Computers and Electronics in Agriculture

Real-time adaptation of a greenhouse microclimate model using an online parameter estimator based on a bat algorithm variant

--Manuscript Draft--

Manuscript Number:	
Article Type:	Research Paper
Keywords:	Protected agriculture, greenhouse modelling, model adaptation, online estimation, metaheuristic algorithms.
Corresponding Author:	Mounir Guesbaya, Ph.D Universite Mohamed Khider de Biskra Biskra, Biskra ALGERIA
First Author:	Mounir Guesbaya, Ph.D
Order of Authors:	Mounir Guesbaya, Ph.D
	Francisco García-Mañas, Ph.D
	Hassina Megherbi, Senior lecturer
	Francisco Rodríguez, Full professor
Abstract:	Greenhouse microclimate modelling is a difficult task mainly due to the strong nonlinearity of the model and the uncertainty of some of its physical and non-physical parameters. The uncertainty stems from the fact that these parameters are unmeasurable or difficult to be measured and some of them are time-varying. All of this indicates the need for the online estimation of these parameters. In this paper, an online parameter estimator is developed based on an enhanced variant of the Bat Algorithm called the Random Scaling-based Bat Algorithm. This work concentrates on two important variables of a greenhouse climate model: the internal air temperature and the internal solar radiation. The developed algorithm estimates the parameters of the greenhouse microclimate model sample-by-sample by minimizing a cost function. Constraints on the search range for the parameters are imposed to respect their physical sense. The online estimator was tested in a real greenhouse, and the experimental results illustrate the successful model adaptation in different agri-seasons, presenting an average error of less than for air temperature prediction and for solar radiation simulation. This proves the usefulness of the developed online parameter estimator as a suitable tool for this type of model adaptation problems.
Suggested Reviewers:	Armando Ramirez Universidad Autónoma Chapingo: Universidad Autonoma Chapingo ariasar_mx@yahoo.com.mx
	Fátima Baptista Universidade de Évora: Universidade de Evora fb@uevora.pt
	Ming Li National Engineering Research Center for Beijing Biochip Technology lim@nertica.org.cn
	Nick Sigrimis Agricultural University of Athens: Geoponiko Panepistemio Athenon ns@aua.gr

Cover Letter

Mounir Guesbaya
University of Mohamed Khider, Biskra
BP 145 RP, Biskra 07000, Algeria

30 April 2021

Dear recipient,

I wish to submit an original research article entitled "Real-time adaptation of a greenhouse microclimate model using an online parameter estimator based on a bat algorithm variant" for consideration by *Computers and Electronics in Agriculture*.

I confirm that this work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere.

In this paper, we report on developing an online parameter estimator for the real-time adaptation of a greenhouse microclimate model. This is significant because the adaptation techniques are of high importance for enhancing the complicated and nonlinear greenhouse systems and for the agriculture domain in general.

We believe that this manuscript is appropriate for publication by *Computers and Electronics in Agriculture* because it involved the application of computer hardware and software to perform the simulations, electronic instrumentation for the data acquisition and the experimental validation, and this all aims for solving problems in agriculture.

We have no conflicts of interest to disclose.

Please address all correspondence concerning this manuscript to me at mounir.guesbaya@univ-biskra.dz

Thank you for your consideration of this manuscript.

Sincerely,

Mounir Guesbaya

Highlights

- An online estimator for the time-varying parameters of a greenhouse microclimate model was developed.
- The online estimator is based on an enhanced bat algorithm with adaptive search space.
- Air temperature and solar radiation are the microclimate variables under study.
- Assessments were performed in a commercial-sized greenhouse with grown crops and active natural ventilation.
- Adaptation of the microclimate model has been successfully performed in real-time.

Real-time adaptation of a greenhouse microclimate model using an online parameter estimator based on a bat algorithm variant

Mounir Guesbaya[a,*], Francisco García-Mañas[b], Hassina Megherbi[c], Francisco Rodríguez[b]

[a] University of Biskra, Department of Electrical Engineering, LI3CUB laboratory, BP 145 RP, Biskra 07000, Algeria

[b] University of Almería, Department of Informatics, CIESOL, ceiA3, E04120 Almería, Spain

[c] University of Biskra, LARHYSS laboratory, BP 145 RP, Biskra 07000, Algeria

Abstract

Greenhouse microclimate modelling is a difficult task mainly due to the strong nonlinearity of the model and the uncertainty of some of its physical and non-physical parameters. The uncertainty stems from the fact that these parameters are unmeasurable or difficult to be measured and some of them are time-varying. All of this indicates the need for the online estimation of these parameters. In this paper, an online parameter estimator is developed based on an enhanced variant of the Bat Algorithm called the Random Scaling-based Bat Algorithm. This work concentrates on two important variables of a greenhouse climate model: the internal air temperature and the internal solar radiation. The developed algorithm estimates the parameters of the greenhouse microclimate model sample-by-sample by minimizing a cost function. Constraints on the search range for the parameters are imposed to respect their physical sense. The online estimator was tested in a real greenhouse, and the experimental results illustrate the successful model adaptation in different agri-seasons, presenting an average error of less than 0.28 °C for air temperature prediction and 20 Wm^{-2} for solar radiation simulation. This proves the usefulness of the developed online parameter estimator as a suitable tool for this type of model adaptation problems.

Keywords: Protected agriculture, greenhouse modelling, model adaptation, online estimation, metaheuristic algorithms.

Corresponding author: Mounir Guesbaya
Email addresses: mounir.guesbaya@univ-biskra.dz (M. Guesbaya), francisco.gm@ual.es (F. García-Mañas), h.megherbi@univ-biskra.dz (H. Megherbi), frrodrig@ual.es (F. Rodríguez)

1. Introduction

The agricultural greenhouse is an enclosure generally based on a metal structure covered by a transparent plastic or glass cover that allows solar radiation to pass through. Inside the enclosed structure, an isolated environment is created, and it is commonly called the greenhouse microclimate. Nowadays, modern agriculture is outstandingly affected by the greenhouse production system, which plays a very important role in enhancing the management, qualities, and quantities of agricultural productions. The continuous optimisation of the greenhouse production system is required to suit the increasing strict standards of the local and international markets. The very essential optimisation level in the hierarchical structure of the greenhouse production system is the microclimate variables prediction and control tasks that affect directly the crop growth and yield (Van Straten et al., 2010; Rodríguez et al., 2015).

The microclimate variables prediction inside a greenhouse has been studied in the literature using different grey-box and black-box models (Fourati., 2014; Rodríguez et al., 2015; Ali et al., 2018; Choabet al., 2019; Hoyo et al., 2019; Hasni et al., 2011; Yu et al., 2016; Li et al., 2020). To reach good prediction performance despite the high nonlinearity of the phenomena and their physical interconnection and the presence of uncertainties, these models were identified using various optimisation or estimation approaches based on either numerical or artificial intelligence algorithms. In all these works, the datasets of one or a few days have been used in the estimation phase and the validation has been carried out in a short period. Thus, they are suitable only for short-term usage. In the long-term applications, they might be inappropriate because of the presence of the time-varying parameters which depend on the external weather conditions and the state of the crop (Vanthoor et al., 2011). Those time-varying parameters are usually unmeasurable, or their measuring instrumentation or procedures are unaffordable (Choabet al., 2019; Guesbaya et al., 2019; Ma et al., 2019), so their online estimation is a fundamental need.

Online parameter estimation consists of estimating the values of the model parameters in parallel with the operation of the model, using the available data from the real system to achieve the model adaptivity. Very few proposals on online parameter estimation and adaptive modelling have been reported in the literature with the application to greenhouses. In (Pérez-González et al., 2018), the authors proposed a two-stage identification methodology consisting of an offline pre-estimation stage and online sample-to-sample estimation stage. It is applied for real-time estimation of the air temperature and relative humidity models. The prediction accuracy in the cited work is satisfactory, showing a good fit between measured and predicted variables. However, only one sample of the measures data has been used for the model adaptation. Consequently, the required sampling time is one second which is very small and will probably increase the complexity and the computational cost. Moreover, the greenhouse used in the experimental study is an empty greenhouse prototype, so the effect of the presence and evolution of the crop state is not assessed. Another interesting study was reported in (Frausto et al., 2003), where the authors have investigated in a first step the modelling of the greenhouse temperature using the auto-regressive models with exogenous variables (ARX) and autoregressive–moving-average (ARMAX) models at the beginning and the middle of each season. In a second step, they have proposed to construct a general model for each type (ARX and ARMAX) from the corresponding seasonal models for the sake of having sufficient accuracy throughout the complete year. Then, they have investigated the retuning of the obtained general models at fixed time intervals (7 and 30 days) and when the accuracy falls below a predefined threshold value (70%). The results were obtained from a simulation study using simulated datasets obtained from Gembloux dynamic greenhouse climate model. They revealed the superiority of the ARX model over the ARMAX and the retuning when the performance falls below a predefined threshold value over fixed time interval retuning. They also revealed the inability of the developed model to maintain acceptable accuracy in the ventilation periods. In (Speetjens et al., 2009), the authors have proved the suitability of using the extended Kalman filter (EKF) for greenhouse climate model adaptation. However, they declared that the estimation only works well when the number of parameters to be estimated is not too large (four parameters). The work shows only the monthly quantitative performance of the model, but not the daily one which is highly important. In the current work, the number of the time-varying parameters to be estimated is ten, and the performance of the model is quantitatively shown in days with superior simulation accuracy in the case of air temperature prediction.

In this paper, an online parameter estimator is developed for real-time adaptation of a greenhouse microclimate model aiming for a successful long term microclimate variables prediction. In recent years, the popularity of nature-inspired optimisation algorithms is expanding, and these algorithms are being developed at an increasing rate (Yang., 2014). One of these well-known algorithms is the bat algorithm (BA), which has been enhanced in different ways (Yang et al., 2013). In this paper, an enhanced variant of BA, proposed in previous work (Guesbaya et al., 2019), called the random scaling-based bat algorithm (RSBA) is used and it constitutes the core of the proposed online

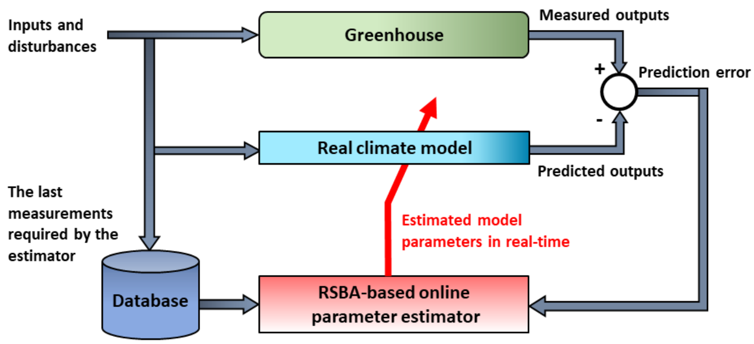

Fig. 1. Principle of the greenhouse microclimate prediction based on real-time parameter estimation

parameter estimator. The RSBA algorithm is chosen to deal with parameters coupling of the greenhouse microclimate model by increasing the possibility of finding a global solution while avoiding local optima. The proposal of this work is summarized in Fig. 1. It aims to accurately predict the internal air temperature directly affecting the crop growth and to simulate the internal solar radiation reaching the crop which in turn affects the internal air temperature. The estimator adapts the nonlinear model by estimating some of the time-varying parameters of its differential equations in a sample-by-sample estimation frequency. The developed online parameter estimation method includes the following considerations:

1. The RSBA-based online parameter estimation is done with a "virtual climate model" of the greenhouse, which is used to simulate the previous time instants (previous scenario) considering the real measured microclimate variables. With an iterative process, the "virtual model" is re-simulated until finding better values for its parameters by minimizing a cost function for the error between the real measurements and the model simulated variables. The new estimated values for the parameters are updated in the original microclimate model as a real-time adaptation.
2. The selection of the number of the previous last time instants for measured inputs, disturbances and outputs to be evoked by the "virtual model" is controlled with a rule-based data selection method.
3. The search ranges of the parameters are designed to be adaptive. They depend on the best corresponding parameters values and a predefined parameter variation ratio.
4. The estimated parameters are constrained to respect their physical sense.
5. Each parameter is estimated only when its corresponding physical phenomenon is active and affecting the

microclimate model output.

