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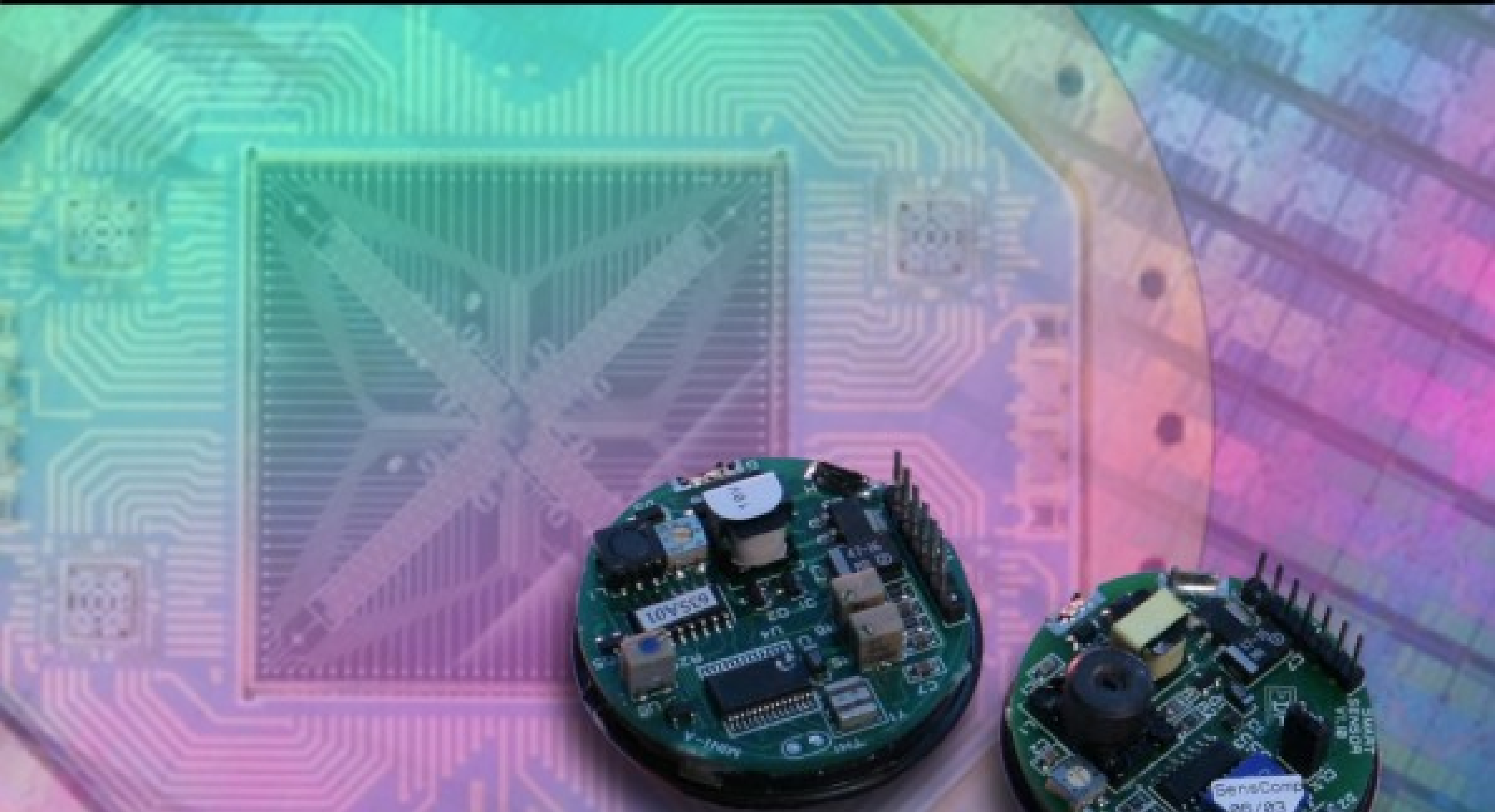

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A Particle Swarm Optimization of Natural Ventilation Parameters in a Greenhouse with Continuous Roof Vents

