humidity, and soil surface temperature (Rodríguez et al., 2015). The complete model plays the role of a real greenhouse in this study. It was calibrated for the greenhouse described in Section 2 and for different seasons of the year.

Fig. 3 presents the control results for a summer day in September, when the crop is in its initial stage and a leaf area index equal to zero is considered. As can be seen, it is a hot day, without relevant changes in the external weather variables since it is a sunny day with little wind. However, the increasing effect of the solar radiation curve makes it difficult to control the temperature at different setpoints. Note that natural ventilation presents cooling limitations because it depends to a large extent on climatic conditions and the characteristics of each greenhouse. For this reason, setpoint changes were simulated and the adaptive PI controller was compared with a PI controller whose parameters (K_{p} = -20 %/K and T_{i} = 1000 s) were not tuned according to the dynamics of the system on that particular day. This illustrates what can happen when a controller originally tuned in autumn is used on a summer day, for example. Although PI control could be considered robust to changes, the aim of this work is to keep the PI well-tuned for varying weather and operating points, so that the temperature control is as desired according to closed-loop specifications for a crop cycle.

Considering the evolution of the greenhouse temperature in Fig. 3, the adaptive controller clearly outperforms the PI controller with fixed parameters, since the temperature is successfully controlled with the adaptive PI over the entire operating range. For quantitative assessment, the integral absolute error (IAE) was calculated as $\mathrm{IAE} = \int |e(t)|\,\mathrm{d}t$, where $e(t)$ is the control error given by each controller, and the control effort (CE) was calculated as $\mathrm{CE} = \int |u_{\mathrm{ven}}(t) - u_{\mathrm{ven}}(t - \Delta t)|\mathrm{d}t$. Compared to the non-adaptive controller, the adaptive PI controller scored 3.2 times less IAE with 2.7 more control effort. These results were expected as the non-adaptive controller can

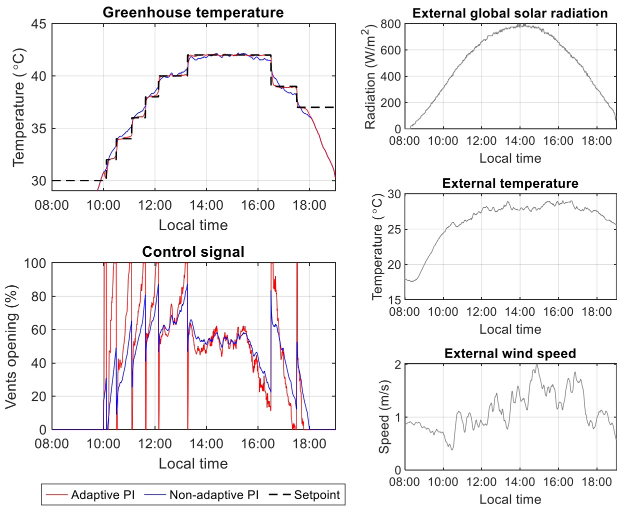

Fig. 3. Simulated control results with real data from September

not track the setpoints in all the operating points. The greater control effort for the adaptive PI controller is due to the peaks in the control signal to reach each new temperature setpoint. Note that the greenhouse described in Section 2 has a reduced ventilation area, so greater changes in the vents opening are needed. Nonetheless, if the control signals of the adaptive and non-adaptive controllers are compared at midday (between 14:00 and 16:00), it can be seen that they are similar (also the CE) but the adaptive PI manages to keep the temperature closer to the setpoint.

Fig. 4 shows the model estimation results and the change of the PI controller parameters for the results of September. Regarding the model estimation using the RSBA, it can be seen that the greenhouse temperature simulated by the model in (2) fits satisfactorily to the temperature measured in the greenhouse (simulated with the complete nonlinear model from Rodríguez et al. (2015)). The mean absolute error (MAE) is 0.11 °C and the maximum absolute error (MaxAE) is 1.22 °C in a range of [19.24, 42.39] °C, which are significantly accurate values for an online estimation of a physical model. Note that the model adaptation starts at 00:00 to keep the fitting error minimized during the complete day, but only the time interval for the daytime control is shown. The evolution of the model parameters is presented in the right column of Fig. 4. Conservative variation rates were used (recall Table 1), but sufficient to ensure a good model estimation and avoid large changes in the values of the PI controller parameters. As for K_{p}, slightly elevated (negative) values are obtained due to the imposed closed-loop specifications (recall Section 4.2) and because of the reduced ventilation capacity of this particular greenhouse.