Consequently, the proposed set of estimation mechanisms and constraints has shown their efficiency by leading to significant advantages compared to the few proposed works in literature. The advantages and features of the proposed method are summarized as follows:

- The chosen sampling time in this work is one minute which is very sufficient for the greenhouse climate prediction and also for additional control adaptation.
- This work pays more attention to the physical aspects of the system nature and also to the computational and algorithmic aspects. The evolution of the estimated parameters is illustrated in all cases. It is an important dynamic to be analysed to understand the real effect of the proposed time-varying parameters on the behaviour of the model, and how to enhance the estimation mechanisms for the sake of optimality. Moreover, the search is restricted to fit the physical nature of each parameter, in turn, the calculated corresponding heat flux.
- The real-time estimation of parameters was based on a "virtual climate model" by minimizing the error between the measured and predicted set of samples of an n last time instants which led to a better adaptation, not only the last time instant.
- The parameters are estimated every time step (sample-by-sample estimation) leading to a very quick and successful microclimate model adaptation even under active natural ventilation actuators and high wind velocities.
- This work is assessed in a commercial-sized greenhouse (floor area of 877 m^2) with a grown tomato crop (high LAI values). Moreover, it is successfully validated in real-time over 15 days in the winter season, under a harsh climate with some cloudy, rainy and windy days.

This paper is organized as follows. In Section 2, the greenhouse facilities, the microclimate model, and the RSBA algorithm are presented. Section 3 describes the methodology of the developed RSBA-based online parameter estimator. In Section 4, the simulation and experimental results are presented and discussed. Finally, Section 5 contains the conclusions and future works.

2. Materials and methods

2.1. Greenhouse facilities

2.1.1. Structure and actuators

The greenhouse utilised in this work is presented in Fig. 2. It is a traditional Mediterranean greenhouse, commonly named “Almería-type” greenhouse. It is located at “Las Palmerillas” Experimental Station which is a property of the Cajamar Foundation (36.79316 latitude, -2.72014 longitude), in Almería, Spain at an altitude of 151 m. The total surface of the greenhouse is 877 m^2 (37.80 m × 23.20 m) and it is protected by a polyethene cover. Under the cover, an approximate area of 600 m^2 is reserved for the crop. The plants are cultivated in coconut coir bags aligned in rows orientated from north to south with a slope of 1%.

The greenhouse is equipped with several actuators to control the microclimate under the cover, providing

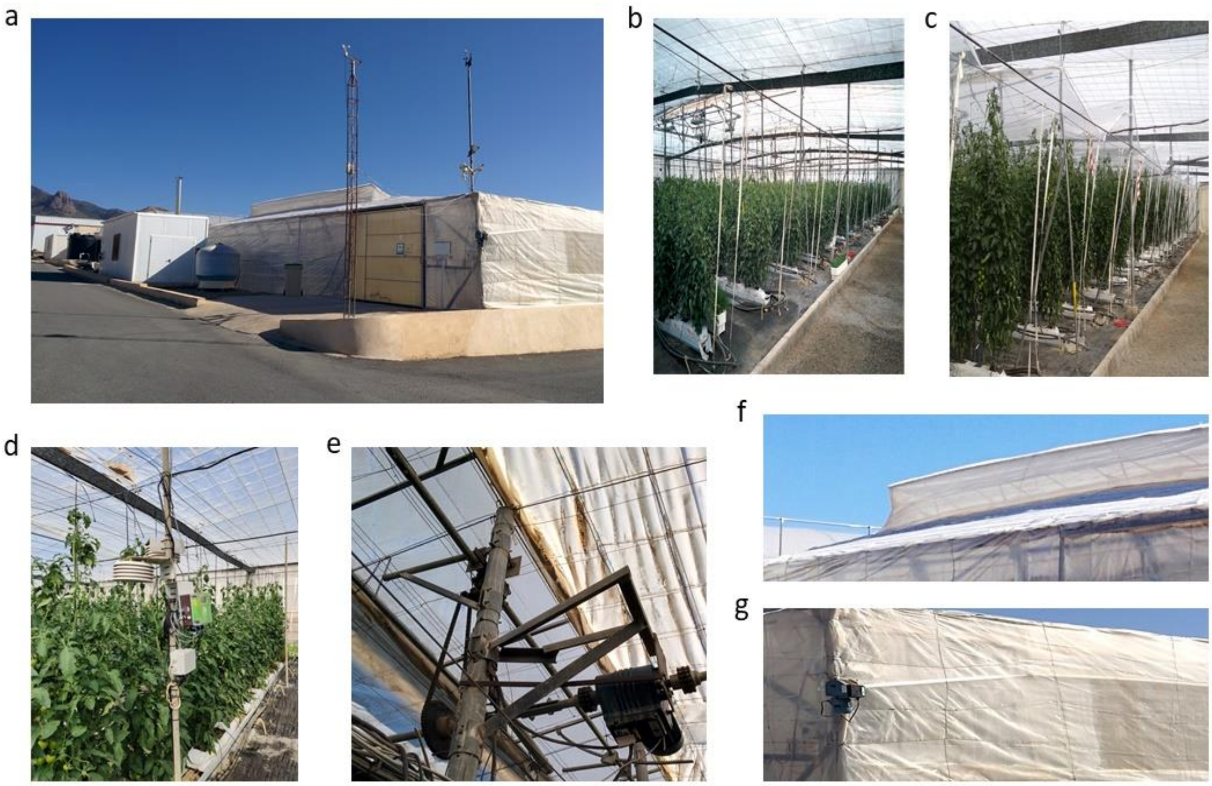

Fig. 2. Greenhouse facilities used for the experimental tests. (a) exterior view; (b) interior view without 2nd cover; (c) interior view with the second cover installed; (d) Example of a commercial data acquisition device, and the inside temperature and humidity sensors; (e) interior view of roof vent; (f) exterior view of roof vent; (g) exterior view of sidewall vent.

adequate conditions required by the plants for optimal crop growth. Thus, the greenhouse facilities are complemented with a humidification and dehumidification system, a carbon dioxide enrichment system, a pipe heating system based on a biomass boiler, and a natural ventilation system, among others. For the natural ventilation system, five zenithal windows (8.36 m × 0.73 m) are installed on the roof of the structure and two lateral windows (32.75 m × 1.90 m) are situated along the north and south sidewalls of the cover.

2.1.2. Data acquisition system

A wide set of sensors is deployed inside and outside the greenhouse to measure all the climatic variables affecting the crop. An external weather station measures air temperature and humidity, solar radiation, CO_2 concentration in the air, and wind velocity. Inside the greenhouse, a protected probe is employed to measure the inside air temperature and relative humidity (see Fig. 2d). Several sensors are installed in different rows of the crop to measure the CO_2 concentration in the air, the solar radiation under the cover and the temperature of the soil surface.

The distributed sensors are connected to a series of data acquisition devices (Compact FieldPoints, National Instruments, Austin, TX, USA), which transmit the measurements through an Industrial Ethernet network to a supervisory and control data acquisition (SCADA) system based on LabVIEW (National Instruments).

The computational unit used for the real-time application is a computer located in the same experimental station near the greenhouse. The computer specifications are Intel Core i7-7700, quad-core and 8 threads with 3.60 GHz (up to 4.20 GHz), 16 GB RAM DDR4 2133 MHz, and equipped with Windows™ 10 64-bit, MATLAB R2017b and LabVIEW™ 2015.

2.1.3. Maintenance and cultural tasks

During a crop season, different maintenance and cultural tasks are usually practised to the plants to ensure a healthy evolution toward the desired growth yield. For this work, two types of maintenance tasks were registered since they affect the state of the crop and/or they have an impact on the greenhouse microclimate. An example of the type of maintenance tasks is the periodical pruning of the plant's leaves to reduce the crop leaf area index (LAI). The type of cultural tasks is related for example to the whitening of the cover and the necessity of regulating the solar radiation transmission through the cover of the greenhouse. The whitening of the cover is usually performed in the months with the highest values of solar radiation (spring and summer) to reduce the net radiation that reaches the crop. For the autumn and winter period, the whitening is removed. Also, during the coldest periods, a floating plastic cover can be installed inside close to the plants to increase the isolation of the crop from the outside weather. All these tasks are considered in the present work to explain the evolution of the microclimate recorded at the greenhouse, as described in Section 3.

2.2. Greenhouse microclimate model

The greenhouse physical interactions taken into consideration in the present work are described in Fig. 3. The greenhouse microclimate dynamics can be generally expressed with the following equation (Rodríguez et al., 2015):

$$\frac{dX}{dt} = f(X, U, D, C, t) \qquad (1)$$

where $X(t)$ is the vector of the state variables which represents the microclimate variables as air temperature, air humidity and air CO_2 concentration among others (soil, cover and plant temperatures), $U(t)$ is the vector of input variables, $D(t)$ is the vector of the disturbances, $C(t)$ is the vector of the time-varying parameters that have to be estimated, and t is the time. In the following subsections, the general equations of the model are briefly explained. In this work, only the inside air temperature and the inside solar radiation are considered, but the proposed methodology and the results can be applied to other state variables.

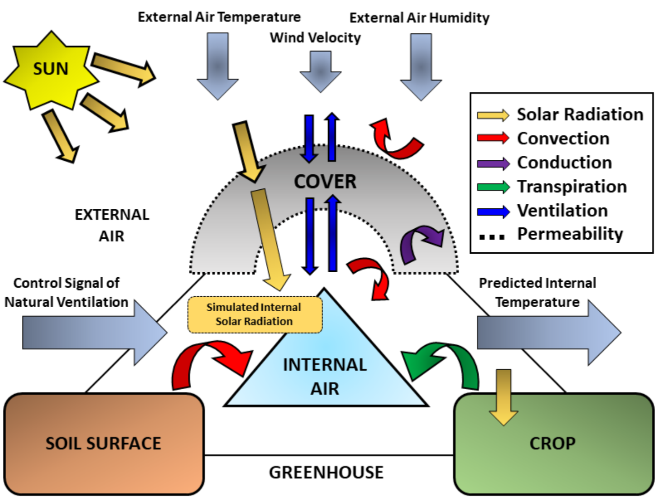

Fig. 3. Greenhouse model components and heat transfer interactions.

2.2.1. Temperature model

The greenhouse air temperature model used in this work is considered a simplified nonlinear pseudo-physical model. It includes a series of terms representing energy balances inside the greenhouse. The model is described with the following differential equation (Rodríguez et al., 2015):

$$C_{ter}\frac{dXT_{in}}{dt} = Q_{sol,a} + Q_{cnv,ss-a} - Q_{cnd-cnv,a-e} - Q_{trp,cr} - Q_{vent,a} \tag{2}$$

$$C_{ter} = C_{sph}\,C_{den}\,\frac{C_{vol}}{C_{area}} \tag{3}$$

where XT_{in} represents the inside air temperature of the greenhouse and Q refers to the heat fluxes occurring inside the greenhouse. $Q_{sol,a}$ is the solar radiation flux absorbed by the air (although it is inert to radiation, most of the simplified models consider this assumption), $Q_{cnv,ss-a}$ is the convective flux between the soil surface and inside air, $Q_{cnd-cnv,a-e}$ represents the convective and conduction fluxes between the inside and outside air (at the cover level), $Q_{trp,cr}$ describes the latent heat effect of crop transpiration, and $Q_{vent,a}$ is the heat lost by natural ventilation. C_{vol} is the greenhouse volume, C_{area} is the greenhouse surface, C_{sph} is the specific heat of the air, and C_{den} is the air density. All the equations of the heat fluxes and the descriptions of their parameters that are not presented in this paper can be found in (Rodríguez et al., 2015).

2.2.2. Solar radiation model

This static model simulates the solar radiation passing through the cover and reaching the crop (Rodríguez et al., 2015). It is combined with the air temperature model as one of its sub-equations based on an empirical term described as follows:

$$V_{sr,cr} = C_{tsw,cv}\,D_{sr,e} \tag{4}$$

where $C_{tsw,cv}$ is the cover solar transmission coefficient which is usually considered constant. In this work, it is considered as a time-varying parameter due to the changing properties of the plastic material with time and because of the external factors affecting the plastic features. Thus, this time-varying parameter has to be estimated in real-time for adaptation to any changes in the greenhouse materials (e.g., cover material, whitening, shading, dirt, etc.). The parameter estimation technique aims to minimize the error representing the difference between the measured and simulated internal solar radiation variables. The estimation of the solar transmission coefficient and the air temperature model parameters at the same time instant is considered as a challenge due to the connection between the models and the need of performing more than one estimation process every time instant. A brief description of the parameters in Eqs (2-4) can be found in the glossary at the end of this paper.