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Abstract: Although natural ventilation plays an important role in the affecting greenhouse climate, as defined by temperature, humidity and CO_2 concentration, particularly in Mediterranean countries, little information and data are presently available on full-scale greenhouse ventilation mechanisms. In this paper, we present a new method for selecting the parameters based on a particle swarm optimization (PSO) algorithm which optimize the choice of parameters by minimizing a cost function. The simulator was based on a published model with some minor modifications as we were interested in the parameter of ventilation. The function is defined by a reduced model that could be used to simulate and predict the greenhouse environment, as well as the tuning methods to compute their parameters. This study focuses on the dynamic behavior of the inside air temperature and humidity during ventilation. Our approach is validated by comparison with some experimental results. Various experimental techniques were used to make full-scale measurements of the air exchange rate in a 400 m^2 plastic greenhouse. The model which we propose based on natural ventilation parameters optimized by a particle swarm optimization was compared with the measurements results. *Copyright © 2009 IFSA.*

Keywords: Optimization, Particle swarm optimization, Greenhouses, Temperature, Humidity, Hydric model, Climate models, Cooling fog system, Metaheuristics

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1. Introduction

Greenhouse ventilation is a key function in the control of greenhouse parameters such as air temperature and air humidity, and influences strongly the growth and development of the crops. In spite of this importance, especially in warm regions, the available knowledge on greenhouse ventilation is scarce. The air exchanged between inside and outside is still predicted with a large uncertainty ascribed to the difficulties of performing accurate measurements. Among the few works published in the literature, some are related to wind tunnel experiments on small-scale greenhouse with both roof and side openings. Other reported measurements on full-scale multispan greenhouses equipped with roof ventilators used the tracer gas techniques [1, 2, 7]. Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart [3, 4], is one of the modernheuristic algorithms. The PSO technique can generate a high-quality solution within shorter calculation time and stable convergence characteristics than other stochastic methods [5]. Much research is still in progress for proving the potential of the PSO in solving complex optimization problems.

2. Problem Formulation

Our objective is to optimize a reduced greenhouse model in which the controlled variables are, indoor temperature (T_i, °C) and water vapour pressure (P_i, Pa) and the actuators are, the fog system (φ_l, power of the evaporative cooling fog system,Wm^{-2}), the vent opening (s, vents opening surface m^2), the soil heat flux (Q_s, Wm^{-2}) and the air heating (Q_a ,Wm^{-2}). Heat and water vapour balances have been first formulated in order to obtain the main equation of the whole model. Then particular equations have been added to complete the model.

3. Block Diagram and Open Loop Results

The block diagram of the greenhouse is shown in (Fig. 1) together with the four actuators s, Q_a, Q_s and φ_l; five input variables have also been considered, T_e (external temperature, °C), P_e (external vapour pressure, Pa), R_g (outside global radiation, Wm-2), V (wind speed, ms^{-1}) and PT_i (saturated vapour pressure at temperature T_i, Pa) these are mainly considered as disturbances in the control loop. Some simulations have been carried out to study the dynamic behavior of the controlled variables T_i and P_i. In these tests, we have also considered the initial conditions for indoor temperature $T_{i(n)}$ and water vapour pressure $P_{i(n)}$ (Fig. 1) [2].

4. Mathematical Model of the Indoor Water Vapour Pressure

In this case a water vapour balance inside the greenhouse is carried out, and the result is [1, 2]:

$$P_{i(n+1)} = P_{i(n)} \exp(-\zeta\,\Delta t) + \left(1 - \exp(-\zeta\,\Delta t)\right)\begin{pmatrix} \dfrac{r\,S\,B\,\gamma\,\tau'}{\xi} & \dfrac{\chi}{\xi} & \dfrac{\gamma\,S\,B}{\xi} & \dfrac{\gamma\,S}{\xi} \end{pmatrix}\begin{pmatrix} R_g \\ P_e \\ PT_i \\ \varphi_l \end{pmatrix}, \qquad (1)$$

where

$$\zeta = \frac{\left(\left(Al\sqrt{C}\ sV\right)+\left(Al\sqrt{C}\ s_0V\right)+d_0+\left(\frac{B\gamma S}{\rho C_p}\right)\right)}{v}, \tag{2}$$