Fig. 5 presents the control results for a winter day in January, when the crop is at an advanced stage of growth and a leaf area index equal to three is considered. In this case, noticeable changes in the external climate variables can be observed, being a cloudy and windy day. With these climatic conditions, it is intended to confirm that the adaptive PI controller works well in another season with different dynamics and its behavior is evaluated when the presence of disturbances is greater. Regarding

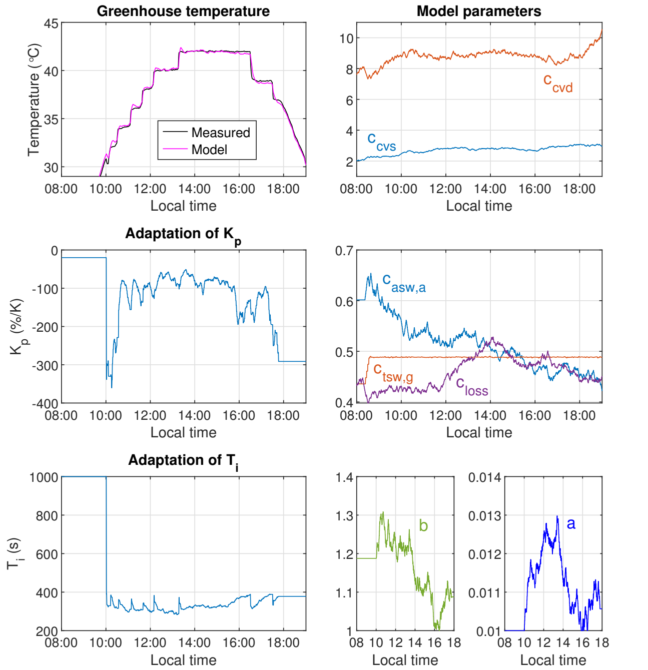

Fig. 4. Details of the adaptive control for the control results of September, shown in Fig. 3

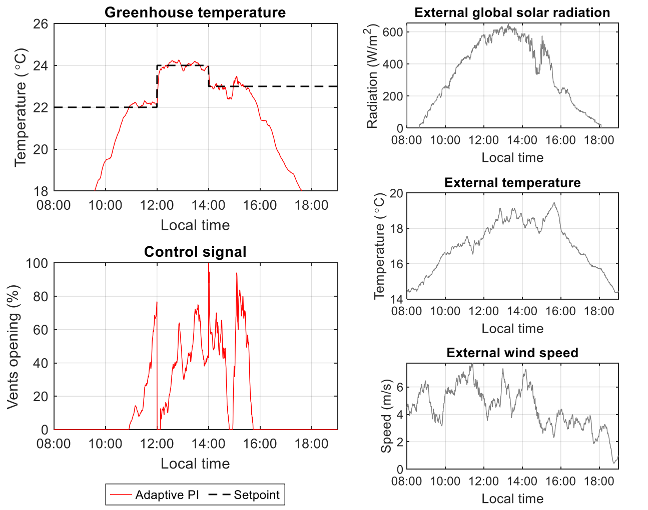

Fig. 5. Simulated control results with real data from January

the greenhouse temperature, the setpoints are correctly tracked with the adaptive PI controller even in spite of the deviation due to the remarkable solar radiation change at 14:40. As for the results presented in Fig. 6 for the model estimation with the RSBA, the MAE is 0.09 °C and the MaxAE is 0.95 °C in a range of [13.77, 24.44] °C. However, the fitness of the model could be better in some moments, as in the change of solar radiation at 14:40. In this sense, some tests should be performed by changing the variation rate of the model parameters to evaluate if the control performance could increase when great or fast changes occur in the process dynamics. In any case, the PI controller parameters are in a reasonable range, taking into account the different values of the model parameters compared to the values estimated for summer.

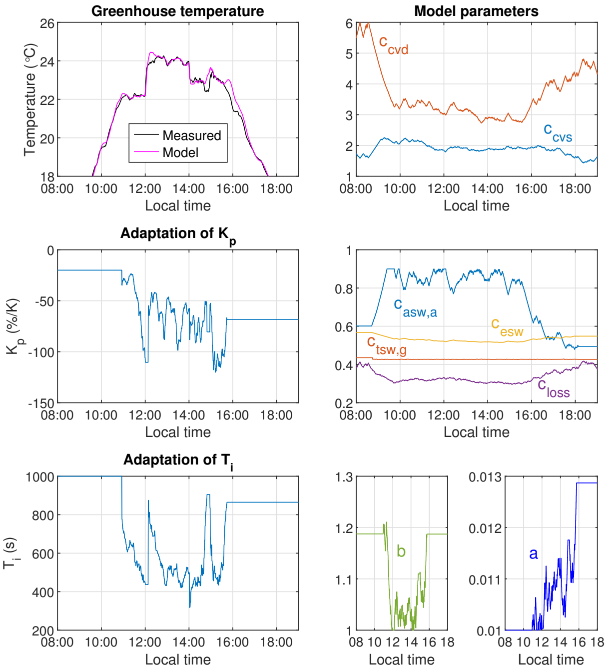

Fig. 6. Details of the adaptive control for the results of January, shown in Fig. 5

6. CONCLUSION

It is concluded that the adaptive PI controller could be used in a greenhouse to control the temperature with natural ventilation throughout a crop cycle. The controller adapts well to changing climatic conditions and different operating points. This makes the proposed control approach attractive for *plug-and-play* application in any greenhouse at any time of the year, considering its practicality due to its design simplicity.

Future work may be aimed at adjusting the features of the RSBA-based online estimator, like the variation rate for the model parameters, so that the model fits as well as possible to the measured temperature at instants with highly changing dynamics, which can result in better values for the controller parameters and increased control performance. The proposed adaptive control will be tested in a real greenhouse and adaptive feedforward compensators will be added for measurable disturbances rejection. In addition, the RSBA-based online estimator could be used for other control solutions that depend on the greenhouse temperature model, such as feedback linearization.

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