2.3. Greenhouse experimental datasets

In this work, three datasets containing the greenhouse climate variables are used. Two datasets were already acquired in different periods of the year and one has been acquired during the real-time testing of the developed online estimator. The first dataset was acquired during the transitional period between the winter and spring seasons, starting from 27 March 2020 to 11 April 2020 (15 days, 21500 samples) as presented in Fig. 4. The second dataset was acquired during the transitional period between the summer and autumn seasons, starting from 01 September 2020 to 15 September 2020 (15 days, 21500 samples) as presented in Fig. 5. The third dataset has been acquired during the winter season starting from 07 January 2021 to 22 January 2021 (15 days, 22000 samples) as presented in Fig. 6.

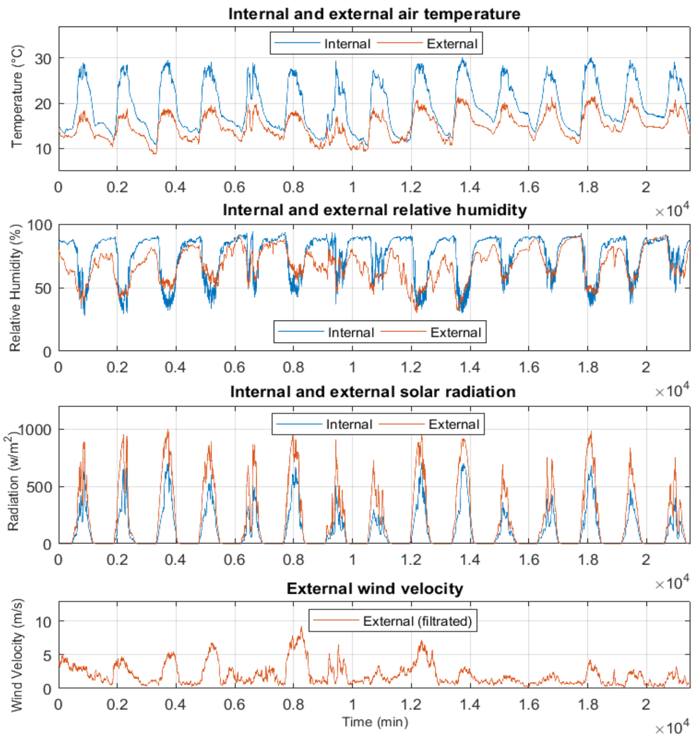

Fig. 4. Dataset of the transitional period between winter and spring seasons starting from 27 March 2020 to 11 April 2020

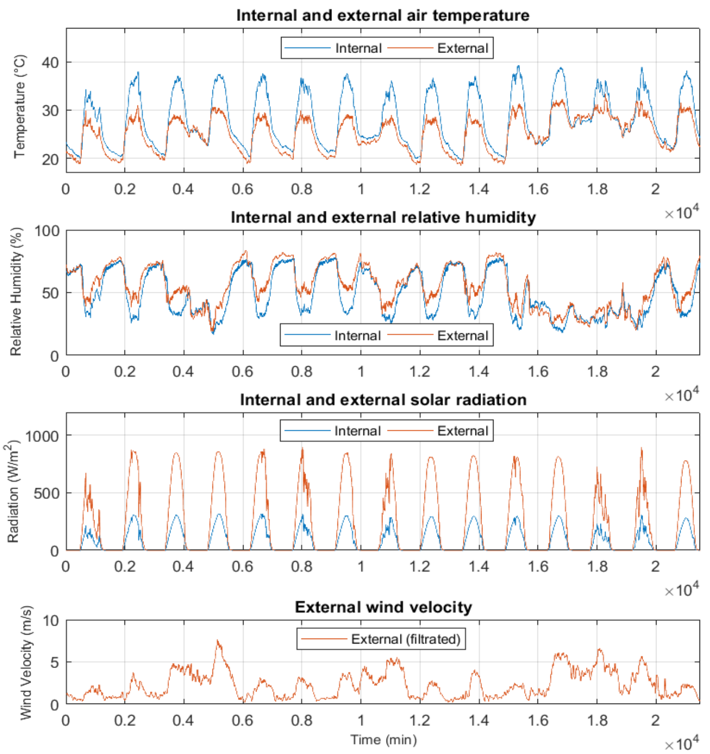

Fig. 5. Dataset of the transitional period between summer and autumn seasons starting from 01 September 2020 to 15 September 2020

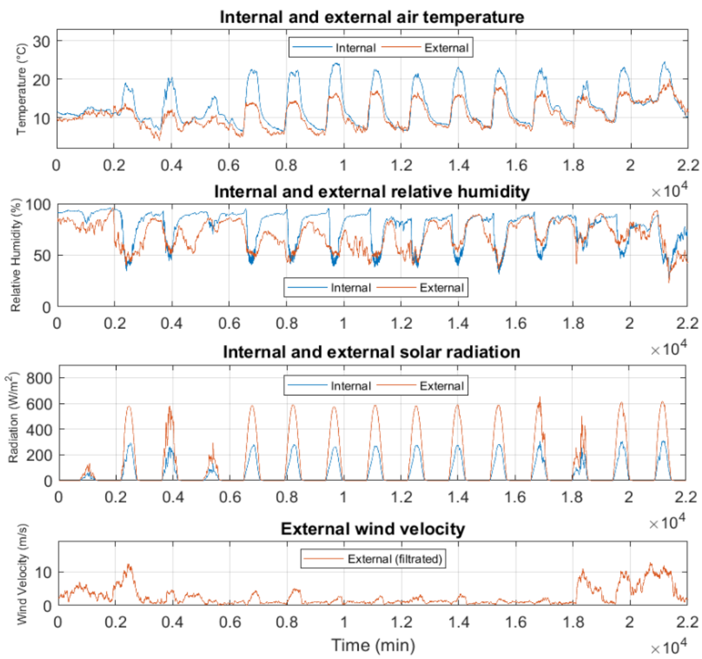

Fig. 6. Dataset acquired during the real-time application of the online estimator in winter season starting from 07 January 2021 to 22 January 2021

2.4. Random scaling-based bat algorithm

The RSBA used in this work is a variant of BA proposed in previous work (Guesbaya et al., 2019). It constitutes the optimisation tool in the proposed online estimator to adapt the values of the parameters of the greenhouse microclimate model. Similar to the BA, each i^{th} virtual bat manipulated by the RSBA is characterized by the position representing the solution x_i and the velocity v_i, in addition to the frequency f_i and the loudness A_i of the emitted pulse and the pulse emission rate r_i. BA is a nature-inspired optimisation algorithm. It has been inspired and developed based on bats' behaviour, imitating their searching on preys using echolocation competence (Yang, 2014). The set of n virtual bats (population) is simulated under a set of rules defined as follows:

- All bats sense distance and differentiate between prey and objects based on echolocation capability.
- Bats fly based on random walk technique with a velocity v_i at position x_i and transmit pulses with a frequency f_i tuned automatically within a given interval $[f_{min}, f_{max}]$.
- The rate of pulse emission r_i is also tuned automatically according to the closeness of the target.
- The loudness A_i is considered variant, starting from a large positive value A_0 to a minimum value A_{min}.

The frequency, velocity and position are updated based on the following terms:

$$f_i^t = f_{min} + (f_{max} - f_{min})\beta^t \quad (5)$$

$$v_i^{t+1} = v_i^t + (x_i^t - x_*^t)f_i^t \quad (6)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (7)$$

where $\beta^t \in [0, 1]$ is a random vector drawn from a uniform distribution, and x_*^t is the current global best solution. According to each bat's pulse emission rate, another new solution is generated locally around x_*^t during the exploitation stage using random walk based on the following term:

$$x_i^{t+1} = x_*^t + \sigma^t \epsilon^t \overline{A^t} \quad (8)$$

where σ^t is the scaling factor that controls the step size of the local random walk, $\epsilon^t \in [-1, 1]$ is a random number, and $\overline{A^t}$ is the average of bats loudness at t.

The enhanced feature included in RSBA is related to the scaling factor σ^t which is not considered constant as in the standard BA. In this sense, the scaling factor in RSBA is considered dynamical based on a random selection mechanism as follows:

$$\sigma^t = \sigma_{min} + (\sigma_{max} - \sigma_{min})\beta^t \qquad (9)$$

where σ_{min} and σ_{max} are respectively the maximum and minimum values of the scaling factor σ^t. The essence of this enhancement is to give more flexibility to the exploitation search steps around the best global solution to increase the chance to reach the optimality. More details of the RSBA can be found in (Guesbaya et al., 2019).

3. Methodology of developing the online parameter estimator

This section presents the methodology to develop the proposed online parameter estimator based on RSBA for greenhouse microclimate adaptive modelling purposes. Implementation efforts have been aimed at demonstrating the potential of the developed estimator to achieve a real-time adaptation of the used microclimate model according to Fig. 1. The online model parameter estimation enhances the accuracy of the internal air temperature prediction and the internal solar radiation simulation at the same time step. The main stages of the methodology and their purposes are illustrated in Fig. 7. They are explained as follows:

1. Offline model calibration: This stage consists of the application of the RSBA to calibrate the greenhouse microclimate model with an offline parameter identification process using real data from the greenhouse. For this offline calibration, all the parameters of the model are considered constant. The identified parameter values are calculated so that they can be used in the next stages for the model sensitivity analysis and as initial parameter values for the next online estimation processes using different datasets of different seasons. The cost function used in this stage to evaluate the calibration of the model is the *Mean Square Error* (MSE).
2. Model sensitivity analysis: In this stage, the sensitivity of the model is studied to understand the influence of its parameters. Two different sensitivity analysis are performed to compare results when assuming constant versus

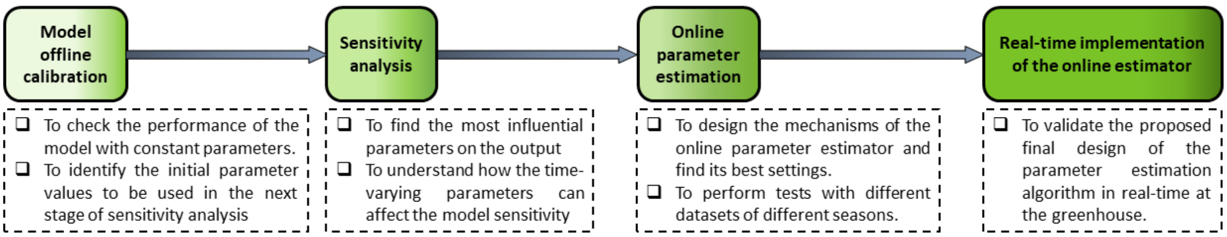

Fig. 7. Proposed methodology to develop the online parameter estimator

time-varying parameters. On the one hand, it aims to investigate how much each parameter affects the model outputs. On the other hand, using different sets of parameter values with the same greenhouse climate dataset of one day helps to examine the change in the model sensitivity affected by the time-varying parameter values. These tests are also performed to facilitate the selection of the variation ratios for the parameters, depending on how sensitive the model is toward each parameter.