$$\xi = \left(\rho C_p Al\sqrt{C}\ sV\right)+\left(\rho C_p Al\sqrt{C}\ s_0 V\right)+\left(\rho C_p d_0\right)+B\gamma S, \tag{3}$$

and

$$\chi = \xi - B\gamma S, \tag{4}$$

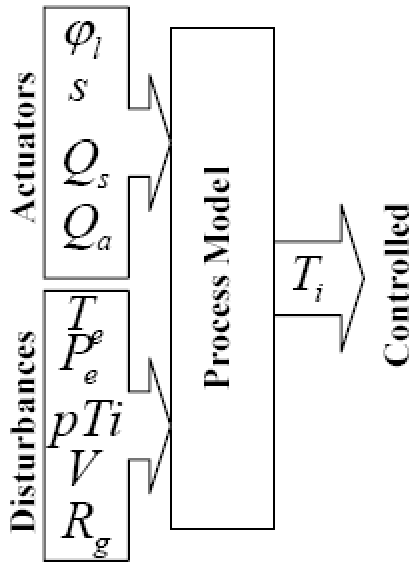

Fig. 1. Block diagram of the controlled green house.

In these equations Δt is the discretisation time step (s), r the ratio A/B (Pa m^2 W^{-1}), with A parameter of the model of transpiration (.), B a parameter of the transpiration model (Wm^{-2} hPa^{-1}), S the exchange surface between two constituents of the greenhouse (m^2), γ the psychrometric constant (hPa K^{-1}), τ' the greenhouse cover transmissivity (.), Al and C parameters of the natural ventilation model (.), s_0 the leakage surface (m^2), d_0 the wind independent leakage rate (m^3 s^{-1}), ρ the air density (kg m^{-3}) and C_p the thermal capacity of the greenhouse air (kg^{-1}K^{-1}). All fluxes are expressed per m2 greenhouse soil area.

5. Mathematical Model of the Indoor Temperature

In this case an energy balance inside the greenhouse is performed from which the temperature is obtained as:

$$T_{i(n+1)} = \frac{h}{v} T_{m(n+1)} + \left(\frac{v-h}{v} \; \frac{\alpha}{v} \; \frac{1}{v} \; \frac{K_l}{v} \; \frac{-K_l}{v} \right) \begin{pmatrix} T_e \\ R_g \\ Q_a \\ P_e \\ P_i \end{pmatrix}, \tag{5}$$

where

$$T_{m(n+1)} = T_{m(n)} \exp\left(-\frac{\Delta t}{\tau}\right) + \left(1 - \exp\left(-\frac{\Delta t}{\tau}\right)\right) \times \wp \times \begin{pmatrix} T_e \\ R_g \\ Q_s \\ Q_a \\ P_e \\ P_i \end{pmatrix}, \tag{6}$$

and

$$\wp = \left(1 \;\; \frac{\alpha h + \beta v}{h(K+K_s)} \; \frac{v}{h(K+K_s)} \; \frac{1}{(K+K_s)} \; \frac{K_l}{(K+K_s)} \; \frac{-K_l}{(K+K_l)} \right), \tag{7}$$

In these expressions, h is the air/soil convective exchange coefficient (W m^{-2} K^{-1}), v the greenhouse volume (m^2), α the absorption of global radiation by the aerial compartment of the greenhouse (.), β the absorption of global radiation by the thermal mass compartment of the greenhouse (.), the two parameters α and β are fractions of the outside incident global radiation (R_g) collectively absorbed by the structure and crop in the former case, and by the soil (thermal mass) in the latter, K_l the latent heat transfer coefficient driven by ventilation (W m^{-2} hPa^{-1}), τ the time constant or characteristic time (s), K the overall heat loss coefficient through the greenhouse cover (W m^{-2} K^{-1}) and K_s the sensible heat transfer coefficient driven by ventilation (W m^{-2} K^{-1}). Q_s the soil heat flux (W m^{-2}) and Q_a the air heat input (W m^{-2}) [1, 2].

