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Optimization of Greenhouse Climate Model Parameters Using Particle Swarm Optimization and Genetic Algorithms

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Abstract
In the world, the greenhouse culture is getting more and more developed to meet the needs of a more competitive market that is conditioned by very strict norms of quality. Greenhouse production systems are getting highly sophisticated but extremely expensive. That is the reason why the greenhousers, who want to be competitive must optimize their investments thanks to strict production conditions. Nowadays, it is commonly admitted that the decisions related to the management of a greenhouse can be classified into different levels, starting from the on –line control, through the optimization of the environment, to the seasonal planning of the behaviour of the agriculture. The main purpose of our work is to optimize the physical sizes of a reduced model of a greenhouse under Mediterranean conditions. Thus, we use a digital simulation based genetic algorithm (GA) and a particle swarm optimization (PSO). The design goal is successfully achieved using the PSO and compared with that obtained using the GA. For the problem at hand, it is found that the PSO outperforms the GA in some of the presented design cases.

Keywords: temperature, pressure, optimization, genetic algorithm, particle swarm optimization, greenhouse, climate models;

1. Introduction

Since the 1970's, improvements in computing facilities together with theoretical and experimental studies have increased our understanding on the physical and physiological processes involved in the Biophysics greenhouse system. Mathematical simulation models for predicting inside climate control have primarily focused on the determination of heating requirement; however other climate control systems

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have been largely ignored although they play an important role, particularly under Mediterranean conditions where the greenhouse production area has tremendously increased over the last ten years. These climate control systems include natural ventilation, evaporative cooling, shading and irrigation control. Analysis of these problems requires consideration of coupled mechanisms involving heat and mass (air, water vapor).

Non linear models describing the above processes are complex and not easy to use in practice because they require a significant solving time together with the knowledge of a large number of model parameters as well as meteorological inputs. In addition, the numerical iterative solution can diverge if the choice of initial conditions is wrong [1].

In order to deal with this important question, our paper presents the theory and the methods involved in the development of a reduced thermal and mass (water vapor) model of the greenhouse and the on-line estimation of its parameters. We mainly focus on a method for identifying the parameters which is based on the genetic algorithms and which optimizes the choice of parameters by minimizing a cost function.

Nomenclature

Al	And C Parameters of the model of natural ventilation (.).
B	Parameters of the model of transpiration ($Wm^{-2}hPa^{-1}$)
C_p	thermal capacity of the greenhouse air component ($Kg^{-1}K^{-1}$)
d_0	leakage (m^3s^{-1})
h	air/sol convective exchange coefficient ($Wm^{-2}K^{-1}$)
K	Overall heat loss coefficient through greenhouse covers ($Wm^{-2}K^{-1}$)
K_l	Latent heat transfer coefficient driven by ventilation ($Wm^{-2}hPa^{-1}$)
K_s	Sensible heat transfer coefficient driven by ventilation ($Wm^{-2}K^{-1}$)
r	Ratio (s/m)
S	Exchange surface between two constituents of the greenhouse (m^2)
s_0	Leakage surface (m^2)
v	greenhouse volume (m^2)
α	Rate absorption of the global radiation by the aerial compartment of the greenhouse (.).
β	Rate absorption of the global radiation by the thermal mass compartment of the greenhouse (.).
Δt	time step of discretization (s)
γ	psychrometric constant ($hPaK^{-1}$)
φ_i	power of the evaporative cooling fog system (Wm^{-2})
ρ	air density (kgm^{-3})
τ	Time constant or characteristic time (s)
τ'	Greenhouse cover transmitivity (.)
ζ	Intermediate parameters of the system
χ	Intermediate parameters of the system

ξ	Intermediate parameters of the system

All fluxes are expressed per m^2 of soil. Dimensionless values are indicated by (.)

2. Problem formulation

Our objective is to optimize a reduced greenhouse model which controlled variables are indoor temperature and relative pressure and actuators are the fog system (amount of generated water vapour), the vent opening (vent opening angle), the soil and the air heating.

Heat and water vapour balances have been first formulated in order to obtain the main equations of the whole model. Then particular equations have been added to complete the model.

Table 1. Notations

Q_{air}	Air heating loads(Wm^{-2})	*s*	Vents opening surface (m^2)
Q_{sol}	Soil heating loads(Wm^{-2})	*Ti*	Indoor temperature (°C)
φ_l	Injected evaporative cooling by fog system (Wm^{-2})	*Te*	outdoor temperature (°C)
p(Ti)	Water vapor saturation pressure at Ti (hPa)	*Pi*	Indoor pressure(hPa)
V	Wind speed (m/s)	*Pe*	outdoor pressure(hPa)
Rg	Outside global radiation (Wm^{-2})		

3. The identification problem

As already exposed with more details in a previous paper [7], identification techniques in the case of greenhouse requires a system approach of the thermal and mass transfers which can be described by 4 types of variables describing the greenhouse and its environment: the entry vector *U(t)*, which describes the initial conditions from which the system evolves; the output vector *Y(t)*, or the set of state variables which can be observed and measured; the current state of the system *X(t)*, which includes the state variables of the system evolving as a function of time and the vectors of unknown system parameters. The dynamic behavior of the system can be described by a set of 2 equations:
A state equation:

$$\frac{dX(t)}{dt} = f\left[X(t), U(t), P\right] \tag{1}$$

An observation equation:

$$Y(t) = g\left[X(t), U(t), P\right] \tag{2}$$

4. Physical modeling of greenhouse climate

4.1 The heat and water vapour balances

In order to reduce the system order of the thermal model; we have considered an empirical approach based on considerations about the characteristic time scales of each thermal component of the system. We have thus considered two main components: The soil and heavy structural elements. With characteristic time scale much longer than our observation time scale. They will be collectively gathered under the form

of a virtual thermal mass characterized by its virtual temperature T_m and thermal capacity C_m. The crop - greenhouse superstructure and the enclosed air space, which characteristic time scale (τc) is low (200< τ_c< 500s) and rather similar to our observation time scale (3600s or 900s). It can be characterized by its temperature T_i and water vapour pressure P_i. The virtual thermal mass equation can be represented by the following differential equation [6]) :

$$C_m \frac{dT_m}{dt} = h(T_i - T_m) + Q_{sol} + \beta \ Rg \tag{3}$$

Where the first term on the right hand side is the heat exchanged with the greenhouse air, the second one is the soil heating flux and the last one, the solar gain directly absorbed by the thermal mass.

Neglecting air inertia in front of the the heavy structure, one can represent the air thermal balance as follows [8]:

$$0 = \alpha \ Rg + Q_{air} + h(T_m - T_i) + K(T_e - T_i) + K_s(T_e - T_i) + K_l(P_e - P_i) \tag{4}$$

where the first term on the right hand side is the solar gain, the second one the air heating, the third one the thermal exchange with the thermal mass, the fourth one is the overall heat exchange between inside and outside and the fifth and last term represents the sensible and latent heat exchanges by ventilation and leakages.The air water vapour balance takes into account the crop transpiration, the water vapour added by fogging and the exchanges with outside, it can be represented by the following equation [9]:

$$C_l \frac{dP_i}{dt} = A\tau \ \ Rg + B(P(T_i) - P_i) - K_l(P_i - P_e) + \varphi_l \tag{5}$$

Where the first term of the right hand side represents the crop transpiration (simply described as a linear function of global radiation and saturation deficit), the second one the exchanges by ventilation and the last one the contribution of the fog system[1].

4.2 Solving the equations

Simultaneous integration of the equations of energy (eq.3 and 4) and water vapour balances (eq.5) leads to a system of 3 equations with 3 unknowns (T_m, T_i, P_i) which can be presented in a recursive form as a function of the past (time n), the instantaneous input vectors (Rg, T_0, V, P_0, $P(T_i)$), of the command variable (Q_{sol}, Q_{air}, φ_l) and of model parameters (included in the matrices line) which are partially to be identified.

The complete system can then be represented is as follows [1]:

$$P_{i(n+1)} = P_{i(n)} \exp(-\zeta \Delta t) + (1 - \exp(-\zeta \Delta t)) \times \begin{pmatrix} \frac{r S B \gamma \tau'}{\xi} & \frac{\chi}{\xi} & \frac{\gamma S B}{\xi} & \frac{\gamma S}{\xi} \end{pmatrix} \begin{pmatrix} R_g \\ P_e \\ P(Ti) \\ \varphi_l \end{pmatrix} \tag{6}$$

With

$$\zeta = \frac{\left(\left(Al\sqrt{C}\ sV\right) + \left(Al\sqrt{C}\ s_0 V\right) + d_0 + \left(B\gamma S / \rho C_p\right)\right)}{v} \tag{7}$$

$$\xi = \left(\rho C_p Al\sqrt{C}\ sV\right) + \left(\rho C_p Al\sqrt{C}\ s_0 V\right) + \left(\rho C_p d_0\right) + B\gamma S \tag{8}$$

$$\chi = \xi - B\gamma S \tag{9}$$

Inside greenhouse temperature gives rise to the following equation [3, 4 & 7] :

$$T_{i(n+1)} = \frac{h}{v} T_{m(n+1)} + \begin{pmatrix} \frac{v-h}{v} & \frac{\alpha}{v} & \frac{1}{v} & \frac{K_l}{v} & \frac{-K_l}{v} \end{pmatrix} \begin{pmatrix} T_e \\ R_g \\ Q_{air} \\ P_e \\ P_i \end{pmatrix} \tag{10}$$

Where

$$T_{m(n+1)} = T_{m(n)} \exp\left(-\frac{\Delta t}{\tau}\right) + \left(1 - \exp\left(-\frac{\Delta t}{\tau}\right)\right) \begin{pmatrix} 1 & \frac{\alpha h + \beta v}{h(K+K_s)} & \frac{v}{h(K+K_s)} & \frac{1}{(K+K_s)} & \frac{K_l}{(K+K_s)} & \frac{-K_l}{(K+K_l)} \end{pmatrix} \begin{pmatrix} T_e \\ R_g \\ Q_{sol} \\ Q_{air} \\ P_e \\ P_i \end{pmatrix} \tag{11}$$

5. Principle of Model parameters identification

The first optimizer which was used for the model parameters identification is a Genetic Algorithm (GA) based on the laws of species evolution, with at each generation a species evolves spreading in order to better adapt to their environment. To apply this method to an optimization problem, we start from an initial population (first generation) which is composed of a set of points in a search space domain. All the searching space points have an assigned chromosome type; this is a different string for each position in the searching space. Binary codification is usually selected to mime chromosomes. Starting from this initial population, a genetic operator set is applied to obtain a new population (new generation). The result of genetic operator application depends on the cost index value of each individual. [2,10,11,12]

PSO is basically developed through simulation of bird flocking in two-dimension space. The position of each agent is represented by XY axis position and also the velocity is expressed by v_x (the velocity of X axis) and v_y (the velocity of Y axis). Modification of the agent position is realized by the position and velocity information. Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest) and its XY position[4,5,6]. This information is analogy of personal experiences of each agent. Moreover, each agent knows the best value so farin the group (gbest) among pbest. This information is analogy of knowledge of how the other agents around them have performed. Namely, each agent tries to modify its position using the following information [10,13,14,15]:

- The current positions (x,y), - The current velocities (v_x,v_y), -The distance between the current position and pbest, 4) The distance between the current position and gbest

This modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k\right) + c_2 rand_2 \times \left(gbest_i - s_i^k\right) \quad (12)$$

Where

v_i velocity of agent i at iteration k; w weighting function; c_i weighting factor; *rand* random number between 0 and 1; s_i^k current position of agent i at iteration k; $pbest_i$ p best of agent i; gbest of the group. The following weighting function is usually utilized in(13).

$$w = -\frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad (13)$$

Where: w_{max} initial weight; w_{min} final weight; $iter_{max}$ maximum iteration number; *iter* current iteration number.

Using Eqs. (13) and (14) a certain velocity, which gradually gets close to pbest and gbest can be calculated. The current position can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (14)$$

Eq. (13) consists of three terms: the first one depends on the particle's previous speed, the second term depends on the distance between the particle's best previous and current position. The last term shows the effect of the swarm's best experience on the velocity of each individual in the group. This effect is considered through the distance between swarm's best experience (the position of the best particle in the swarm) and the ith particle's current position. Eq. (15) simulates the flying of the particle toward a new position.

The role of the inertia weight w is considered very important in PSO convergence behavior [15,16]. The inertia weight is employed to control the impact of the previous history of velocities on the current velocity. In this way, the parameter w regulates the trade-off between the global and local exploration abilities of the swarm.

A large inertia weight facilitates global exploration (searching new areas), while a small one tends to facilitate local exploration, i.e. finetuning the current search area. A suitable value for the inertia weight w usually provides balance between global and local exploration abilities and consequently a reduction on the number of iterations required to locate the optimum solution.

The reminding parameters of the temperature and pressure balance equations to be optimized are the following:T_{m0}, h, α,τ, β, B, $Al\sqrt{C}$, s_0, d_0, Pi_0.

Once we have chosen the parameters to be optimized, one must define also their numerical limits. Thus, we have defined the search space for the different parameters as shown in Table2[1,17].

Table 2: Search space of the parameters

	$Al\sqrt{C}$	s_0(m)	d_0(m)	B	h ($Wm^{-2}K^{-1}$)
Min	0	0	0	0	0.5
Max	0.3	1	1	0.2	30
	A	B ($Wm^{-2}hPa^{-1}$)	τ (s)	T_{m0} (°C)	Pi_0(Pa)
Min	0.2	1	2	10	13
Max	0.8	9.5	1100	32	30

As objective function, we have considered the equations of air temperature *Ti* defined by the relations (10), our objective being to minimize the difference between measured and calculated values with the selected parameters.

6. Results and Discussion

The inside air temperature and humidity simulation models were identified using the described approaches for a greenhouse between 01 and 08 july located near Avignon in south-east France. The greenhouse had a tomato-crop area of 416 m2, in a double roof plastic house. Several actuators and sensors were installed and connected to an acquisition and control system based on a personal computer and a data acquisition and control card using a sampling interval of 1 hour. Only few seconds are required to identify the parameters of the reduced model with a personal computer.

Since the PSO and GA algorithms depend only on the objective function to guide the search, it must be defined before the algorithms are initialized. With experimental to (5), a Mean Quadratic Errors (MQE) is chosen as the objective function in this study defined by[18]:

$$MQE = \frac{1}{N}\sum_{j=1}^{N}\left[T_i(j) - T_{i\exp}(j)\right]^2 \tag{15}$$

Where N is the number of data; *Ti* the indoor temperature calculates Ti_{exp} the indoor temperature experimental The contribution of this paper is to apply the proposed PSO algorithm to minimize the MQE value.

In the present simulations, the packet software of Matlab is programmed to implement the above PSO algorithm, the related values assigned to the variables of the PSO algorithm are given by sampling number N = 161, the number of the population particles = 2000, the velocity decline parameter w = 0, the strength parameter for the local attractors and the global attractor c1=2, c2=2, and number of iterations N_{iter}=1000 in the current search.

For the genetic algorithm, a simple crossover and a binary mutation were performed. Fitness is also defined as an indicator for measuring the individual's quality for survival. Its concept is similar to that of an objective function in conventional optimization problems. Relatively good individuals with higher fitness reproduce, and relatively bad individuals with lower fitness die during evolution. An individual with maximum fitness means an optimal solution. The evolution speed is significantly affected by the degree of diversity of the population. A lower diversity prevents the evolution of the population. In this study, therefore, several (200) individuals in another population are added to the original population in order to maintain the diversity of the population. The search procedure by the genetic algorithm is as

follows. Step 1: the initial population is generated at random. Step 2: some individuals are added to the original population from another population. Step 3: genetic operations, crossover and mutation, are applied to those individuals. Through the crossover, some individuals are newly created according to the crossover rate (80%), and other sorts of individuals are then newly generated according to the mutation rate (0.5%). From these operations, new individuals are obtained. Step 4: the fitness of all individuals is calculated using the identified neural-network model. Step 5: the individuals with higher fitness are selected and retained for the next generation. An optimal value can be obtained by repeating these procedures [19, 20].

Table 3: Best parameter values identified by the particle swarm optimization.

$Al\sqrt{C}$	s_0(m)	d_0(m)	β	h ($Wm^{-2}K^{-1}$)
0.2996	0.4700	0.1768	0.0630	15.7719
A	B ($Wm^{-2}hPa^{-1}$)	τ (s)	T_{m0} (°C)	Pi_0(Pa)
0.2152	5.0746	738.8353	18.9187	23.5662

Table 4: Best parameter values identified by the genetic algorithm.

$Al\sqrt{C}$	s_0(m)	d_0(m)	β	h ($Wm^{-2}K^{-1}$)
0.2933	0.9841	0.9444	0.03	4.0156
A	B ($Wm^{-2}hPa^{-1}$)	τ (s)	T_{m0} (°C)	Pi_0(Pa)
0.3711	3.8472	949.5763	15.1894	29.9254

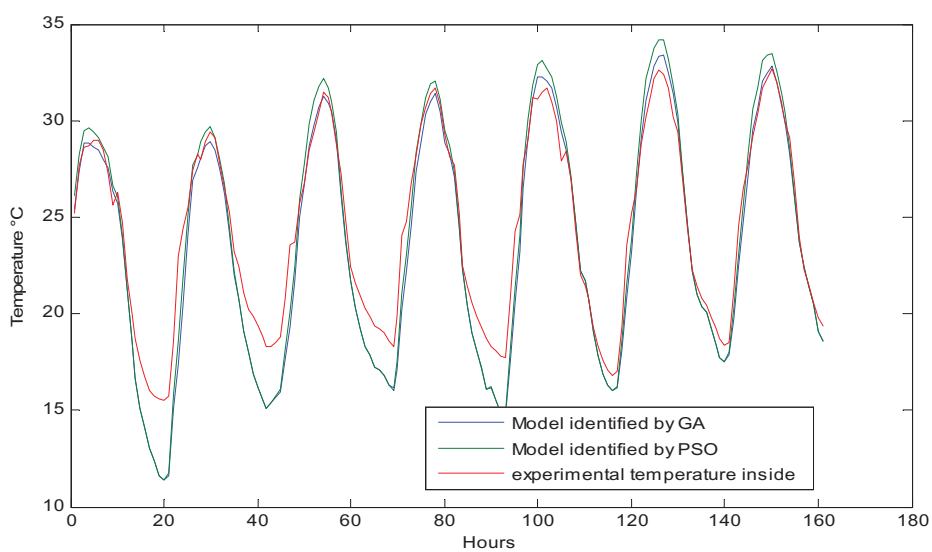

Fig 1. Temperature inside greenhouse

The selection of models is done comparing the errors between the experimental data and the model identified by a genetic algorithm and the errors between the experimental, and the calculus with the model identified by the PSO, calculating the Mean Relative Error (MRE), the Mean Absolute Error (MAE), the Standard Error (SE) and the Mean Quadratic Errors (MQE). The four-error measures are given by the following relations[21]:

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|T_i(j) - T_{i\exp}(j)\right| \tag{16}$$

$$MRE = \frac{1}{N}\sum_{j=1}^{N}\frac{\left|T_i(j) - T_{i\exp}(j)\right|}{T_i(j)} \times 100 \tag{17}$$

$$MQE = \frac{1}{N-1}\sum_{j=1}^{N}\left[T_i(j) - T_{i\exp}(j)\right]^2 \tag{18}$$

Table 5: Statistical accuracy measures

The errors	MQE	MAE	MRE	SE
Model identified by GA algorithm	0.1341	1.2735	2.7633e-004	0.1349
Model identified by PSO algorithm	0.1280	1.2373	2.5834e-004	0.1288

The best results obtained by the genetic algorithm and particle swarm optimization are given in Table3 and Table4. Fig1 compare the results given by the PSO and GA Algorithms with the experimental values. It's clear from fig1 that a good agreement can be seen between the experimental results and the simulation obtained from the tow algorithm, both in terms of dynamics and intensity of the signal. In order to estimate the validity of our algorithms, we have calculated the errors between the experimental and simulated results. We can see (Table 5) that, for the present problem the performance of the PSO is better than GA. The PSO Algorithm improves very significantly the precision of the simplified greenhouse model. Identification of the physical parameters of a simplified model describing the interactions between crop and climate in a horticultural greenhouse can be seriously improved in terms of calculation time and accuracy of the results, by using a PSO algorithm instead of the GA Algorithm.

7. Conclusions

The application of particle swarm optimization (PSO) to optimized parameters of a greenhouse climate model with Continuous Roof Vents has been carried out. Comparison with GA has been made. The PSO, a recently developed stochastic efficient optimization algorithm, shows excellent ability to optimized a greenhouse climate model. An attractive advantage of PSO is the ease of implementation in both the context of coding and parameter selection. The algorithm is much simpler and intuitive to implement than complex, probability based selection and mutation operators required for evolutionary algorithms such as the GA. Furthermore, the obtained results showed that the PSO outperforms the GA for the problem at hand.

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