3. Online parameter estimation: In this stage, the final structure of the developed online parameter estimator is accomplished as illustrated in Fig. 8. It involves a combination of mechanisms that are designed based on the results of the previous stages and some trial-and-error procedures. For the estimation process, ten parameters of the greenhouse microclimate model are considered time-variant. The microclimate model is effectively adapted by online estimating the values of the time-varying parameters to minimize the cost function for this stage which is the *Root Mean Square Error* (RMSE) representing the error between the real measured data and the model simulated variables. The RMSE penalizes errors greater than 1, which helps in avoiding undesirable large error

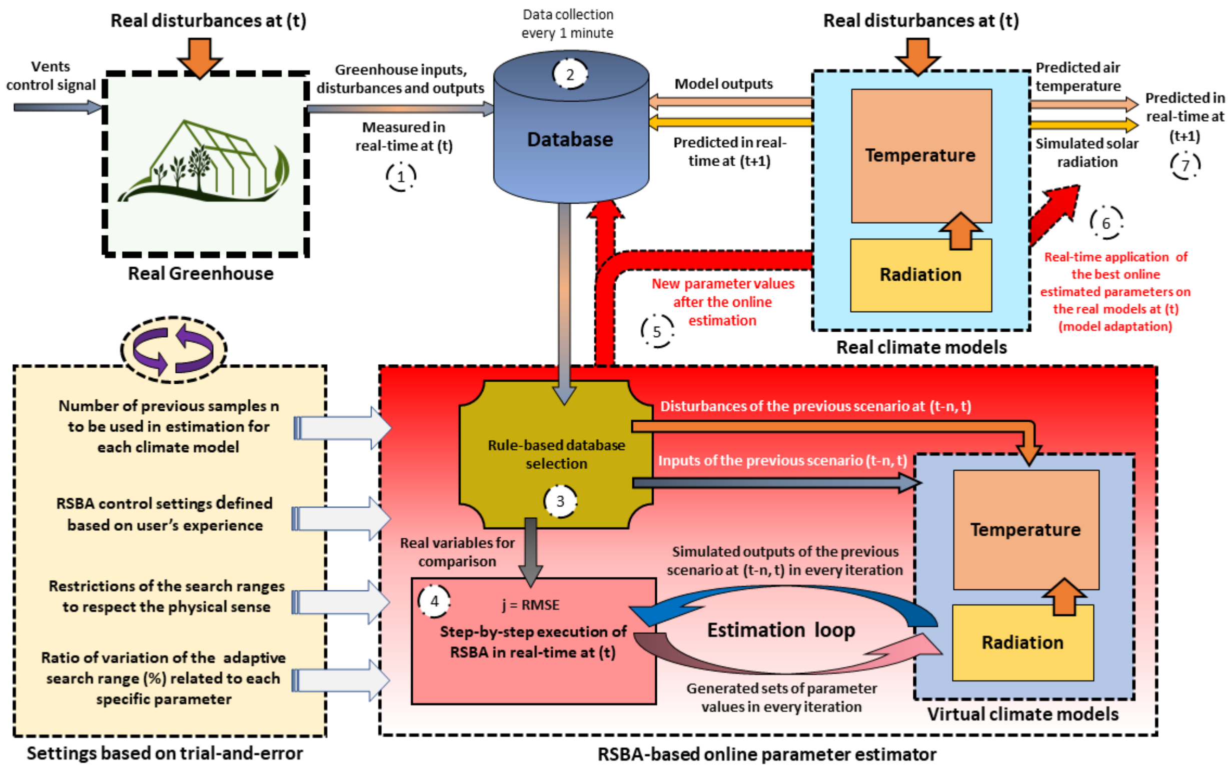

Fig. 8. Online estimator mechanism and its real-time application scheme

oscillations. The online estimation is performed with real datasets of different seasons to assess the adaptation capability of the estimator against different climate conditions. The proposed estimation mechanisms, settings and constraints are described as follows:

a. Air temperature and solar radiation models are adapted together as two targets but with different execution times for their respective online parameter estimation processes.

b. The online estimation processes for both models are performed based on two other "virtual models" identical to the original ones. The "virtual models" are used to simulate the previous scenario consisting of the n last time instants at $[t-n,\ t]$ based on the last previous inputs, outputs and disturbances at $[t-n,$ $t]$. This means that the selected n data samples are used for the estimation process in a sub-algorithm with an identical greenhouse microclimate model. This sub-algorithm is used as a testbed where all the potential solutions (sets of parameter values) generated by the RSBA are evaluated to find optimal values for the model parameters by minimizing a cost function for the error between the real n data samples and the model simulated variables. This aims to optimise the performance of the "virtual models" in simulating the previous scenarios at $[t-n,\ t]$ according to a specific number of iterations; then adapting the original models by applying the best-estimated parameters in real-time at t before predicting the next predicted sample at $(t+1)$.

c. The number n of previous time instants representing the last scenario at $[t-n,\ t]$ can be adjusted to suit the characteristics of each phenomenon to be simulated thanks to a rule-based data selection algorithm. The rule-based data selection algorithm is programmed in a nested way with the "virtual model" sub-algorithm to provide it with the needed previously measured data (inputs and disturbances) that represents the selected past time instants.

d. The RSBA is used as it is described in Section 2.3 except for the search ranges which are originally constant but, in this work, most of them are programmed to be dynamic and adaptive based on the physical nature of each parameter which determines how it varies in time. As described in Fig. 9, the adaptive search range of each parameter j varies between the boundaries of a larger range that represents the constraints for the adaptive range. The variation of each adaptive range is determined based on the current best parameter value at t according to a specific variation ratio $\pm R_j\%$ of the best parameter value itself (neighbourhood of variation) as presented in the following terms:

$$LB_j^t = C_j^t - R_j\% \qquad (10)$$

$$UB_j^t = C_j^t + R_j\% \qquad (11)$$

where LB_j^t and UB_j^t are respectively the lower and upper boundaries of the search range of the parameter to be estimated and C_j^t is the current value of the specific parameter j at t.

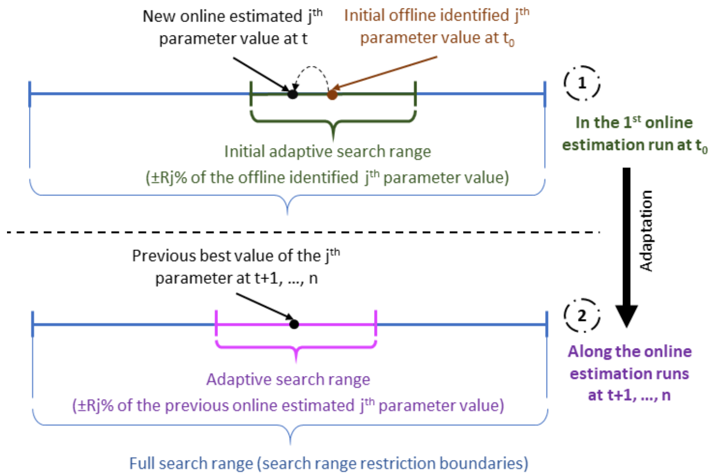

Fig. 9. The adaptive reduced search ranges and their restriction

e. A set of constraints are defined to restrict each adaptive search range (see Fig. 9). They are defined based on the common ranges mentioned in the literature for greenhouse microclimate modelling (Rodríguez et al., 2015; Choab et al., 2019), the physical nature of each parameter and some trial-and-error procedures performed with the microclimate model during the development of this work. It is important to highlight that, at each time instant, the parameters being estimated are only the ones related to an active physical process of the greenhouse microclimate at that moment t. For instance, the parameters related to radiation are online estimated only when radiation is greater than 5 $\mathrm{Wm^{-2}}$, the parameters related to ventilation are online estimated only when the vents of the greenhouse are open according to a control signal greater than 0%, and the parameters related to transpiration are online estimated only when the crop exists in the greenhouse with a LAI greater than 0.1 $\mathrm{m^2_{leaf} m^{-2}_{ground}}$. Otherwise, the values of those parameters are constant, equal to the last estimated value when the corresponding physical process was active.

4. Real-time application of the proposed online parameter estimator: The last stage is dedicated to the application of the developed parameter estimator at the real greenhouse. It is considered a crucial stage to validate the real-time adaptation of the greenhouse microclimate model under a real crop growth situation.

4. Results and discussion

This section presents the quantitative and qualitative results obtained for each development stage of the explained online parameter estimator. The statistical criteria used to evaluate all the results in the following sub-sections are: *Mean Absolute Error* (MAE), *Max Absolute Error* (MaxAE), *Coefficient of Determination* (R^2), *Residual Error* (RE), MSE and RMSE. For the simulation processes (except the real-time implementation), the used computational unit is a computer consisting of an Intel Core i7-4810MQ with an octa-core processor, 2.8 GHz, 16 GB RAM DDR3 1600 MHz, running a Windows™ 10 64-bit with MATLAB R2017b. The online parameter estimator has been coded in MATLAB and the following estimator developing processes were also carried out in MATLAB.

4.1. Offline model calibration

The offline model calibration procedure to identify the values of all the parameters of the greenhouse microclimate model can be found in (Rodríguez et al., 2015). An offline model calibration process intends to obtain the best possible simulation results of the internal air temperature and solar radiation, assuming constant parameter values. Additionally, the analyses performed in this stage can help in determining adequate search ranges for the parameters. The results of the simulation with offline calibrated parameters will be compared to the simulation results using the online estimated parameters to demonstrate the superiority of the developed online estimator.

To offline calibrate the greenhouse model, two different datasets were used in this stage, one from the winter-spring period (see Fig. 4) and another one from the summer-autumn period (see Fig. 5). Three days of the winter-spring dataset (3rd, 4th and 5th days) were selected for the calibration process as a climate-diversified target (calm and turbulent days) and both full datasets were used for validation. The simulation step time was fixed as 1 minute, which is suitable to investigate the greenhouse microclimate dynamics. The settings of the RSBA were chosen based on the personal experience with the algorithm and some trial-and-error processes, resulting as follows: the number of bats is 20, the maximum number of iterations is 500, the minimum and maximum frequency respectively are $f_{min} = 0$ and

$f_{max} = 2$, the loudness of the initial bats is $A_{\mathrm{i}}^{0} = 1$, the rate of pulse emission of the initial bats is $r_i = 0$ and $r_i^0 = 0.2$ and the constants α and γ are equal to 0.8. The scaling parameter randomly variates in a range of $\sigma \in [1, 10^{-3}]$.

The search ranges and the calibrated parameter values after the offline calibration are presented in Table 1. Fig. 10 and 11 present the air temperature and the solar radiation simulation results, respectively. It can be observed that the model calibration process was successful according to the acceptable fit between the measured and the simulated variables. Table 2 contains the statistical results based on the evaluation criteria, with a $MAE = 0.75$ °C, $MSE = 1.12$ °C^2 and $R^2 = 0.96$ showing a good error value.

Fig. 12 presents the graphical results of validating the offline calibrated air temperature model with the

Table 1. Search ranges and calibrated parameter values in the offline calibration procedure

Parameters	$\mathrm{C_{asw}}$	$\mathrm{C_{cnv,ss-a}}$	$\mathrm{C_{cnd-cnv,a-e}}$	$\mathrm{C_A}$	$\mathrm{C_{B_d}}$	$\mathrm{C_{B_n}}$	$\mathrm{C_{ven,d}}$	$\mathrm{C_{ven,w}}$	$\mathrm{C_{loss}}$	$\mathrm{C_{tsw,cv}}$
Range	[0.1, 0.9]	[1, 35]	[1, 30]	[0.2, 0.7]	[4, 26]	[4, 26]	[15, 35].10^{-3}	[0.1, 1]	[0.1, 1]	[0.1, 1]
Calibrated value	0.42	13.43	10.32	0.26	8.27	10.28	0.0016	0.11	0.2	0.56