6. Ventilation

Ventilation may be either forced (mechanically, as by fans) or natural (caused by thermal buoyancy and/or wind pressures) Mechanical ventilation is typically designed to provide a maximum air exchange rate suitable for the local climate. Wind-driven ventilation is linearly proportional to wind speed and can be vigorous. Ventilation by thermal buoyancy depends on air temperature difference and the elevation difference between inlets and outlets but is not likely to be vigorous in practical applications. However, it can be adequate for greenhouse ventilation if properly designed and controlled. A significantly greater understanding of the subtleties of natural ventilation has developed over the past decade. New greenhouse designs allow for adequate side and roof ventilation. The extreme is the open roof greenhouse, which is most useful in gutter-connected greenhouses that cover large areas and are without sufficient sidewall area to provide adequate inlet area. The critical factor in designing natural ventilation is properly sized inlets and outlets. As a first rule, total inlet area should be equivalent to total outlet area. For example, upwind and downwind sidewall vents should be approximately the same area. Or, for thermal buoyancy ventilation, sidewall vents should have approximately the same combined area as the roof (ridge) vent. The ventilation rate G_v is a linear function of wind speed V, the vent opening s, as well as leakages both dependant (s_0) and independent of the wind speed (d_0). Thus, we have:

$$G_v = \frac{(s + s_0)Al\sqrt{C}V}{2} + d_0, \quad (8)$$

The four remaining parameters of the temperature and pressure balance equations to be optimized are: $Al\sqrt{C}$, s_0, d_0, β. The values identified for these parameters using the classical algorithm during a one week sequence are $Al\sqrt{C} = 0{,}2$, $s_0 = 0$, $d_0 = 0$, $\beta = 0$ [6].

With the Simulated annealing Algorithm, 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 Table 1 [1, 2].

Table 1. Search space of the parameters to be identified.

	$Al\sqrt{C}$	s_0	d_0	β
Min	0	0	0	0
Max	0.3	1	1	0.3

7. Particle Swarm Optimization

PSO is one of the optimization techniques and a kind of evolutionary computation technique. The method has been found to be robust in solving problems featuring nonlinearity and non-differentiability, multiple optima, and high dimensionality through adaptation, which is derived from the social-psychological theory. The features of the method are as follows:

1. The method is developed from research on swarm such as fish schooling and bird flocking.
2. It is based on a simple concept. Therefore, the computation time is short and requires few memories [8, 10, 11].
3. It was originally developed for nonlinear optimization problems with continuous variables. It is easily expanded to treat a problem with discrete variables. According to the research results for birds flocking are finding food by flocking.

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. 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 [8, 12, 13, 15]:

– The current positions (x, y),
– The current velocities (v_x, v_y),

– The distance between the current position and pbest
– 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:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k\right) + c_2 rand_2 \times \left(gbest_i - s_i^k\right), \tag{9}$$

where

v_i^k 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; $pbest_i$ pbest of agent I; $gbest$ gbest of the group. The following weighting function is usually utilized in (9).

$$w = -\frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter\ , \tag{10}$$

where $w_{\max}$ initial weight; $w_{\min}$ final weight; $iter_{\max}$ maximum iteration number; $iter$ current iteration number.

Using Eqs. (9) and (10) a certain velocity, which gradually gets close to pbest and gbest can be calculated. The current position can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1}, \tag{11}$$

Eq. (9) 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 i^{th} particle’s current position. Eq. (11) 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 [9, 15]. 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*p 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.

8. Results and Conclusions

The inside air temperature and humidity simulation models were identified using the described approaches for a greenhouse between 14 and 22 May 1991 located near Avignon in south-east France. The greenhouse had a tomato-crop area of 416 m^2, 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 algorithm depends only on the objective function to guide the search, it must be defined before the PSO algorithm is initialized. With experimental to (5), a Mean Quadratic Errors (MQE) is chosen as the objective function in this study defined by [14]:

$$MQE = \frac{1}{N}\sum_{j=1}^{N}\left[T_i(j) - T_{i\exp}(j)\right]^2, \tag{12}$$

where N is the number of data; T_i the indoor temperature calculates $T_{i\exp}$ the indoor temperature experimental The contribution of this paper is to apply the proposed PSO algorithm to minimize the MQE value.