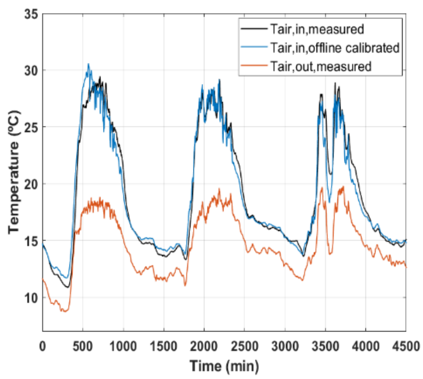

Fig. 10. Inside air temperature prediction after the offline calibration

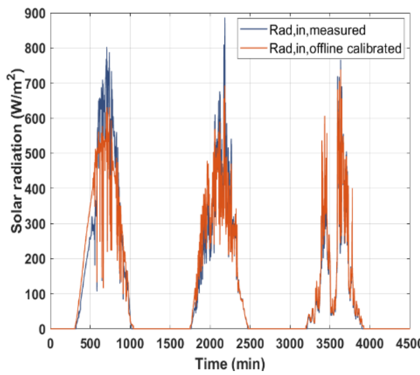

Fig. 11. Inside solar radiation simulation after the offline calibration

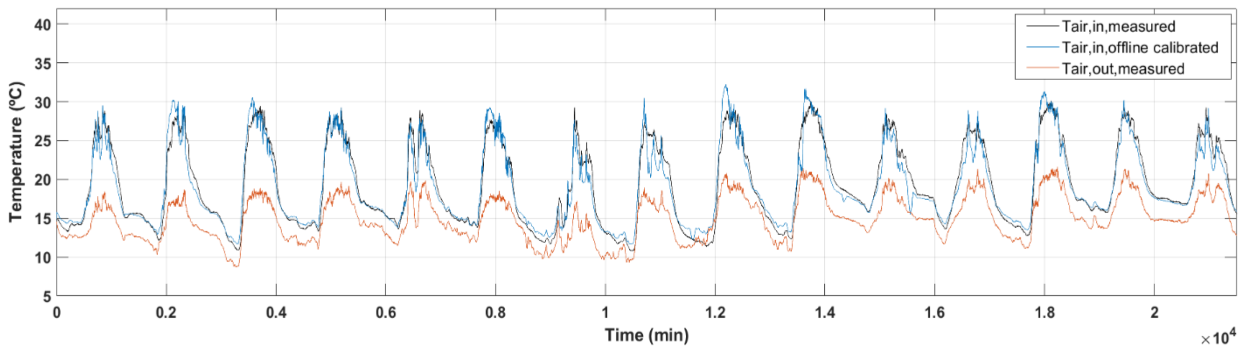

Fig. 12. Internal air temperature simulation: validation of the calibrated model with a large dataset in winter-spring period

Table 2. Statistical evaluation of internal air temperature simulation: calibration and validation results in short-term and long-term periods

	MAE (°C)	MSE (°C^2)	RMSE (°C)	MaxAE (°C)	Interval (°C)
Calibration in winter-spring	0.75	1.12	1.06	3.88	[10.9, 29.5]
Validation in winter-spring	0.98	1.78	1.33	6.39	[10.8, 30]
Validation in summer-autumn	1.65	6.22	2.49	8.05	[19.7, 39.3]

Table 3. Statistical evaluation of internal radiation simulation: calibration and validation results in short-term and long-term periods

	MAE (W m^{-2})	MSE (W^2 m^{-4})	RMSE (W m^{-2})	MaxAE (W m^{-2})	Interval (W m^{-2})
Calibration in winter-spring	19.72	1736.24	41.6	271.56	[0, 890]
Validation in winter-spring	29.37	3592.86	59.94	496.81	[0, 910]
Validation in summer-autumn	54.68	7826.46	88.4	299.73	[0, 530]

complete winter-spring dataset. According to the graphical results, it can be noticed that the simulation accuracy for the air temperature model in other days of the same dataset has decreased, showing larger errors between the model outputs and real measured variables. As shown in Tables 2 and 3, the accuracy decreases even more in the validation process against the summer-autumn dataset (the graphical results are not presented), evidencing an unsuccessful long-term prediction performance for the offline calibrated model. Similar conclusions can be obtained for the radiation model, according to Fig. 13 and Table 3. The mispredicted radiation values in most of the days can negatively affect the prediction of air temperature in turn. Therefore, the long-term simulation results should be improved, which highlights the necessity of applying an online estimator for model adaptation purpose.

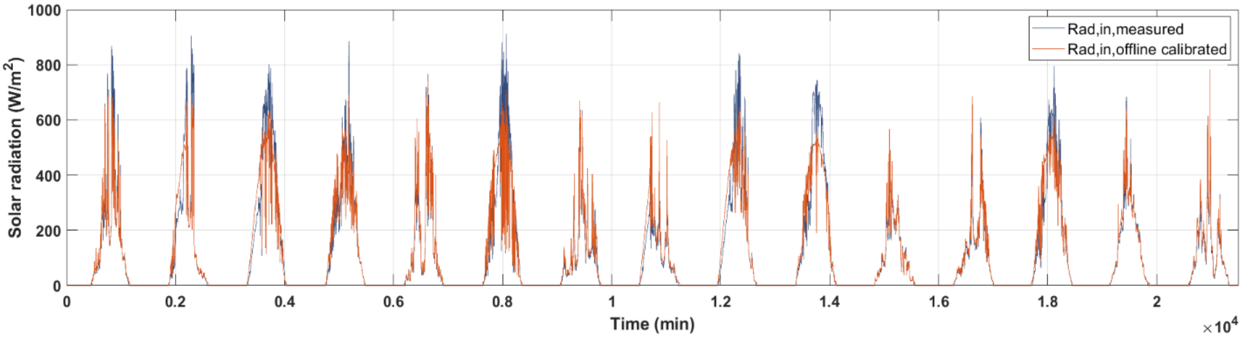

Fig. 13. Internal solar radiation simulation: validation of the identified model against a large database in winter-spring period

4.2. Sensitivity Analysis

In this section, a sensitivity analysis is performed for the air temperature model. Firstly, the sensitivity of the model using constant parameters is investigated during the diurnal and nocturnal periods as shown in Fig. 14. It can

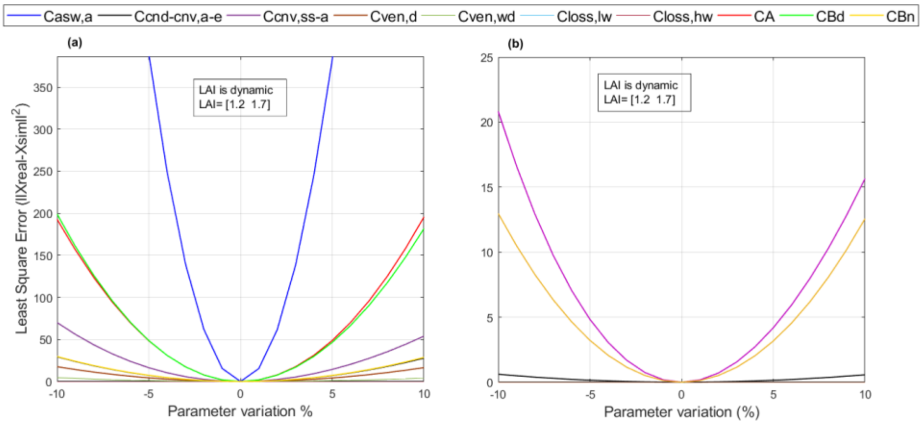

Fig. 14. Sensitivity analysis of the inside air temperature model. (a) the diurnal period; (b) the nocturnal period

be noticed in the diurnal period analysis that C_{asw} is the most influential parameter on the system, which is logical since it is related to solar radiation. The transpiration parameters C_A and C_{B_d} have also noticeable relevance, which is also logical according to the fundamental effect of the crop transpiration process. Apart from the parameter $C_{cnv,ss-a}$ related to the important effect of the soil surface temperature, and the rest of the parameters mostly have a non-relevant influence. In the nocturnal period, it can be observed that only two parameters mainly affect the system: $C_{cnv,ss-a}$, which explains the role played by the soil, as a heat accumulator during the day and as a heat releaser during the night, and C_{B_n}, which represents the effect of crop transpiration at night.

Furthermore, the sensitivity of the model using time-varying parameters has been investigated. This has been achieved by performing three sensitivity analysis processes with a real dataset of 1440 samples (1 day). The results are shown in Fig. 15 for three different sets of the main parameters presented in Table 4. It can be concluded that different sensitivity responses can be obtained when using time-varying parameters. Besides, it is noticed that increasing the parameters $C_{cnv,ss-a}$ and $C_{cnd-cnv,a-e}$ radically affects the model sensitivity, and they also alter the order of the most influential parameters. This also can be seen as a logical influence since the convection and

Table 4. Different sets of parameters used for the sensitivity analysis for time-varying parameters.

Parameters	C_{asw}	$C_{cnv,ss-a}$	$C_{cnd-cnv,a-e}$	C_A	C_{B_d}	$C_{ven,d}$	$C_{ven,w}$
Set 1	0.59	3.88	1	0.42	14	0.0021	0.23
Set 2	0.2	20	17	0.65	9	0.0024	0.6
Set 3	0.35	35	22	0.35	11	0.0027	0.4

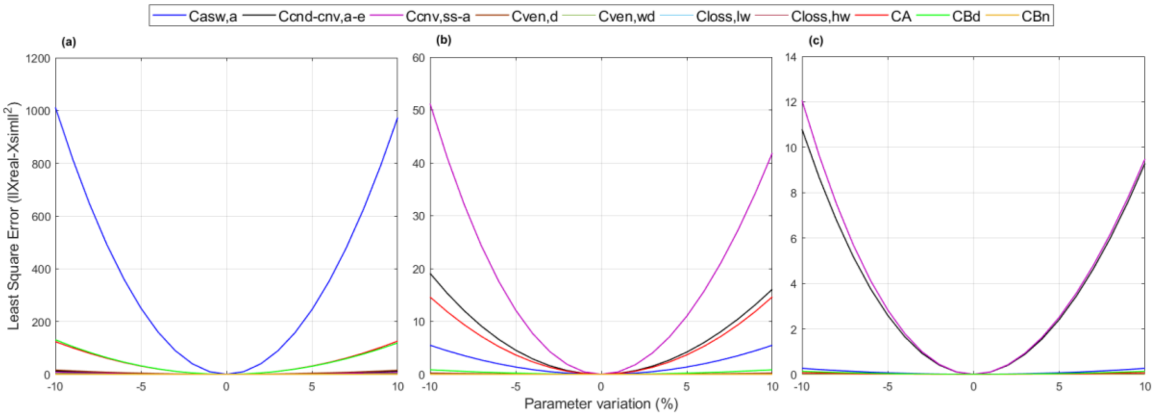

Fig. 15. Sensitivity analysis of the inside air temperature model according to different sets of parameters. (a) set 1; (b) set 2; (c) set 3

conduction processes depend on temperature differences which are indirectly affected by all of the climate variables. In contrast, increasing or decreasing the rest of the parameters affects the model sensitivity but not as much as $\mathrm{C_{cnv,ss-a}}$ and $\mathrm{C_{cnd-cnv,a-e}}$ which are considered as the most influencing time-varying parameters according to this test.

4.3. Online parameter estimation

In this sub-section, the problem of model adaptation is solved in simulation by using the developed online parameter estimator described in the methodology section. The settings for the estimator are chosen in this section as follows. The execution time of the parameter estimation process for each model is chosen to be:

- 1 minute for the estimation of the parameters affecting the air temperature model. This time is equal to the simulation step time of the model (sample-by-sample estimation).
- 20 minutes for the estimation of the parameter affecting the radiation model (requiring 20 past samples).

The number n of the previous time instants representing the last scenario at $[t-n,\ t]$ for each model is selected as:

- $n=3$ for the air temperature model adaptation. If it is greater than 3, it could generate undesirable fluctuations in the predicted variable. If it is less than 3, the information would not be sufficient for an efficient model adaptation process, leading to an inaccurate prediction.
- $n=60$ for the solar radiation model adaptation because the radiation parameter varies very slow in time. Changing it at a faster rate could generate an undesirable divergence in the radiation simulation, in turn, negatively affecting the air temperature prediction.

The dynamic search ranges $[LB_j,\ UB_j]$ used in the RSBA are adaptively updated based on the defined variation ratio for each parameter as presented in Table 5. The search range of the time-varying parameter $\mathrm{C_{tsw,cv}}$ in the solar radiation model is considered constant $[0, 1]$ but not adaptive. This allows the estimator to directly reach the lowest or the greatest values in the search range in case the shade screen or the cover whitening process are applied to or removed from the greenhouse. Moreover, when the greenhouse cover is deteriorated or becomes stained, the radiation inside the greenhouse can be correctly simulated thanks to the online estimation of $\mathrm{C_{tsw,cv}}$ in real-time. The defined constraints to restrict each adaptive search range are presented in Table 6.

Fig. 16 and 17 present the graphical results after simulating the online parameter estimator with the internal air temperature and internal solar radiation models using the dataset of winter-spring period. The corresponding heat fluxes evolution and the variation of the estimated parameters are presented in Fig. 18 and 19, respectively. The same test was performed with the dataset of summer-autumn and its results are presented only numerically in Table 7. In general, the graphical simulation results show a very promising performance based on the remarkable accurate fit between the measured and the simulated variables in comparison to the results of the offline calibrated model.

Table 5. Variation ratios for each parameter representing the adaptivity rates of the search ranges

Time-varying parameters	Variation ratios	Physical characteristics and effect on the air temperature model
$\mathrm{C_{asw}}$	$\pm 2\%$	- Medium variation ratio affected by external climate and covering material. - Model sensitivity is high due to the direct effect of solar radiation on the inside air, soil surface and crop.
$\mathrm{C_{cnv,ss-a}}$ and $\mathrm{C_{cnd-cnv,a-e}}$	$\pm 10\%$	- Very fast variation ratio affected directly by soil surface, inside and outside air temperature differences and indirectly by radiation, ventilation and transpiration. - Model sensitivity is very high because they are the most influential parameters.
$\mathrm{C_A}$ and $\mathrm{C_{B_{d/n}}}$	$\pm 0.2\%$	- Very slow variation ratio affected by crop transpiration process which follows the very slow crop growth evolution (LAI). - Model sensitivity is medium, essentially affecting the inside air but with less influence than solar radiation.
$\mathrm{C_{ven,d}}$, $\mathrm{C_{ven,w}}$ and $\mathrm{C_{loss}}$	$\pm 7\%$	- Fast variation ratio affected by the opening of vents and wind velocity which varies quickly. - Model sensitivity is low but it has a fast effect, highly dependent on wind velocity.

Table 6. Restrictions of the adaptive search ranges of each parameter

Parameters	$\mathrm{C_{asw}}$	$\mathrm{C_{cnv,ss-a}}$	$C_{cnd-cnv,a-e}$	$\mathrm{C_A}$	$\mathrm{C_{B_d}}$	$\mathrm{C_{B_n}}$	$\mathrm{C_{ven,d}}$	$\mathrm{C_{ven,w}}$	$\mathrm{C_{loss}}$	$\mathrm{C_{tsw,cv}}$
Range restriction	[0.1, 0.9]	[1, 100]	[1, 300]	[0.2, 0.7]	[4, 26]	[4, 26]	$[15, 35].10^{-3}$	[0.1, 1]	[0.1, 1]	[0.1, 1]

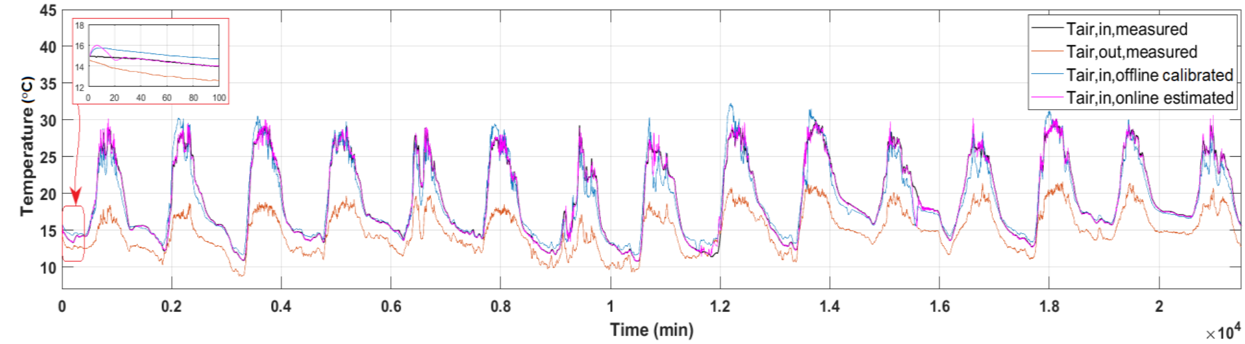

Fig. 16. Internal air temperature prediction using the online parameter estimator in winter-spring period

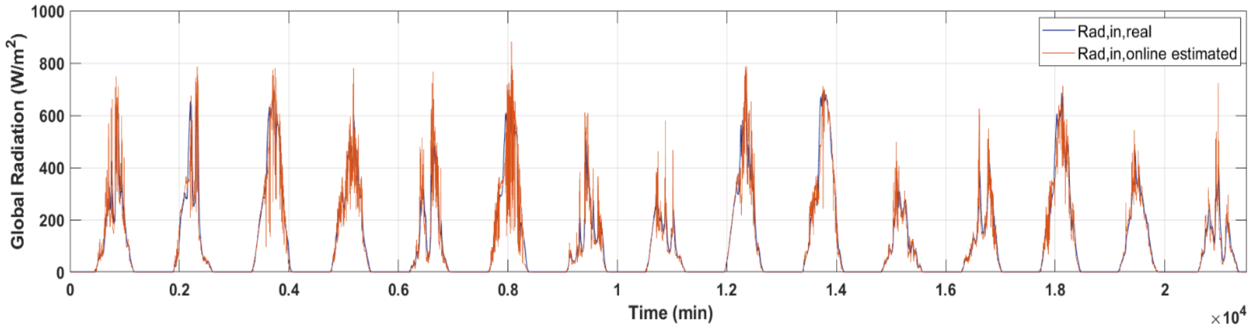

Fig. 17. Internal radiation simulation using the online parameter estimator in winter-spring period

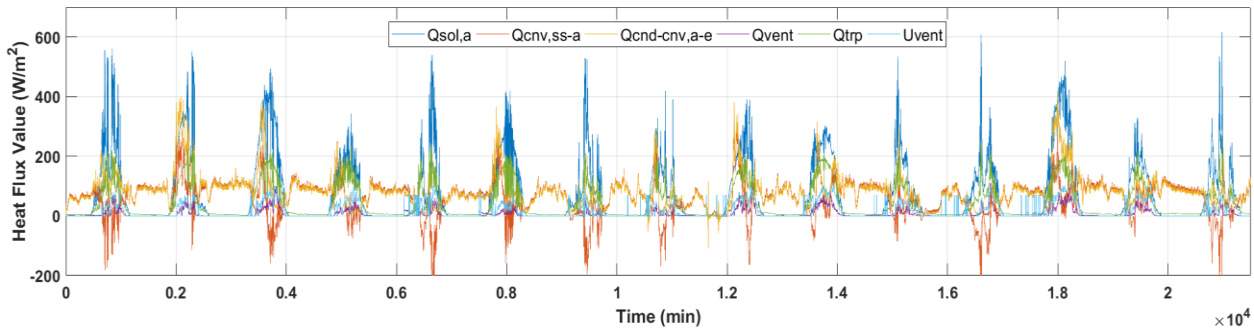

Fig. 18. Heat flux evolution for the online parameter estimator with the dataset of winter-spring period

Statistical indices to evaluate the performance of both estimations are presented in Table 7 and 8, and the evolution of the residual error with both datasets is shown in Fig. 20. Regarding the comparison of these results with the ones obtained with the offline calibrated model, it can be observed that the performance with the adaptive model has highly improved thanks to the online estimation of the parameters. For the air temperature model, the prediction using the online estimated parameters with the winter-spring dataset presents a $\mathrm{MAE} = 0.22\ °\mathrm{C}$, meaning that the average error is decreased by 77.5%, which proves the high efficiency of the estimator, an $\mathrm{MSE} = 0.21\ °\mathrm{C}^2$, and a

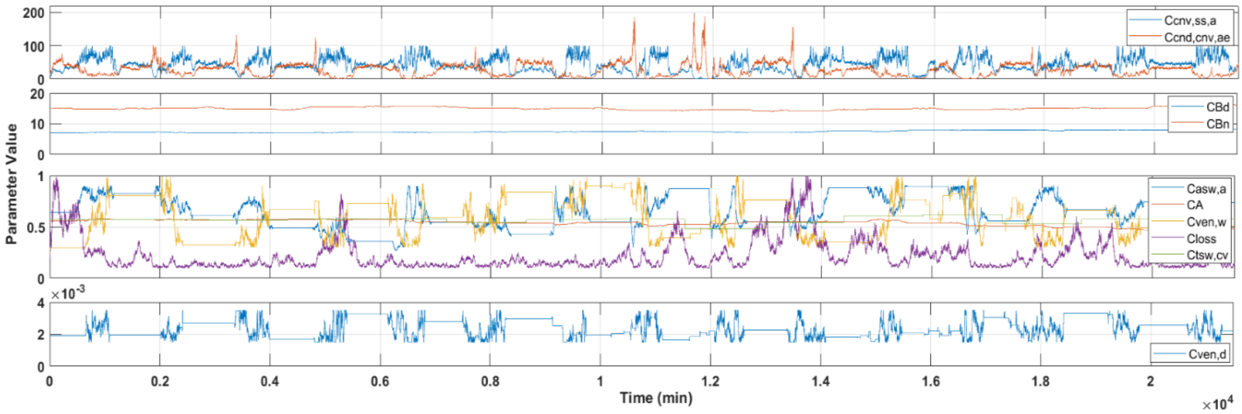

Fig. 19. Variation of the online estimated parameters with the dataset of winter-spring period

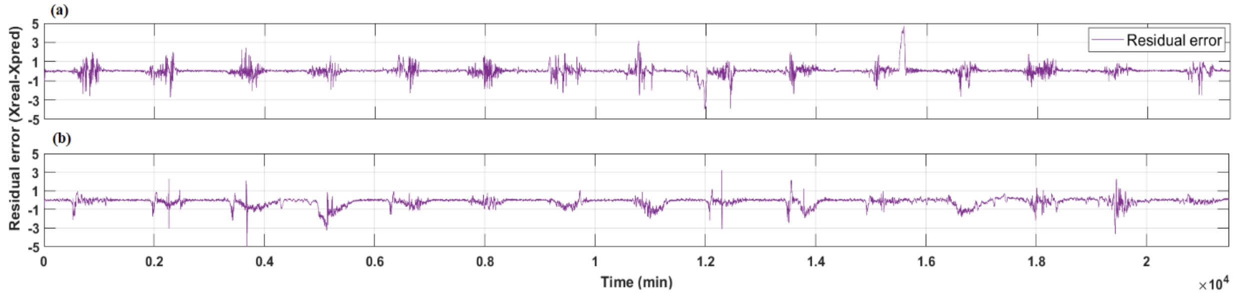

Fig. 20. Evolution of the residual error of the air temperature prediction using the online parameter estimator. (a) with winter-spring dataset; (b) with summer-autumn dataset.

Table 7. Statistical evaluation of internal air temperature simulation using online parameter estimation

	MAE (°C)	MSE (°C^2)	RMSE (°C)	MaxAE (°C)	Interval (°C)
Winter-spring	0.22	0.21	0.46	4.68	[10.8, 30]
Summer-autumn	0.27	0.23	0.48	5.57	[19.7, 39.3]

Table 8. Statistical evaluation of internal solar radiation simulation using online parameter estimation

	MAE (W m^{-2})	MSE (W^2 m^{-4})	RMSE (W m^{-2})	MaxAE (W m^{-2})	Interval (W m^{-2})
Winter-spring	19.81	2065.70	45.45	467.02	[0, 910]
Summer-autumn	8.15	318.7	17.85	201.05	[0, 530]

MaxAE = 4.68 °C as a sporadic value, since it surpassed 4 °C only once in 15 days. In the second online parameter estimation simulation with the summer-autumn dataset, the online estimator succeeded very quickly in adapting the model to suit the different climate conditions in less than 40 prediction steps (40 minutes) at the nocturnal period (see Fig. 16). The corresponding statistical evaluation presents a MAE = 0.27 °C, meaning that the average error is decreased by 83.6%, a $MSE = 0.23\ °C^2$ and a MaxAE $= 5.57\ °C$ as an acceptable sporadic value that does not surpass 3 °C in most of the 15 days. The residual error evolution for the summer-autumn dataset (see Fig. 20b) shows in some days a decrease in prediction accuracy compared to the residual error obtained with the winter-spring dataset. Nonetheless, it is still considered much better than the result obtained with the offline calibrated model. In this sense, this is a very promising response of the estimator, highlighting a powerful capability which is that the user might be able to avoid the offline model calibration process by directly applying the online estimator for such similar greenhouse facilities under similar climate conditions. A resembling results enhancement is observed for the simulation of the internal radiation with the online parameter estimator. The statistical results present a decrease in the average error by 32.56% with the winter-spring dataset which is considered as the harshest one (especially in terms of solar radiation) and by 85.1% with the summer-autumn dataset.