There are two general conditions to terminate the PSO algorithm: (a) the objective function of the global best is less than a pre-specified value or (b) the number of iterations achieves the maximum allowable number $Nitr$. In this study, the second criterion is adopted to terminate the search process.

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 = 192, lower and upper bounds are $lb = [0\ \ 0\ \ 0\ \ 0]$ and $lb = [0{,}3\ \ 1\ \ \ 1\ \ 0{,}3]$, 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.

As shown in Fig. 3, the average of the differences between the experimental data of the temperature and with the air temperature values given by the model identified by the classical algorithm was 4.7 °C, with a maximum difference of 10.0832. And comparing the experimental data of the temperature and with the air temperature values given by the model identified by the PSO, the average of differences was 2.02°C, with a maximum difference of 8.4985 as shown in Fig. 4.

The selection of models is done comparing the errors between the experimental data and the model identified by a classical 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:

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|T_i(j) - T_{i\exp}(j)\right|, \tag{13}$$

$$MRE = \frac{1}{N}\sum_{j=1}^{N}\frac{\left|T_i(j) - T_{i\exp}(j)\right|}{T_i(j)} \times 100, \tag{14}$$

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

The best results obtained by the Genetic Algorithm are given in Table 2. Fig. 2 compares the results given by the PSO and Classical Algorithms with the experimental values. Good agreement can be seen between the experimental results and the simulation obtained from the Genetic Algorithm, both in terms of dynamics and intensity of the signal. In order to estimate the validity of our algorithm, we have calculated the errors between the experimental and simulated results. We can see (Table 3) that, with respect to the classical algorithm, 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 classical Marquardt Algorithm.

In this paper, we have successfully applied the PSO algorithm to identified parameters of Natural Ventilation in a Greenhouse with Continuous Roof Vents. In the model of greenhouses estimation of PSO-based algorithm, a set of ventilation parameters is refereed to as a particle, then the velocity and position updating formulas are performed on the particles to force them toward better positions. At the same time, the pre-specified objective function MQE can be minimized. To demonstrate the estimation performance, several examining conditions are considered, including different sizes of noises and different random sets of initial populations. The simulation results obtained from the PSO and classical methods are compared. They clearly reveal the effectiveness of the proposed PSO algorithm in estimating parameters of Natural Ventilation in a Greenhouse with Continuous Roof Vents.

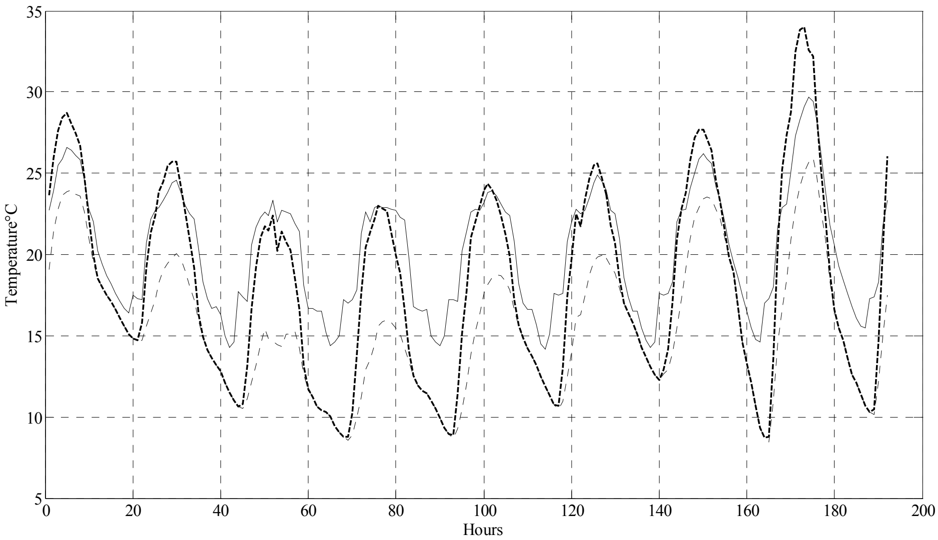

Fig. 2. Temperature inside greenhouse: experimental temperature inside─(continuous line); Model identified by classic algorithm ─(dot line); Model identified by PSO ─(dash line).