Concerning the evolution of the heat fluxes with the online estimated parameters, Fig. 18 shows logical amplitudes and variations according to the modelled physical behaviour and the physical nature of each heat flux. Regarding the variation of the estimated parameters, it shows a good tendency in terms of respecting the pre-defined search range constraints (search limits) and search range adaptations (Table 6). It is highly interesting and very important to investigate the dynamic of the online estimated parameters to understand the model responses. Analysing the graphs of the evolution of the estimated parameters helps to enhance the proposed model, the developed online estimator, the selected settings, and the applied constraints. Furthermore, it helped in determining the best settings based on the continuous observation of parameters variation through trial-and-error processes.

Regarding the computational burden of the developed online estimator, it was found that the average time consumed by one step of the online parameter estimation process with the air temperature model is 2.0396 seconds, and the average time consumed by one step of the online parameter estimation process with the radiation model is 0.0038 seconds. Thus, both estimation processes are performed at the same time instant, in which the average total time consumption is 2.0434 seconds, which only represents 3.4% of the total time step (60 seconds). The time consumption of the developed parameter estimator scheme is suitable for real-time application. Moreover, it leaves a sufficient time gap for the online parameter estimation of more microclimate models and the online optimisation of controllers for greenhouse control applications.

4.4. Real-time implementation of the online parameter estimator

The real-time validation of the developed online estimator at the commercial-sized greenhouse is performed in the winter season, in a period starting from 07 January 2021 to 22 January 2021 (15 days, 22000 samples). The real evolution of the climate variables registered in this period is shown in Fig. 6. The application period presented some cloudy, rainy and windy days, which are different from the usual weather in the region, and thus, they are considered as a challenging microclimate scenario to be predicted due to the strong variation of the external weather variables. Another detail to be considered as a challenge for the developed estimator is that a second polyethene cover was installed inside the greenhouse on top of the tomato crop (see Fig. 2c) to offer the plants more favourable climate conditions. The impact of the installation of this second cover was not highly relevant since it did not cover all the greenhouse surface, only the crop area but not the corridor, so, it did not create a second isolated environment inside the greenhouse. Thus, its effect from a physical point of view was assumed to cause an additional attenuation in the solar radiation reaching the crop and a slight reduction in the internal ventilation flux.

The estimator was executed in real-time to online estimate the model time-varying parameters sample-by-sample to adapt it to the real changing conditions. The aim of the test performed at the real greenhouse is to investigate if the estimator is sufficiently capable to adapt the model in real-time, moreover, considering the effect of the second cover on the internal air temperature and solar radiation.

Fig. 21 presents the graphical result of the inside air temperature prediction using the online parameter estimator in real-time. It can be observed that the fit between the predicted and measured variables is impressive. The results are very satisfactory for all days, calm ones and even for the rainy, cloudy and windy days as highlighted in Fig. 22 and 23. Table 9 presents the statistical evaluation results of the inside air temperature prediction using the online parameter estimator in real-time. It presents a $\mathrm{MAE} = 0.22\ °\mathrm{C}$, a $\mathrm{MSE} = 0.18\ °\mathrm{C}^2$, and a $\mathrm{MaxAE} = 3.49\ °\mathrm{C}$, which does not surpass 3 °C in most of the days. The residual error evolution for the real-time estimation in Fig. 27a shows a better evolution than the evolution obtained with the simulation using the online parameter estimation in the winter season, as presented in Section 4.3. It can be noticed that there are some peaks in the residual error during the transition from night to day (or vice versa). It happens when the inside air temperature starts to increase (or decrease) rapidly due to the solar radiation effect. It is also related to the change in $\mathrm{C_{cnd-cnv,a-e}}$, and $\mathrm{C_{asw,a}}$ values as a response

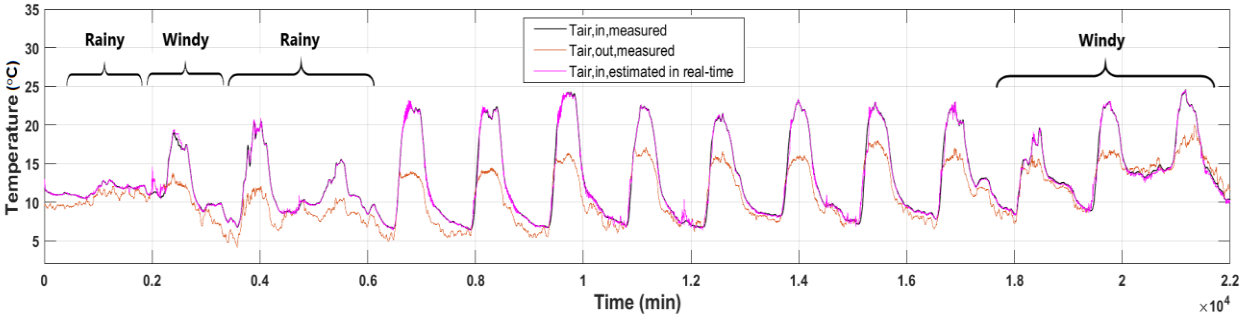

Fig. 21. Internal air temperature prediction using the online parameter estimator in real-time from 07 January 2021 to 22 January 2021

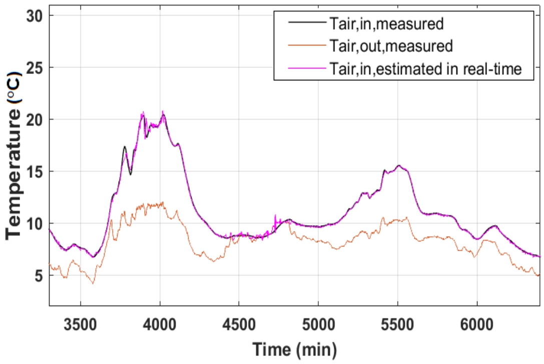

Fig. 22. Air temperature prediction using the online parameter estimator in real-time in two days with rainy climate conditions

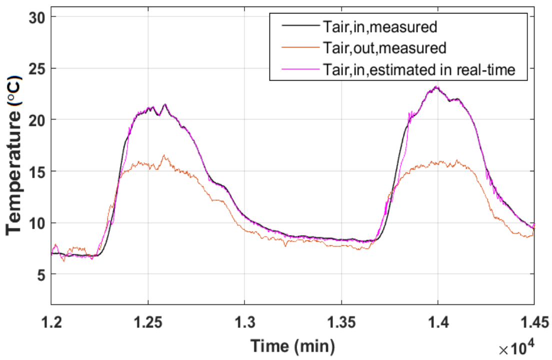

Fig. 23. Air temperature prediction using the online parameter estimator in real-time in two days with calm climate conditions

of the parameter estimator while adapting the model.

Fig. 24 shows the graphical result of the adaptation, in this case, of the inside solar radiation model thanks to the real-time parameter estimation. The fit between the measured and predicted variables is good and all the radiation variations are well fitted. It also proves the efficiency of the real-time estimator in adapting more than one model as a multi-objective task. The corresponding statistical results are presented in Table 10, showing very good values for

Table 9. Statistical evaluation of internal air temperature simulation using the online parameter estimator in real-time

	MAE (°C)	MSE (°C^2)	RMSE (°C)	MaxAE (°C)	Interval (°C)
Winter season (real-time validation)	0.22	0.18	0.43	3.49	[6.4, 24.5]

Table 10. Statistical evaluation of internal solar radiation simulation using the online parameter estimator in real-time

	MAE (W m^{-2})	MSE (W^2 m^{-4})	RMSE (W m^{-2})	MaxAE (W m^{-2})	Interval (W m^{-2})
Winter season (real-time validation)	4.62	89.56	9.46	62.47	[0, 309]

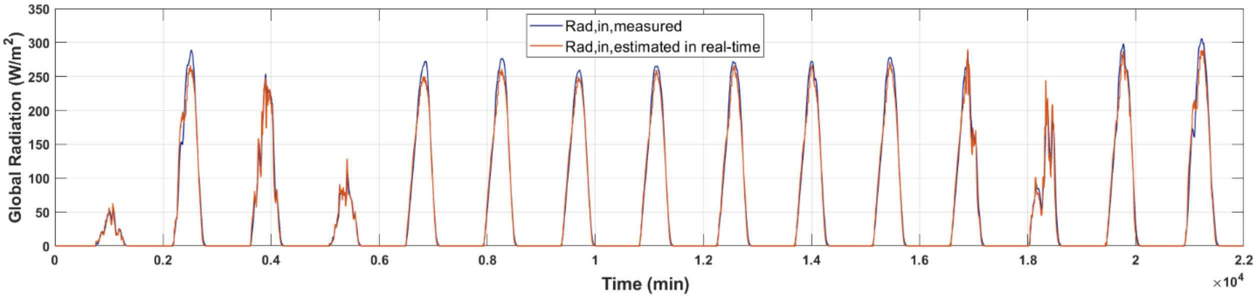

Fig. 24. Internal solar radiation adaptation using the online parameter estimator in real-time from 07 January 2021 to 22 January 2021

radiation simulation in real-time. The evolution of the residual error using the online parameter estimator in real-time is presented in Fig. 27b showing a very promising result.

The real-time evolution of the heat fluxes is shown in Fig. 25. The first important aspect to be mentioned is that it was assumed previously that the physical effect of the second cover could mean more attenuation mainly on the radiation reaching the crop, and partly on the heat loss due to natural ventilation. Thus, as a confirmation of the assumption, in comparison to the evolution of the heat fluxes corresponding to the online estimation tests in Section 4.3, it can be noticed that: (i) The amplitude of the solar radiation heat flux $\mathrm{Q_{sol,a}}$ is decreased averagely by 39.3% as a main effect of the second cover. (ii) It can be graphically noticed that the amplitude of the heat loss flux due to natural ventilation $\mathrm{Q_{vent,a}}$ is also decreased, however, this is also dependent on wind velocity.

The evolution of the parameters estimated in real-time is presented in Fig. 26, where, it can be observed that: (i) The parameters vary while respecting the restrictions defined for each parameter range. (ii) The values of the parameters respect the defined variation neighbourhood $\pm R_j\%$ according to their physical nature. (iii) The values of the parameters change only when the corresponding physical process is active, as explained in Section 3.

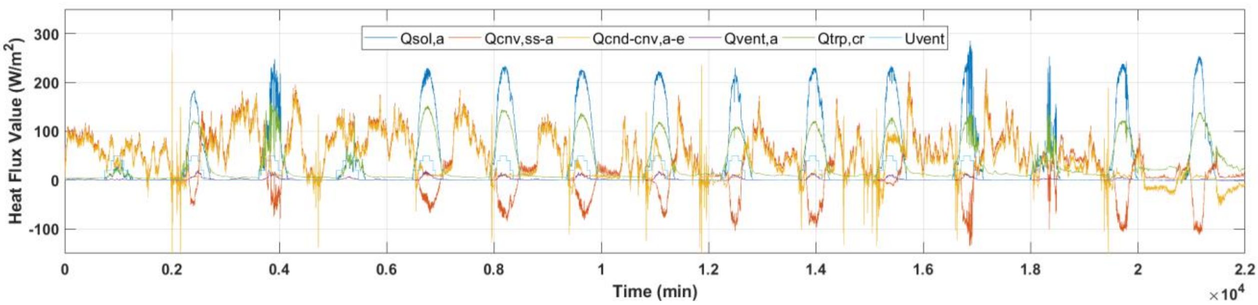

Fig. 25. Heat flux evolution for the real-time parameter estimation from 07 January 2021 to 22 January 2021