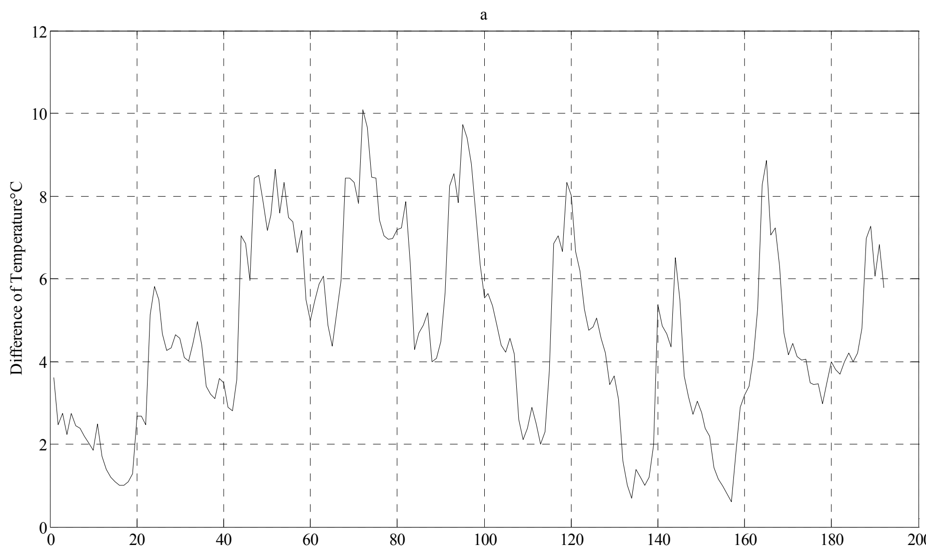

Fig. 3. Difference of temperature between the experimental, and the calculus with the model identified by a classical algorithm.

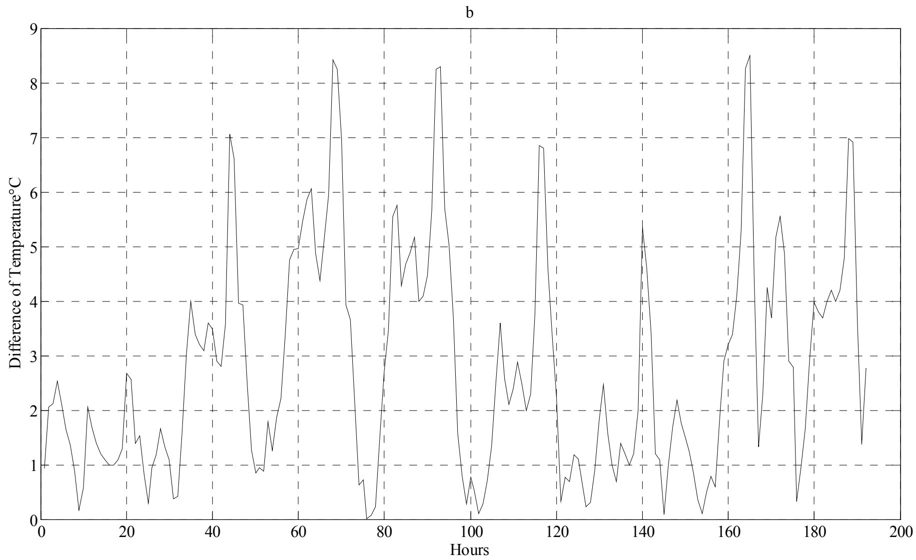

Fig. 4. Difference of temperature between the experimental and the calculus with the model identified by the PSO.

Table 2. Best parameter values identified by the Genetic Algorithm.

	$Al\sqrt{C}$	s_0	d_0	β
Min	0	0	0	0

Table 3. Statistical accuracy measures.

The errors	**MQE**	**MAE**	**MRE**	**SE**
Model identified by classical algorithm	0.3771	4.7015	0.0014	0.3790
Model identified by PSO algorithm	0.2481	2.7622	5.9928e-004	0.2494

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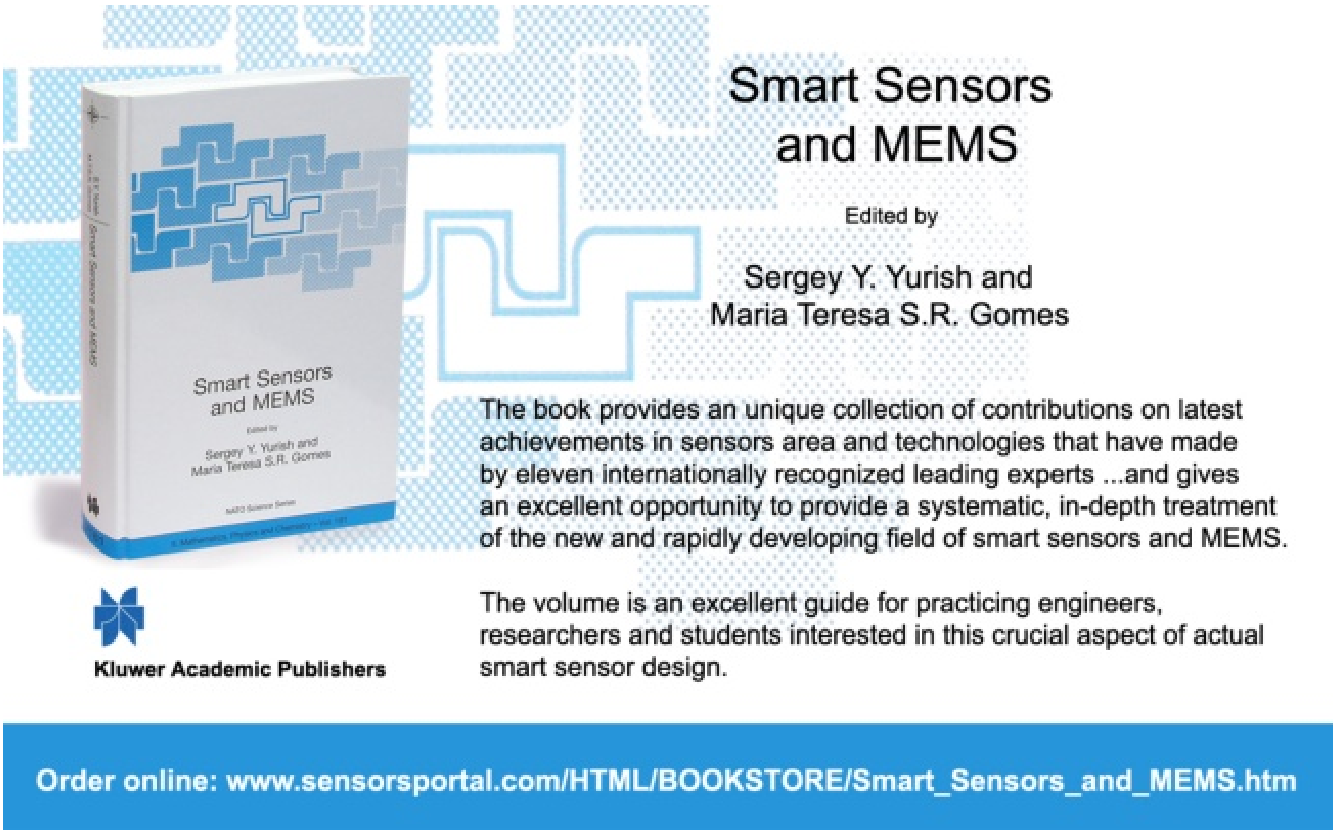

Guide for Contributors

Aims and Scope

Sensors & Transducers Journal (ISSN 1726-5479) provides an advanced forum for the science and technology of physical, chemical sensors and biosensors. It publishes state-of-the-art reviews, regular research and application specific papers, short notes, letters to Editor and sensors related books reviews as well as academic, practical and commercial information of interest to its readership. Because it is an open access, peer review international journal, papers rapidly published in *Sensors & Transducers Journal* will receive a very high publicity. The journal is published monthly as twelve issues per annual by International Frequency Association (IFSA). In additional, some special sponsored and conference issues published annually.

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- Sensor instrumentation;
- Virtual instruments;
- Sensors interfaces, buses and networks;
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