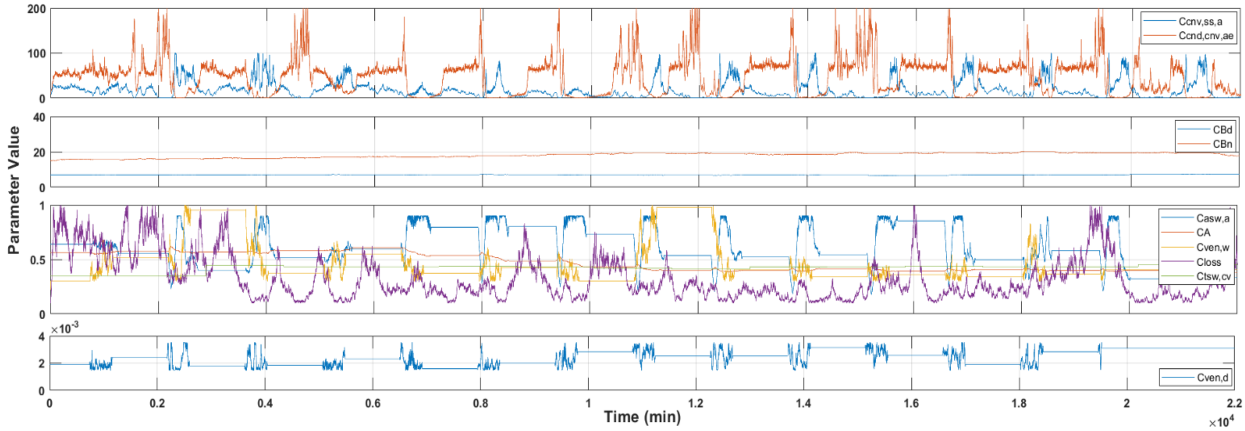

Fig. 26. Variation of the estimated parameters in real-time from 07 January 2021 to 22 January 2021

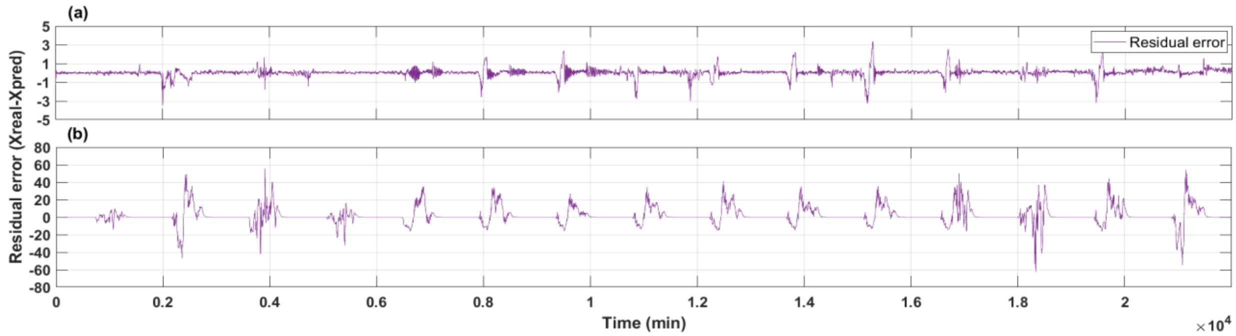

Fig. 27. Evolution of the residual error based on the real-time estimation. (a) air temperature prediction; (b) solar radiation simulation

In this last stage, the real-time model adaptation was successfully achieved without changing any settings of the online estimator, neither re-programming its algorithm nor applying new mechanisms or restrictions. This proves the efficiency and robustness of the implemented online estimator against the uncertainties and its efficiency for long-term applications.

5. Conclusions

In this work, an online parameter estimator applied to a greenhouse microclimate model has been developed based on the RSBA as an enhanced variant of the nature-inspired bat algorithm. The online estimator development was accomplished in four phases. Firstly, an offline model calibration using real experimental data was achieved. Secondly, a sensitivity analysis to investigate the influence of each parameter on the model outputs is performed. Thirdly, an online estimation using real datasets of different seasons was simulated. The performance of the developed online parameter estimator and the greenhouse microclimate model have been evaluated from both physical sense and statistical points of view. Graphical results and evaluation indices results show the very satisfactory performance of the online estimator in terms of:

- The accuracy in predicting and simulating the internal air temperature and solar radiation due to the successful microclimate model adaptation.
- The efficiency of the online parameter estimation mechanism respecting the defined constraints, thus, respecting the physical sense of the time-varying parameters.
- The robustness of the online estimator against the challenging weather conditions (clouds, rain and wind) and the uncertainty after installing the second plastic cover.
- The limited total time consumption of every parameter estimation processes, allowing for a future adaptation of more microclimate models and controllers in real-time.

Finally, the real-time implementation of the proposed online estimator was tested in an experimental greenhouse under Mediterranean climate conditions. The results exhibited an outstanding performance of the estimator in adapting the models to accurately predict and simulate the internal air temperature and solar radiation. This proves that the developed estimator is an efficient tool for greenhouse microclimate model adaptation.

As a future perspective, the developed online estimator can be applied to predict other climate variables considering the greenhouse as a multiple-input multiple-output system (MIMO). It could also be applied to different greenhouse facilities thanks to its adaptation capability. To improve the estimation mechanism, some of the mentioned trial-and-error procedures will be substituted, if possible, by relating the estimator settings to the corresponding modelled dynamics to facilitate the automatic selection of those settings or even their adjustment in real-time. Furthermore, the developed online estimator could be applied and evaluated with different control methods for greenhouse microclimate control purpose.

Acknowledgements

This work was supported by the University of Biskra, Laboratory of Identification, Command, Control and Communication (LI3CUB), in collaboration with the University of Almería, the research group of Automatic Control, Robotics and Mechatronics (ARM). It has been funded by the National R+D+i Plan Project DPI2017-85007-R of the Spanish Ministry of Science, Innovation and Universities and ERDF funds. Author M. Guesbaya is supported by the Exceptional National Program (PNE) grant of the Algerian Ministry of High Education and Scientific Research. Author F. García-Mañas is supported by an FPU grant from the Spanish Ministry of Science, Innovation and Universities. The authors appreciate the collaboration of the staff at "Las Palmerillas" Experimental Station of the Cajamar Foundation. The authors would also like to thank Pr. Jorge Antonio Sánchez Molina (Associate Professor, University of Almería) for his assistance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ali, R.B., Bouadila, S. and Mami, A., 2018. Development of a fuzzy logic controller applied to an agricultural greenhouse experimentally validated. *Applied Thermal Engineering,* Volume 141, pp. 798-810. DOI: 10.1016/j.applthermaleng.2018.06.014

Choab, N., Allouhi, A., El Maakoul, A., Kousksou, T., Saadeddine, S. and Jamil, A., 2019. Review on greenhouse microclimate and application: Design parameters, thermal modeling and simulation, climate controlling technologies. *Solar Energy,* Volume 191, pp. 109-13. DOI: 10.1016/j.solener.2019.08.042

Cunha, J. B., Couto, C., and Ruano, A. E. B., , 1997 . Real-time parameter estimation of dynamic temperature models for greenhouse environmental control. *Control Engineering Practice,* Volume 5, pp. 1473-1481. DOI: 10.1016/S0967-0661(97)00145-7

Fourati, F., 2014. Multiple neural control of a greenhouse. *Neurocomputing,* Volume 139, pp. 138-144. DOI: 10.1016/j.neucom.2014.02.052

Frausto, H.U., Pieters, J.G. and Deltour, J.M., 2003. Modelling greenhouse temperature by means of auto regressive models. *Biosystems Engineering,* 84(2), pp. 147-157. DOI: 10.1016/S1537-5110(02)00239-8

Guesbaya, M. and Megherbi, H., 2019. Thermal modeling and prediction of soilles greenhouse in arid region based on particle swarm optimization: Experimentally validated. International Conference on Advanced Electrical Engineering (ICAEE), Algiers, IEEE, pp. 1-6. DOI: 10.1109/ICAEE47123.2019.9015190

Guesbaya, M., Megherbi, H. and Megherbi, A.C., 2019. Random scaling-based bat algorithm for greenhouse thermal model identification and experimental validation. The 4th International Conference on Electrical Engineering and Control Applications (ICEECA), Constantine, Springer, pp. 47-62. DOI: 10.1007/978-981-15-6403-1_4

Hasni, A., Taibi, R., Draoui, B. and Boulard, T., 2011. Optimization of greenhouse climate model parameters using particle swarm optimization and genetic algorithms. *Energy Procedia,* Volume 6, pp. 371-380. DOI: 10.1016/j.egypro.2011.05.043

Hoyo, A., Moreno, J.C., Guzmán, J.L. and Rodríguez, F., 2019. Robust QFT-based feedback linearization controller of the greenhouse diurnal temperature using natural ventilation. *IEEE Access,* Volume 7, pp. 64148-64161. DOI: 10.1109/ACCESS.2019.2916412

Li, K., Sha, Z., Xue, W., Chen, X., Mao, H. and Tan, G., 2020. A fast modeling and optimization scheme for greenhouse environmental system using proper orthogonal decomposition and multi-objective genetic algorithm. *Computers and Electronics in Agriculture,* Volume 168, p. 105096. DOI: 10.1016/j.compag.2019.105096

Ma, D., Carpenter, N., Maki, H., Rehman, T.U., Tuinstra, M.R. and Jin, J., 2019. Greenhouse environment modeling and simulation for microclimate control. *Computers and Electronics in Agriculture,* Volume 162, pp. 134-142. DOI: 10.1016/j.compag.2019.04.013

Pérez-González, A., Begovich-Mendoza, O. and Ruiz-León, J., 2018. Modeling of a greenhouse prototype using PSO and differential evolution algorithms based on a real-time LabView™ application. *Applied Soft Computing,* Volume 62, pp. 86-100. DOI: 10.1016/j.asoc.2017.10.023

Rodríguez, F., Berenguel, M., Guzmán, J.L., Ramírez-Arias, A., 2015. *Modeling and control of greenhouse crop growth.* s.l.:Springer International Publishing Switzerland. DOI: 10.1007/978-3-319-11134-6

Speetjens, S. L., Stigter, J. D. and Van Straten, G., 2009. Towards an adaptive model for greenhouse control. *Computers and Electronics in Agriculture,* Volume 67, pp. 1-8. DOI: 10.1016/j.compag.2009.01.012

Van Straten, G., van Willigenburg, G., van Henten, E. and van Ooteghem, R., 2010. *Optimal control of greenhouse cultivation.* s.l.:CRC press. DOI: 10.1201/b10321

Yang, X. Y., 2014. Nature-inspired optimization algorithms. 1 ed. s.l.:Elsevier. DOI: 10.1016/C2013-0-01368-0

Yang, X. S. and He, X., 2013. Bat algorithm: literature review and applications. *International Journal of Bio-inspired Computation*, 5(3), pp. 141-149. DOI: 10.1504/IJBIC.2013.055093

Yu, H., Chen, Y., Hassan, S.G. and Li, D., 2016. Prediction of the temperature in a Chinese solar greenhouse based on LSSVM optimized by improved PSO. *Computers and Electronics in Agriculture,* Volume 122, pp. 94-102. DOI: 10.1016/j.compag.2016.01.019

Vanthoor, B.H.E., Van Henten, E.J., Stanghellini, C. and De Visser, P.H.B., 2011. A methodology for model-based greenhouse design: Part 3, sensitivity analysis of a combined greenhouse climate-crop yield model. *Biosystems Engineering*, 110(4), pp. 396-412. DOI: 10.1016/j.biosystemseng.2011.08.006

Glossary

Q	Heat flux (W m^{-2})
C_{vol}	Greenhouse volume (m^{3})
C_{area}	Greenhouse surface (m^{2})
C_{sph}	Specific heat of the air (J kg^{-1} K^{-1})
C_{den}	Air density (kg m^{-3})
$D_{sr,e}$	External solar radiation (W m^{-2})
$C_{asw,a}$	Greenhouse air absorption coefficient of the short-wave radiation (Unitless)
$C_{cnv,ss-a}$	Coefficient of convection between the soil surface and internal air (W m^{-2} K^{-1})
$C_{cnd-cnv,a-e}$	Coefficient of convection and conduction between internal and external air (W m^{-2} K^{-1})
C_{A}	Transpiration coefficient dependent on the crop state and internal radiation (Unitless)
$C_{B_{d/n}}$	Transpiration coefficient dependent on the crop state and vapour pressure deficit for diurnal and nocturnal periods (kg m^{-2} h^{-1} kPa^{-1})
$C_{ven,d}$	Discharge coefficient (Unitless)
$C_{ven,w}$	Wind effect coefficient (Unitless)
C_{loss}	Ventilation loss through greenhouse air leakage (m^{3} s^{-1})
$C_{tsw,cv}$	Cover solar transmission coefficient (Unitless)

Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: