Model based predictive control of greenhouse climate for reducing energy and water consumption ⋆

X. Blasco [a,*] M. Martínez [a] J.M. Herrero [a] C. Ramos [a] J. Sanchis [a]

[a] *Predictive Control and Heuristic Optimization Group*

Department of Systems Engineering and Control

Universidad Politécnica de Valencia.

Camino de Vera S/N, 46022-Valencia, Spain.

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Abstract

This work focuses on development of control algorithms by incorporating energy and water consumption to maintain climatic conditions in greenhouse.

Advanced control algorithms can supply solutions to modern exploitations. The new developments usually require accurate models (probably multivariable and non-linear ones) and control methodologies capable of using these models. As an additional requirement it is important for the final application to be easy to use, so advanced control will not mean an increase in complexity of the manipulation of the installation.

This article shows an alternative to classical climate control. It is based on two fundamental elements: an accurate non-linear model and a model based predictive control (MBPC) that incorporate energy and water consumption. Genetic Algorithms (GAs) play a key role in these two elements because functions to solve are non-convex and with local minima. First of all GAs supply a way to adjust the non-linear model parameters obtained from first principles, and finally GAs open the possibility of using non-linear model in the MBPC and of establishing a flexible cost index to minimize energy and water consumption. The results on a plastic greenhouse with arch-shaped roofs and for Mediterranean area are presented, important reduction in energy and water used in the cooling system (nebulization) is obtained.

Key words: Greenhouse Control, Non-linear Predictive Control, Genetic Algorithms, Non-linear Identification, Optimization

1 Introduction and motivation

Nowadays agricultural exploitations have to adapt to a more competitive environment and therefore to incorporate new technologies. One way of getting profitable crops consists of using greenhouse and hydroponic crop (Boodley, 1996; Nelson, 2002). Improvements in these new crops need, among other advances, improvements in all greenhouse control systems and in particular in climate control. There exist diverse worthwhile variables to be controlled in this kind of installations, and in particular, this work tries to control the inside air temperature and humidity.

An important determining factor in the profitability of the hydroponic crop inside greenhouse installations is the exploitation cost. A consumption of water [1] and energy for keeping the climatic variables under control around the setpoints is required in this kind of installations. In particular, the water costs are more and more noteworthy in the Mediterranean region, since the droughts are more frequent and intense. So it seems to be important to take into account both water and energy costs.

This work focuses on the implementation of a controller whose aim consists

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∗ Corresponding author. DISA-Universidad Politécnica de Valencia.

Camino de Vera S/N, 46022-Valencia, Spain.
Email address: xblasco@isa.upv.es (X. Blasco).
URL: ctl-predictivo.upv.es (X. Blasco).

[1] Consumption of water is involved in climatic control when nebulization system is used as cooling system in summer time. Irrigation costs are not in the scope of this work.

of the costs minimization maintaining performance in an acceptable range. This is an innovative approach, since traditional controllers seldom take into account the costs in an explicit manner, and provide the control actions by focusing almost always on the performance. So the costs for keeping that performance might be unacceptable.

A model based predictive control (MBPC) is used in this new approach, since this kind of controllers offers a wide flexibility in selecting the control objectives. So it is possible to select the exploitation cost of the installation as the main objective.

A good dynamic model of the process is essential in order to achieve a good performance of the controller. In the case of the greenhouse some important non-linearities arise (mainly due to biological phenomena related to the plants life) which can be reasonably modelled by first principles equations [2]. Nevertheless it is a hard task to adjust the parameters of this kind of models. In this work, the adjustment is stated as a minimization problem which is solved by Genetic Algorithm (GA) (Holland, 1975; Goldberg, 1989). The optimization problem can be composed of non-convex functions and search spaces, so if classical optimization methods are used, local minima can be obtained. In this way, the complexity of the optimization problem justifies selecting a global optimization technique as GAs.

The controller implementation is also stated as a very complex optimization problem which must be solved at each sample time. In this case, the problem is also solved by using GAs with the same justification. The drawback of this technique consists of the large computational burden, although in this type

[2] Equations obtained from physical and biological phenomena.

of applications it is not a problem, since the sample time is big enough (2 minutes) in order to make the required calculations.

All the experimental data used in this work have been collected from a rose hydroponic crop inside greenhouse located in the IVIA (Valencian Institute for Agricultural Research) in Moncada (Valencia-Spain) with Mediterranean climate. It is a plastic greenhouse of 240 m^2 with arch-shaped roofs. Roof windows, heating system and nebulization are used to maintain inside climate conditions.

The structure of the article is the following, first of all the obtaining of the non-linear model used by the controller is shown (section 2). Later (section 3), the methodology used for the non-linear model parameters identification is described, together with the obtained model and the validation. After that (section 4) the fundamentals of the selected control strategy are briefly shown (model based predictive control - MBPC). Besides (section 5), the special features of the implemented controller based on costs optimization criteria are described in depth. The results (section 6) from the proposed control for several summer days are shown. And finally (section 7) conclusions and future work are presented.

2 Greenhouse climate model

The first step for an advanced control design is the development of a dynamic model. Model quality is a fundamental aspect to achieve adequate control performances. It is possible to divide models into two groups (Johansson, 1993; Pronzalo and Walter, 1997):

(1) First principles models. Those that provide physical phenomena by means of differential equations (usually by state space models). In this type of models, parameters have a physical interpretation.

(2) Black box models. Those that try to approximate the behaviour without a priori information, for instance, polynomial fitting, Neural Networks, Fuzzy Sets, etc.

It is difficult to select a priori the most useful type of model. Both can have a very good quality. First ones are more understandable but their development is difficult and very expensive. The second group has no physical meaning but is easier to obtain.

Biologists and agronomist engineers have invested a lot of time to improve physical and physiological models for all process inside greenhouses and, although some black box models have been tested, they usually prefer first principles models. Usually because this type of models offers a closer interpretation of phenomena (Baille et al., 1994, 1996). This work exploits this alternative and in this section shows how a non-linear state space model is obtained from first principles, other alternative approaches can be found at (Coelho et al., 2005; Piñón et al., 2005).

For climate modelling purpose, the greenhouse is considered as an air volume delimited by the walls, the canopy and the ground. Process model in state space form can be obtained from mass and energy balance, including plants biological behaviour, this approach is similar to recent ones (Ghoumari et al., 2005). Two subsystems can be established, air volume and ground, this last one acts as a thermal mass (Albright et al., 1985; Boulard et al., 1996). The relevant state variables to describe climatic behaviour are inside temperature

T_i and relative humidity H_i (or absolute humidity x_i) in the air volume and ground temperature T_m (called thermal mass temperature). From water mass and energy balance, the state space equations are defined by [3]:

$$\rho v_i \frac{dx_i}{dt} = F_v + C_{sat}(E + fog) \tag{1}$$

$$v_i \rho c_p \frac{dT_i}{dt} = Q_s - Q_{cc} + Q_m - C_{sat}(Q_e + Q_n) - Q_v + W \tag{2}$$

$$A_i C_m \frac{dT_m}{dt} = Q_{sm} - Q_m - Q_f \tag{3}$$

An input-output diagram model is shown in figure B.1, where variables to be controlled are T_i, H_i, manipulated variables are window (MV_α), heating (MV_W) and fog system (MV_{fog}) and measurable disturbances are solar radiation (S_o), wind speed (V), outside temperature and humidity (T_o and x_o).

3 Model parameters identification with GAs

First principles models supply models with approached physical sense but, as it can be seen at appendix A, there are lots of parameters most of them difficult to adjust. There exists a well known set of techniques for linear model identification (Johansson, 1993; Pronzalo and Walter, 1997) but the climate greenhouse model is clearly non-linear.

Accepted alternatives for parameter identification in non-linear models are based on minimization of a norm of errors vector. The errors vector is usually composed of differences between experimental process outputs and model outputs in a specific time horizon. The complexity of the function to minimize

[3] Appendix A shows more details about notation and important model non-linearities.

(due to model non-linearities, saturations, etc.) can avoid the use of classical numeric optimization (Gauss-Newton based methods) because of non-convex problems and local minima problems. Therefore global optimization is required, for this purpose GAs can offer good solutions (Holland, 1975; Goldberg, 1989). A recent application of GAs to greenhouse model parameters identification as already been performed by (Hasni et al., 2006). The disadvantage of GAs is the high computational cost, although for some types of applications it is acceptable (Haupt and Haupt, 1998; Chambers, 2000).

A generic process model can be represented by a set of differential equations building a state space model:

$$\dot{\mathbf{z}}(t) = f(\mathbf{z}(t), \mathbf{u}(t), \zeta) \tag{4}$$
$$\hat{\mathbf{y}}(t) = g(\mathbf{z}(t), \mathbf{u}(t), \zeta) \tag{5}$$

where:

- $f(.)$ and $g(.)$: functions that establish model structures. They can be linear or not.
- ζ: model parameters to identify.
- $\mathbf{u}(t)$: model input vector (m inputs).
- $\hat{\mathbf{y}}(t)$ model output vector (l outputs).
- $\mathbf{z}(t)$: state variables vector (n state variables).

Identification of parameters ζ is obtained by the minimization of a function of model output error (difference between experimental outputs and model outputs for the same inputs, $\mathbf{e} = \mathbf{y} - \hat{\mathbf{y}}$). Then, in general, a proposed cost function to minimize is:

$$J(\zeta) = f\left(\|\mathbf{y} - \hat{\mathbf{y}}\|_{qK}\right) = f\left(\|\mathbf{e}\|_{qK}\right) \tag{6}$$

Where $\|.\|_q$ represents a norm of a vector and K represents a weighting coefficient of each vector element[4] (K is usually a diagonal matrix or a vector).

The cost function selected plays an important role in parameter identification, there is no ideal cost function, all of them have their advantages and disadvantages, then it is the user who has to decide according to the requirements. In classical identification methods 2-norm is used just to avoid problems with the numerical optimization. But 2-norm introduces distortion in model error evaluations (Aström and Wittenmark, 1995), for instance, there is an overreduction for low errors. A fair way to treat model errors is to use 1-norm that introduces no distortion. Therefore the proposed cost function is based on 1-norm and can be detailed as follows:

$$J(\zeta) = \|\mathbf{y} - \hat{\mathbf{y}}\|_{1_K} = \sum_{j=1}^{te}\sum_{i=1}^{l} k_{ij}|y_i(j) - \hat{y}_i(j)| \tag{7}$$

where:

- te: experimental samples.
- k_{ij}: weighting coefficient of output i for sample j.
- $y_i(j)$: sample j of process output i.
- $\hat{y}_i(j)$: sample j of model output i.
- l: number of outputs.

In this problem weighting factors k_{ij} are used to normalize outputs of the multivariable process (Herrero et al., 2002), each output represents a different magnitude and it is necessary a normalization to enable comparison in the

[4] Definition of q-norm of a vector ($\mathbf{x} = [x_1, \ldots, x_n]$) is $\|\mathbf{x}\|_q = (|x_1|^q + \ldots + |x_n|^q)^{(1/q)}$. The most common q-norms are 1 and 2. If a weighting coefficient is present, the definition is $\|\mathbf{x}\|_{qK} = (k_1|x_1|^q + \ldots + k_n|x_n|^q)^{(1/q)}$.

cost function. Once the cost index is selected, it is necessary to consider two additional aspects:

- Model adaptation and selection of the parameters to identify.
- Experimental planning.

For climatic greenhouse model (figure B.1) state equations (1), (2) and (3) are adapted directly to equations (4) and (5).

For the parameters selection, the following aspects have been considered: selected parameters represent those physical magnitudes with higher uncertainty. Fifteen parameters have been selected, some of them are related to the rose crop and the others with heat transmission coefficient and reference temperature of the greenhouse [5].

$$\zeta = [gws_{max} \;\; gws_{min} \;\; L \;\; k \;\; gwb \;\; \tau \;\; a \;\; G_o \;\; Ac \;\; C_m \;\; h_m \;\; T_{ref} \;\; \alpha_m \;\; k_a \;\; fog_{max}]^T \tag{8}$$

This set of parameters is proposed to tune the model for summer [6] period and, it has to adjust dynamic behaviour for day and night. Model inputs, outputs and state variable are:

$$\mathbf{u}(t) = [MV_\alpha \;\; MV_{fog} \;\; MV_W \;\; S_o \;\; T_o \;\; H_o \;\; V]^T \tag{9}$$
$$\hat{\mathbf{y}}(t) = [T_i \;\; H_i]^T \tag{10}$$
$$\mathbf{z}(t) = [x_i \;\; T_i \;\; T_m]^T \tag{11}$$

[5] Appendix A shows a description of every parameter and intervals of possible values obtained from preliminary analysis.

[6] For summer time, the heating system is considered to be disconnected (MV_W is not considered).

Experimental planning has to define:

(1) Input signals selection (shape and sample time). Experiment length.
(2) Process operation conditions.

Operating conditions of the greenhouse are highly conditioned by disturbances as solar radiation, outside temperature, etc. They have a degree of periodicity (period of one day) but there exists a random component from one day to another. Then, minimum length considered for identification is 24 hours. To include most of the conditions, collected data comes from daily operations with the current control system and experiment length is set to multiple of 24 hours. Sample time is set to 15 seconds, enough to show significant dynamic behaviour of all variables involved in greenhouse climate.

3.1 Results and validation

With previous considerations, parameters ζ are identified taking experimental data from two non consecutive days of June (the June 11 and 15, 2004). For this application a specific GA is adjusted with 10.000 individuals and 50 iterations (general description of GAs is showed at appendix B). Results of identification process are in range of agronomist forecast:

$$\begin{aligned}\zeta^* = [&0.011 \quad 0.00435 \quad 0.796 \quad 0.52 \quad 0.0368 \quad 0.418 \quad 0.0017 \quad 0.0005 \quad 17.907 \\ &126594 \quad 8.4 \quad 18.8329 \quad 0.04629 \quad 7.8685 \quad 0.00435]^T\end{aligned} \tag{12}$$

Figure B.2 shows a comparison between experimental data and model output for optimal parameter set ζ^*. Temperature and relative humidity are compared. Statistics (Table B.1) for this comparison show an adequate model adjustment:

For validation purpose, additional data is collected corresponding to several days of June, July and August. Validation is done by simulating with the same parameters for all data set collected. Figure B.3 shows comparison for the day where model presents the best results (June 20, 2004) and the worst results (July 28, 2004). Statistical validation results are presented in Table B.2. Results are good enough for controller design purpose.

4 Model based predictive control by using genetic algorithms

Model Based Predictive Control (MBPC) is one of the most intuitive and powerful control techniques. This methodology can be summarized in a few words:

> With a process model and its past behaviour it is possible to produce predictions of the process dynamic evolution for different control laws. If we could set a cost for each one of these predictions it is possible to select the best control law to achieve a fixed objective.

This easy and intuitive way to describe how MBPC works has been the basis of its success in industry. Several research work and industrial applications have shown its control capabilities (Qin and Badgwell, 2003). In particular, for greenhouse control MBPC has already been applied in different ways (Blasco et al., 2001; Coelho et al., 2005; Lecomte et al., 2005; Piñón et al., 2005).

Described in more detail, all of the controllers with this methodology have three fundamental elements (fig. B.4):

(1) A **Predictor** that supplies controlled variables predictions for different manipulated variables combination (control law). These predictions are based on process information (model and measures of variables).

(2) A **Cost function** that assigns a cost to each prediction depending on previous fixed objectives.

(3) An **Optimization technique** to look for the best control law.

Finally **Receding horizon** is applied, that is, at each sample time, optimization is recomputed with all new available measures.

Usually the bottleneck of this methodology is the Optimization Technique. Accurate models commonly have to include non-linearities, or even if linear models are accurate enough, realistic cost function could introduce non-linearities. All this aspects generally produce quite difficult optimization problems. A Genetic Algorithm (GA) is a competitive way to solve difficult optimization problems when computing time is enough.

Then combining MBPC with GA results in a promising alternative to solve complex control problems. This alternative was already proposed and analyzed for SISO (single-input single-output) transfer function model with additional non-linearities as saturation, dead-zone and backlash (Martínez et al., 1998). This work extends MBPC with GA to MIMO (multi-input multi-output) processes by using a state space representation that is a general way to model non-linear processes.

MBPC control structure is similar in SISO (see (Martínez et al., 1998)) and MIMO models (fig. B.5).

5 Greenhouse climate control application

To describe MBPC application to a greenhouse climate control all MBPC elements are detailed: predictor, cost function and optimization technique for the greenhouse climate control.

5.1 Predictor

The predictor is based on the state space model developed in previous section.

To improve robustness and performances, predictions are obtained from model outputs corrected by a disturbance model (see figure B.6):

$$\mathbf{y}(t) = \mathbf{y}_u(t) + \mathbf{n}(t) \tag{13}$$

- $\mathbf{y}_u(t) = [y_{u1}(t), y_{u2}(t)]^T = [T_{iu}(t), H_{iu}(t)]^T$, array of model controlled variables.
- $\mathbf{n}(t) = [n_1(t), n_2(t)]^T$, array of correction variables based on non-measured disturbance model.
- $\mathbf{y}(t) = [y_1(t), y_2(t)]^T = [T_i(t), H_i(t)]^T$, array of corrected controlled variables.
- $\mathbf{u}(t) = [u_1(t), u_2(t), u_3(t)]^T = [MV_\alpha(t), MV_{fog}(t), MV_W(t)]^T$ array of manipulated variables.
- $\mathbf{d}(t) = [S_o(t), T_o(t), H_o(t), V(t)]^T$, array of measured disturbances.

Non-measured disturbance model is usually adjusted to reduce effects of non-modelled dynamics and noises. A good adjustment when models are linear is ARIMA model (Clarke et al., 1987a,b). When process model is non-linear a minimal structure for disturbance model in order to avoid steady state errors is:

$$n_i(t) = \frac{1}{\Delta}\xi_i(t) \tag{14}$$

where $\Delta = (1 - z^{-1})$ and $\xi_i(t)$ is a zero mean white noise.

With this structure, predictions for time '$t+j$' with information collected until time 't' are:

$$\mathbf{y}(t+j|t) = \mathbf{y}_u(t+j|t) + \mathbf{n}(t+j|t) \tag{15}$$

where $y_{ui}(t+j|t)$ are obtained from state space model and $n_i(t+j|t)$ from the following development, at time 't+1':

$$n_i(t+1)\Delta = \xi_i(t+1) \rightarrow n_i(t+1) = n_i(t) + \xi_i(t+1) \tag{16}$$

The best prediction of $n_i(t+1)$ with information available until time 't' ($n_i(t+1|t)$) is[7]:

$$n_i(t+1|t) = n_i(t) \tag{17}$$

Past data of $n_i(t)$ needed in the calculus is obtained from difference between measured controlled variables and controlled variables from model:

$$n_i(t) = y_i(t) - y_{ui}(t) \tag{18}$$

Then:

$$n_i(t+1|t) = y_i(t) - y_{ui}(t) \tag{19}$$

[7] ξ_i is a white noise with zero mean and then its best estimation is zero.

Repeating this for $t+2,\ldots,t+j$ the best estimation for correcting variables results in:

$$\mathbf{n}(t+j|t) = \mathbf{y}(t) - \mathbf{y}_u(t) \tag{20}$$

5.2 Cost function

The cost function is the MBPC component in charge of setting performances that designer has established. Its function is to assign a value to each proposed control law during prediction horizon. This component has also to include all constraints involved in control. Finally predictions with behaviour near to control objective (set by designer) must have a lower value of cost function (a minimization problem is established).

At this point, a new approach for greenhouse climate control is proposed. Usually controllers are designed to follow a setpoint, for instance, it is normal to adjust at least a temperature setpoint and the controller has to propose a control action to achieve and maintain it despite disturbances. Different and successful implementation can be found in nowadays installations (Martínez et al., 2005). But this type of control can suffer from a lack of efficiency: consumption of energy and water are not directly taken into account in the controller design.

With the cost function, MBPC supplies a flexible mechanism to include most of designer objective. In particular, for this application it is very important to maintain climate condition under the minimum cost in energy and water. It is not really necessary to maintain a specific setpoint, it is enough to maintain climatic variables into a range of values.

The proposed cost function is then:

$$J(\bar{\mathbf{u}}) = J_1(\bar{\mathbf{u}}_1) + J_2(\bar{\mathbf{u}}_2) + J_3(\bar{\mathbf{u}}_3) \tag{21}$$

where

- $\bar{\mathbf{u}} = [\bar{\mathbf{u}}_1^T, \bar{\mathbf{u}}_2^T, \bar{\mathbf{u}}_3^T]^T$
- $\bar{\mathbf{u}}_1 = [\Delta MV_\alpha(t), \Delta MV_\alpha(t+1), \ldots, \Delta MV_\alpha(t+n_u^\alpha)]^T$
- $\bar{\mathbf{u}}_2 = [MV_{fog}(t), MV_{fog}(t+1), \ldots, MV_{fog}(t+n_u^{fog})]^T$
- $\bar{\mathbf{u}}_3 = [MV_W(t), MV_W(t+1), \ldots, MV_W(t+n_u^W)]^T$

As in all predictive controller, a control horizon is established for each manipulated variable: n_u^α, n_u^{fog} and n_u^W. These parameters set the degree of freedom for the controller, low value means conservative control law and high values aggressive control law.

Terms in (21) are detailed as follows:

$$J_1(\bar{\mathbf{u}}_1) = \frac{K_1}{100 \cdot n_u^\alpha} \sum_{j=1}^{j=n_u^\alpha} |\Delta MV_\alpha(t+j)| \tag{22}$$

$$J_2(\bar{\mathbf{u}}_2) = \frac{K_2}{100 \cdot n_u^{fog}} \sum_{j=1}^{j=n_u^{fog}} MV_{fog}(t+j) \tag{23}$$

$$J_3(\bar{\mathbf{u}}_3) = \frac{K_3}{100 \cdot n_u^W} \sum_{j=1}^{j=n_u^W} MV_W(t+j) \tag{24}$$

Notice that objectives to minimize are directly related to energy and water consumption:

- $J_1(\bar{\mathbf{u}}_1)$ evaluates spent energy to open windows. Only variations of MV_α produce energy consumption.
- $J_2(\bar{\mathbf{u}}_2)$ evaluates the water used by fog system.

- $J_3(\bar{\mathbf{u}}_3)$ evaluates consumed heating system energy.

For terms J_2 and J_3 absolute value is not necessary because only positive values of MV_{fog} and MV_W are possible for this type of actuators. Every term are normalized dividing by the maximum value of manipulated variable (100%) and the number of allowed movement for each manipulated variable (n_u^α, n_u^{fog} and n_u^W respectively), then, maximum possible value of J_k is always one. Relative importance of economic aspects for each term could be adjusted by weighting factors K_1, K_2 and K_3. In the zone of interest for this greenhouse (Spanish Mediterranean area) costs in water are very important then K_2 has to be greater than K_1 in summer time and heating system is disconnected $K_3 = 0$. And for winter time, fog system is disconnected $K_2 = 0$ and heating system consumption is much more expensive than windows movement, then $K_3 \geq K_1$.

For inputs variable, it is important to include process physical limits in the optimization problem, then the following constraints have to be included:

$$\bar{\mathbf{u}}_{min} \leq \bar{\mathbf{u}} \leq \bar{\mathbf{u}}_{max} \tag{25}$$

where $\bar{\mathbf{u}}_{min}$ and $\bar{\mathbf{u}}_{max}$ are vectors with the actuator physical limits.

To adjust performances, in this case climate conditions, a set of constraints is added to output variables. The objective is to maintain climate conditions into a range of value ($[H_{min}, H_{max}]$ and $[T_{min}, T_{max}]$) for all prediction horizon N:

$$\bar{\mathbf{y}}_{min} \leq \bar{\mathbf{y}} \leq \bar{\mathbf{y}}_{max} \tag{26}$$

where:

- $\bar{\mathbf{y}} = [y^T(t+1|t), \ldots, y^T(t+N|t)]^T$
- $\mathbf{y}(t+j|t) = [T_i(t+j|t), H_i(t+j|t)]^T$
- $\bar{\mathbf{y}}_{min} = [\mathbf{y}_{min}^T(t+1), \ldots, \mathbf{y}_{min}^T(t+N)]^T$
- $\mathbf{y}_{min}(t+i) = [T_{min}, H_{min}]^T, \quad i = 1 \ldots N$
- $\bar{\mathbf{y}}_{max} = [\mathbf{y}_{max}^T, \ldots, \mathbf{y}_{max}^T]^T$
- $\mathbf{y}_{max}(t+i) = [T_{max}, H_{max}]^T, \quad i = 1 \ldots N$

Prediction $\mathbf{y}(t+j|t)$ is obtained with the non-linear model corrected by non-measured disturbance model, see (15).

The optimization problem to solve at each sample time is then:

$$\begin{aligned} &\min_{\hat{\mathbf{u}}} J \\ s.t.: \; &\bar{\mathbf{u}}_{min} \leq \hat{\mathbf{u}} \leq \bar{\mathbf{u}}_{max} \\ &\bar{\mathbf{y}}_{min} \leq \bar{\mathbf{y}} \leq \bar{\mathbf{y}}_{max} \end{aligned} \tag{27}$$

Remark that this formulation focuses on minimizing costs to maintain a range of climate condition and not on performance specifications.

5.3 Optimization technique

Optimization problem (27) is a difficult constrained non-linear problem, and a GA is a reasonable alternative if derived computational cost is allowed.

However, (27) cannot be solved directly because of constraints. It is necessary a reformulation to adapt it for a GA. There are several ways to consider constraints (Coello, 2002) and most of them are based on *Penalty functions*. By addition of the penalty function term, the constrained problem is transformed into an unconstrained one. Only constraints on GA search space are maintained (usually the physical limit of actuators). Penalty function has to be designed to consider the degree of violation of each constraint.

It is convenient for the penalty function to take as low as possible values but always above the values of cost index for the solution that does not violate constraints. The objective is to establish a clear difference between feasible and unfeasible solutions.

The proposed solution reformulates cost function as follows:

$$J_p(\bar{\mathbf{u}}) = J(\bar{\mathbf{u}}) + offset + \sum_{k=1}^{k=4} \phi_k(\bar{\mathbf{u}}) \tag{28}$$

Penalty function ϕ_k is associated with performance constraints:

- Violations of $T_i(t+j|t) \leq T_{max}$ for some j are penalized with $\phi_1(\bar{\mathbf{u}})$.
- Violations of $H_i(t+j|t) \leq H_{max}$ for some j are penalized with $\phi_2(\bar{\mathbf{u}})$.
- Violations of $T_i(t+j|t) \geq T_{min}$ for some j are penalized with $\phi_3(\bar{\mathbf{u}})$.
- Violations of $H_i(t+j|t) \geq H_{min}$ for some j are penalized with $\phi_4(\bar{\mathbf{u}})$.

where:

$$\phi_1(\bar{\mathbf{u}}) = \frac{1}{15} \sum_{j=1}^{N_2} \max\{0, (T_i(t+j|t) - T_{max})\} \tag{29}$$

$$\phi_2(\bar{\mathbf{u}}) = \frac{1}{20} \sum_{j=1}^{N_2} \max\{0, (H_i(t+j|t) - H_{max})\} \tag{30}$$

$$\phi_3(\bar{\mathbf{u}}) = \frac{1}{15} \sum_{j=1}^{N_2} \max\{0, (T_{min} - T_i(t+j|t))\} \tag{31}$$

$$\phi_4(\bar{\mathbf{u}}) = \frac{1}{20} \sum_{j=1}^{N_2} \max\{0, (H_{min} - H_i(t+j|t))\} \tag{32}$$

Remark that every penalty function has a weighting factor to adjust relative importance of different types of violation: $1/15$ for constraints on temperature and $1/20$ for constraints on humidity.

As maximum value of every J_k (see eq. (22), (23) and (24)) is one, it is easy to adjust a maximum value of cost function (21). If weighting constants are adjusted in such a way that: $K_1, K_2, K_3 \in [0, 1]$ then maximum value of $J(\mathbf{u})$ is never greater than 3. Then $offset$ parameter (minimum penalization value) can be adjusted to ensure solutions with any type of constraints violation have always a higher value of J_p than those solutions with no violation:

$$offset = \begin{cases} 3, \exists\, k: \ \phi_k(\bar{\mathbf{u}}) \neq 0 \\ \\ 0, \text{otherwise} \end{cases} \tag{33}$$

If all individuals of the GA violate any of the constraints, functions $\phi_k(\bar{\mathbf{u}})$ penalize depending on the degree of violation. Then GA tends to generate solutions with lower degree of violation at each iteration.

With this formulation, the optimization problem to solve at every sample time is:

$$\min_{\bar{\mathbf{u}}} J_p \ , \quad s.t. \quad \bar{\mathbf{u}}_{min} \leq \bar{\mathbf{u}} \leq \bar{\mathbf{u}}_{max} \tag{34}$$

6 Results for summer time

The evaluation of the proposed algorithm is done with summer time data, when the heating system is disconnected. It is possible to do the same evaluation for winter time, by tuning the model, disconnecting the fog system and connecting the heating one.

Experimental data have been collected from four different days. The data are composed of information about disturbances (solar radiation, outside temperature, outside relative humidity and wind speed) and information about the control system which is just now working at the greenhouse (controlled variables such as the inside relative temperature and humidity and manipulated variables such as the opening window angle and the fog system both in percentage). There are only three possible values for the fog system 0, 50 and 100%. The setpoints that are just now present in the system are:

- To keep a relative humidity of 60% $\pm 1\%$.
- To keep an inside temperature in $[18^oC, 25^oC]$.

The control system is based on independent closed-loops, and besides it contains some heuristic rules to prevent the system from incoherences.

In order to make possible the comparison between the current controller and the proposed MBPCGA controller, both of them will aim at the same objectives, although the last one will take into account the minimization of water and energy consumption. So, those objectives are stated as the following constraints:

- To keep a relative humidity in $[50\%, 70\%]$.
- To keep an inside temperature in $[18^oC, 25^oC]$.

The controller considers the model from section 3 whose parameters (8) are set as (12).

The values of the controller parameters are:

- Control horizons $n_u^{\alpha} = 1$ and $n_u^{fog} = 2$. Low values have been chosen to get a conservative control, since too abrupt changes in the actuators are not good for the installation maintenance. Besides, in the greenhouse case, as the actuators saturate very often, they limit a lot the operation range, and so it would not be possible to apply a more aggressive control.

- Prediction horizon $N = 5$. A low value has been selected to avoid predictions from big errors due to bad predictions of the disturbances. In a standard MBPC control, the prediction horizon is expected to be large enough to involve the controlled variables transient. But in the greenhouse case, the impossibility of predicting accurately the future disturbances, discourages the designer from choosing too large horizons in order to avoid prediction errors and so a noticeable reduction of the controller performance.
- Controller sample time $T_s = 120$ *seconds*. The controlled variables dynamics is slow enough to allow this sample time.
- All the measures used by the controller are filtered. So, the measures are collected every 15 *seconds*, and a mean value of the measures taken at a period of 120 *seconds* is calculated.
- The disturbances prediction during the prediction horizon is assumed to be constant and equal to the last measured value.

The main genetic algorithm parameters are:

- Population individuals number $NIND = 200$.
- Generations number $MAXGEN = 35$.
- Crossover and mutation probabilities $P_c = 0.8$ and $P_m = 0.01$.

These parameters have been selected to satisfy the sample time and to get a good enough solution. So, under a Matlab® version 7.1 application in a Pentium®4, 3.4GHz with Windows® XP Professional, the computational cost for each iteration is about 84 seconds, which clearly satisfies the sample time. Besides, if the application is transferred to a programming language and operative system more efficient for real time, the computational cost can be even smaller. Anyway, the controller implementation in Matlab® is a valid solution.

The control for four different days with different features has been analysed:

(1) June 11, 2004 (Fig. B.7 and Fig. B.8). At night, a high humidity, little wind and low temperature are present. During the day, the humidity is low, the wind speed is normal and the temperature is mild.
(2) June 15, 2004 (Fig. B.9 and Fig. B.10). At night, there are a mild humidity, almost no wind and low temperature. During the day, the humidity is low, the wind speed is normal and the temperature is mild.
(3) June 20, 2004 (Fig. B.11 and Fig. B.12). At night, a low humidity, no wind and a mild temperature are present. During the day, there are a low humidity, a normal wind and a high temperature. It is noticeable that some clouds at midday cause a worthwhile decrease in solar radiation.
(4) July 28, 2004 (Fig. B.13 and Fig. B.14). High humidity and temperature are present during all the day, and the wind is not present at night and normal during the day.

Two different types of figures for each selected day are shown to evaluate the results:

- The first one shows the process variables for both the current controller and the MBPCGA. Besides, the constraints and the disturbances (outside temperature and humidity, wind speed and solar radiation) are shown, so as the manipulated variables (opening window angle and fog system percentages).

- The second one shows performances and costs. Performances are represented as the absolute value of constraints violations at each sample time for both controlled variables (relative humidity and temperature) and average (discontinuous plot). Costs are represented as the accumulated cost for each actuator (opening window and fog system) which is normalized with respect to the maximum possible value. For the opening window the maximum value means totally opening and closing the window all the day at each sample time, and for the fog system it means totally connecting the fog system all the day.

Table B.3 sums up information about performances and costs. It shows the average and standard deviation of the constraints violations (in ^oC for temperature and in % for relative humidity). The table also shows the accumulated cost during all the simulated day (in % with respect to the maximum cost). Best values for each day are marked in bold type.

By analysing Table B.3, it can be said that:

- None of both controllers keep temperature and humidity in the specified range, because when constraints are violated, the actuators saturate and do not present more degrees of freedom (they are working on the limits).
- In all the cases, both controllers behave in a similar way with respect to temperature.
- The MBPCGA is better than the current controller, with respect to humidity.
- It is noticeable the lesser energy and water consumption with the MBPCGA controller, in all the cases. Only in the case (4), this improvement is not so

noticeable because both controllers provide an almost null cost (in this case the actuators saturation and the lack of degrees of freedom are an evidence all the day).

7 Conclusion

This work offers an alternative to greenhouse climatic control via model based predictive control. As the proposed prediction model is non-linear and not easy to adjust, the adjustment is stated as an optimization problem which is solved by GAs. Besides, as the model is non-linear, it is not viable to get an analytical solution to the optimization problem in which the control problem is stated. So again, a GA is used, which is running at each sample time while time constraints are satisfied.

The main advantage of using predictive control with GAs results in a more flexible way of stating the cost function. The proposed controller tries to minimize energy and water costs to achieve temperature and relative humidity performances inside an objectives range which takes part of the problem as constraints. It is possible to decrease costs, keeping or even improving installation performances, as it is shown in the obtained results. An important reduction in energy and water used in nebulization system is observed.

Despite the control structure is advanced, it is easy to use. Farmers only have to select the desired temperature and humidity ranges for the installation operation. Even these ranges can be set by default as the values shown in the experiments of the article. The proposed controller acts on the window and fog system by minimizing costs, but trying to keep the humidity and temperature inside the specified range as well.

Once the viability of the solution has been proved, future work focuses on exploring new ways of improving performances, while trying to minimize costs, because this is a key factor for the exploitation profitability. These ways can be for instance, better predictions by statistical estimations of disturbances, dynamic humidity and temperature ranges during the day, analysis of different objectives ranges (for instance, the controller can work in two ways, the economic one and the high performance one).

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A Detailed greenhouse climatic model

A.1 Extended notation

Range of possible values is indicated for identifiable parameters. Exact value is indicated for constant or known parameters.

- A: Windows area, 130 m^2.
- A_c: Loss coefficient of conduction and convection, [2, 20].
- A_i: Greenhouse surface area, 240 m^2.
- a: Constant for renewal volumetric flow, [0.0005, 0.1].
- α: Opening window angle, ^{o}.
- α_m: Rate of absorbed heat by thermal mass, [0.01, 0.3].
- α_{max}: Maximum window angle, 12^o.
- C_m: Thermal mass heat capacity, [100000, 500000] $J\ ^oC^{-1}\ m^{-2}$.
- c_p: Air heat capacity, 1003 $J\ Kg^{-1}\ ^oC^{-1}$.
- C_{sat}: Air saturation coefficient, dimensionless.
- D_i: Air water vapour deficit, KPa.
- Δ: Slope of water vapour saturation, KPa^oC^{-1}.
- E: Crop evapotranspiration, $Kg_{H_2O}\ s^{-1}$.
- F_v: Water rate in the air renewal flow, $Kg_{H_2O}\ s^{-1}$.
- fog: Water rate of fog system, $Kg_{H_2O}\ s^{-1}$.

- fog_{max}: Maximum water rate of fog system, [0.001, 0.005] $Kg_{H_2O}\ s^{-1}$.
- F_v: Water rate in the air renewal flow, $Kg_{H_2O}\ s^{-1}$.
- G: Renewal air flow, $m^3\ s^{-1}$.
- G_o: Losses of renewal air flow, [0.0005, 0.01].
- γ: Psycrometric constant, 0.066 KPa^oC^{-1}.
- gwb: Boundary-layer conductance, [0.001, 0.05] $m\ s^{-1}$.
- gws: Stomatal conductance, $m\ s^{-1}$.
- gws_{max}: Maximum stomatal conductance, [0.01, 0.03] $m\ s^{-1}$.
- gws_{min}: Minimum stomatal conductance, [0.0001, 0.005] ms^{-1}.
- h_m: Conductivity coefficient between air and thermal mass, [1,20] $W\ m^{-1}\ ^o\ K^{-1}$.
- H_i: Inside relative humidity, %.
- H_o: Outside relative humidity, %.
- k: Extinguishing coefficient of radiation, [0.1, 0.7].
- k_a: Conductivity coefficient between thermal mass and ground, [0.5, 10] $W\ m^{-1}\ ^o\ K^{-1}$.
- L: Leaves area index, [0.5 2] $m^2_{leaves}\ m^{-2}_{ground}$.
- λ: Latent heat of vaporization, $J\ Kg^{-1}$.
- MV_α: Windows opening manipulated variable, %.
- MV_{fog}: Fog system manipulated variable, discrete $[0, 50\%, 100\%]$.
- MV_W: Heating system manipulated variable, %.
- P: Atmospheric pressure, 98.1 KPa.
- $psat$: Saturation pressure, KPa.
- Q_{cc}: Energy exchange by conduction and convection phenomena, W.
- Q_e: Energy loss due to crop evapotranspiration, W.
- Q_f: Energy loss through ground, W.
- Q_m: Energy exchange with thermal mass, W.

- Q_n: Energy loss by nebulization, W.
- Q_s: Solar energy supplied to air volume, W.
- Q_{sm}: Energy stored by the thermal mass during the day, W
- Q_v: Energy exchange due to window ventilation, W.
- ρ: Air density, 1.25 $Kg_{air}\ m^{-3}$.
- Rn: Solar radiation absorbed by the crop, $W\ m^{-2}$:
- S_o: Solar radiation, $W\ m^{-2}$.
- T_i: Inside temperature, ^oC.
- T_m: Thermal mass temperature, ^oC.
- T_o: Outside temperature, ^oC.
- T_{ref}: Ground temperature at reference depth, [10, 20] ^oC.
- τ: Transmission coefficient of the greenhouse, [0.4,0.9].
- V: Wind speed, $m\ s^{-1}$.
- v_i: Greenhouse volume, 850 m^3.
- W: Energy from heating system, W.
- W_{max}: Maximum power of heating system, 5000 W.
- x_i: Inside absolute humidity, $Kg_{H_2O}\ Kg_{air}^{-1}$.
- x_o: Outside absolute humidity, $Kg_{H_2O}\ Kg_{air}^{-1}$.
- x_{sat}: Absolute saturation humidity, $Kg_{H_2O}\ Kg_{air}^{-1}$.
- z_{ref}: Reference depth, 6 m.

A.2 Complementary climatic model equations

Opening window angle:

$$\alpha = \frac{MV_\alpha}{100}\alpha_{max} \tag{A.1}$$

Water rate of fog system:

$$fog = \frac{MV_{fog}}{100} fog_{max} \tag{A.2}$$

Energy from heating system:

$$W = \frac{MV_W}{100} W_{max} \tag{A.3}$$

Water rate in the air renewal flow:

$$F_v = \rho G(x_o - x_i) \tag{A.4}$$

Renewal air flow (Boulard and Draoui, 1995):

$$G = AV(a\alpha + G_o) \tag{A.5}$$

Air saturation coefficient:

$$C_{sat} = \begin{cases} 1 & x_i < x_{sat} \\ 0 & x_i = x_{sat} \end{cases} \tag{A.6}$$

Absolute to relative humidity conversion:

$$H_i(t) = \begin{cases} 100 & H_i > 100 \\ H_i & H_i \leq 100 \end{cases} \tag{A.7}$$

$$H_i = \frac{100 x_i P}{0.611 psat(T_i)}$$

$$p_{sat}(T) = 0.61 \left(1 + 1.414 \sin(5.82e^{-3}T)\right)^{8.827} \tag{A.8}$$

Crop evapotranspiration (Monteith, 1973):

$$E = \frac{A_i(\Delta Rn + 2L\rho\, C_p\, D_i\, gwb)}{\left(\Delta + \gamma\left(1 + \frac{gwb}{gws}\right)\right)\lambda} \tag{A.9}$$

$$\Delta = p_{sat}(T_i + 0.5) - p_{sat}(T_i - 0.5) \tag{A.10}$$

$$Rn = (1 - e^{kL})\tau So \tag{A.11}$$

$$D_i = p_{sat}(T_i)(1 - H_i/100) \tag{A.12}$$

$$\lambda = (3.1468 - 0.002365(T_i + 273)10^6 \tag{A.13}$$

$$\begin{aligned} gws = {} & gws_{min} + (gws_{max} - gws_{min}) \cdot \\ & \cdot \left[1 - exp\left(-\frac{Ss}{160}\right)\right] g_D \end{aligned} \tag{A.14}$$

$$g_D = \begin{cases} \frac{0.39}{0.029+D_i} & D_i \geq 0.361 \\ 1 & D_i < 0.361 \end{cases}$$

Solar energy supplied to air volume:

$$Q_s = A_i \tau So \tag{A.15}$$

Energy exchange by conduction and convection phenomena:

$$Q_{cc} = A_i A_c (T_i - T_o) \tag{A.16}$$

Energy loss due to crop evapotranspiration:

$$Q_e = \lambda E \tag{A.17}$$

Energy exchange due to window ventilation:

$$Q_v = \rho c_p G(T_i - T_o) \tag{A.18}$$

Energy loss by nebulization:

$$Q_n = \lambda fog \tag{A.19}$$

Energy exchange between thermal mass and inside air:

$$Q_m = A_i h_m (T_m - T_i) \tag{A.20}$$

Energy stored by the thermal mass during the day:

$$Q_{sm} = \alpha_m Q_s \tag{A.21}$$

Energy loss through ground:

$$Q_f = A_i k_a \left(\frac{T_m - T_{ref}}{z_{ref}} \right) \tag{A.22}$$

B Genetic algorithms

Optimization technique choice depends on the type of problem to solve. If it is possible the analytical solution is the best one: it is the most exact one and the least computer time consuming. But for complex models and indexes, optimization problem is so difficult that an analytical solution is impossible and even classical numerical solutions are not always available because most of the complex problems are non-convex and/or multimodal. For these optimization problems GAs are a good alternative, they have demonstrated very good performances.

GAs are optimization techniques based on simulated species evolution. Problem solution is obtained from evolution through several generation of a population formed from a set of possible solutions. Evolution is performed following rules represented by genetic operator: selection, crossover and mutation.

Principal differences between GA implementations come from:

- Chromosome codification.
- Genetic operators.

For this work both GA implementations (for identification and for control) have the same characteristics and only vary in some parameters to fulfill computational cost requirement and solution quality: search space, number of individuals and generations are different for each case. Principal characteristics are:

- Real value codification.
- Linear ranking.
- Selection operator: Stochastic Universal Sampling.
- Crossover operator: Linear combination with a crossover probability of $P_c = 0.8$.
- Mutation operator: Oriented mutation with a mutation probability of $P_m = 0.01$.

For more information see (Holland, 1975; Goldberg, 1989; Michalewicz, 1996).

Table B.1

Statistics for predicted identification errors.

Error	mean	max	standard dev.
$T_i(^oC)$	0.67	2.71	0.56
$H_i(\%)$	2.69	15.70	2.82

Table B.2

Statistics for predicted identification errors.

Error	mean	max	standard dev.
June 20, 2004			
$T_i(^oC)$	0.62	1.81	0.46
$H_i(\%)$	3.67	23.65	4.14
July 28, 2004			
$T_i(^oC)$	0.92	3.48	0.64
$H_i(\%)$	6.61	20.89	6.22

Table B.3

Results comparison for several summer days.

		Performances				Cost (% acc)	
		T (^oC)		H (%)		Windows	Neb
		mean	std	mean	std	acc	acc
Jun 11, 2004	MBPCGA	**1.6**	**1.7**	**9.5**	**9.6**	**0.12**	**5.64**
(1)	Current	**1.6**	1.8	15.0	14.2	3.17	10.30
Jun 15, 2004	MBPCGA	**2.3**	**2.1**	**9.4**	**9.5**	**0.17**	**3.00**
(2)	Current	2.4	2.3	14.8	14.3	1.84	11.63
Jun 20, 2004	MBPCGA	**2.1**	**2.4**	**7.2**	**8.3**	**0.20**	**4.95**
(3)	Current	**2.1**	2.6	13.9	14.3	2.61	12.40
Jul 28, 2004	MBPCGA	**2.3**	**2.6**	**13.5**	12.2	**0**	**0**
(4)	Current	3.1	3.2	19.6	**12.1**	1.26	0.48

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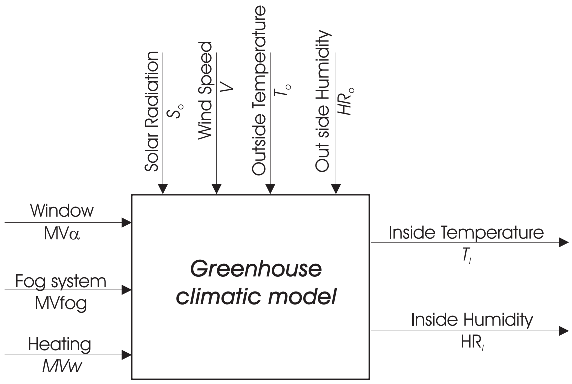

Fig. B.1. Greenhouse climatic model.

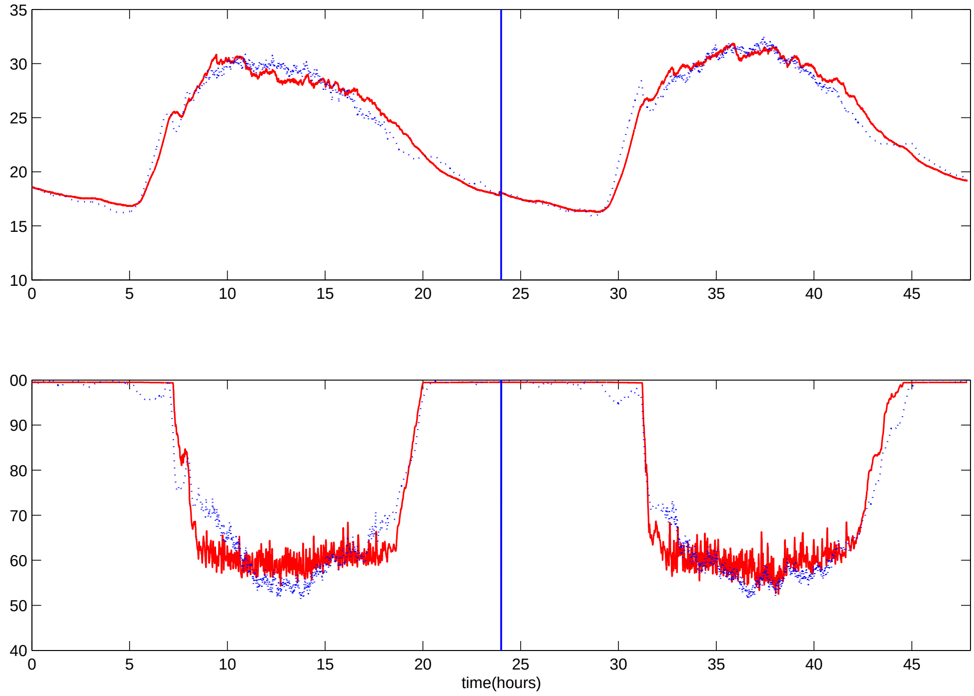

Fig. B.2. Experimental (continuous plot) and model (discontinuous plot) T_i and H_i, for June 11 (left) and June 15 (right), 2004.

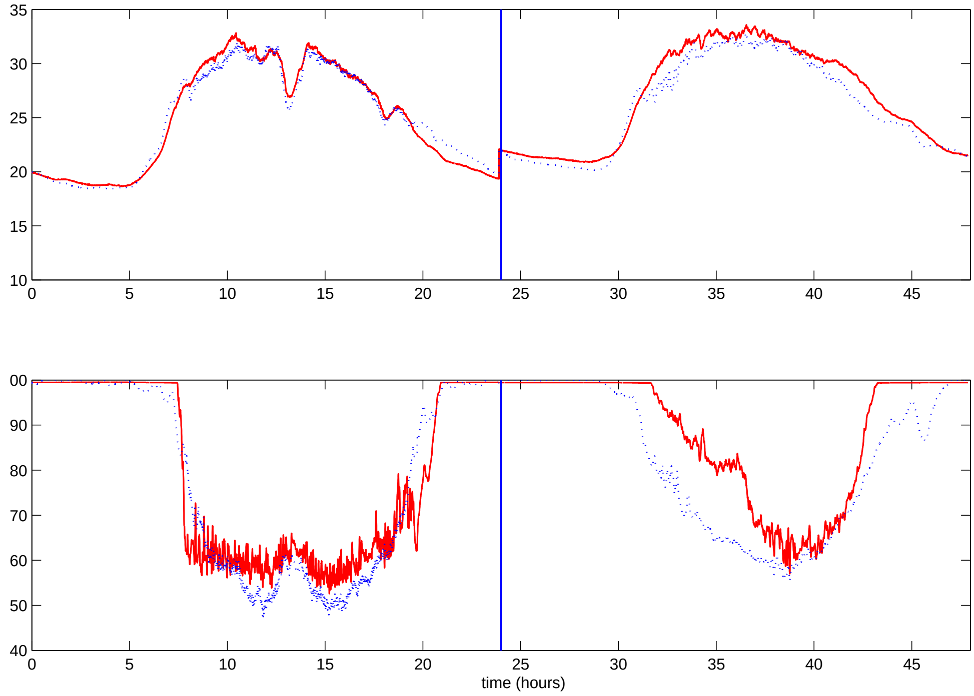

Fig. B.3. Experimental (continuous plot) and model (discontinuous plot) T_i and H_i, for June 20 (left) and July 28 (right), 2004.

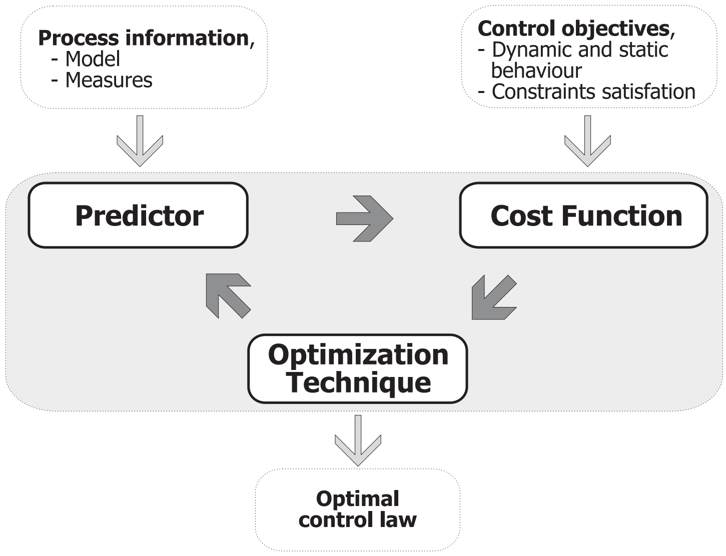

Fig. B.4. Model Based Predictive Control basic elements.

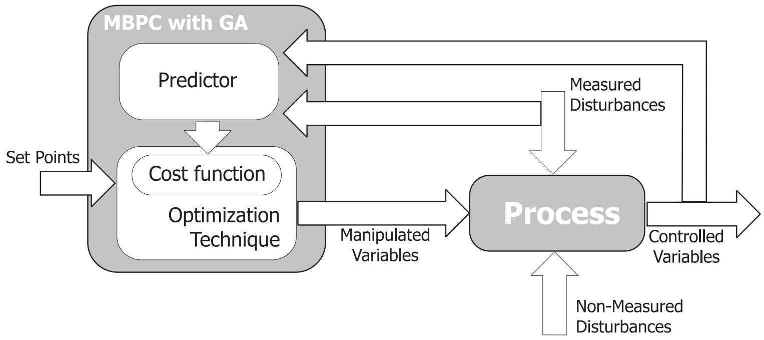

Fig. B.5. MIMO Control structure for Model Based Predictive Control with GA.

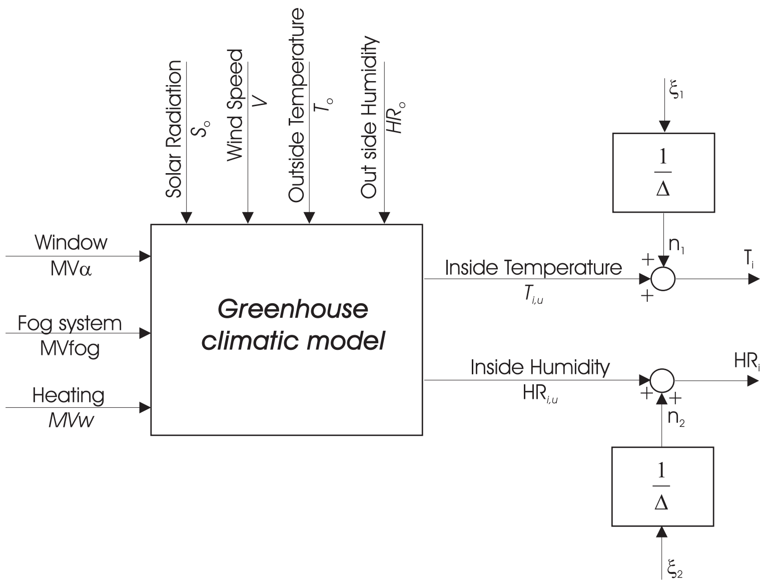

Fig. B.6. Climatic greenhouse model used for prediction.

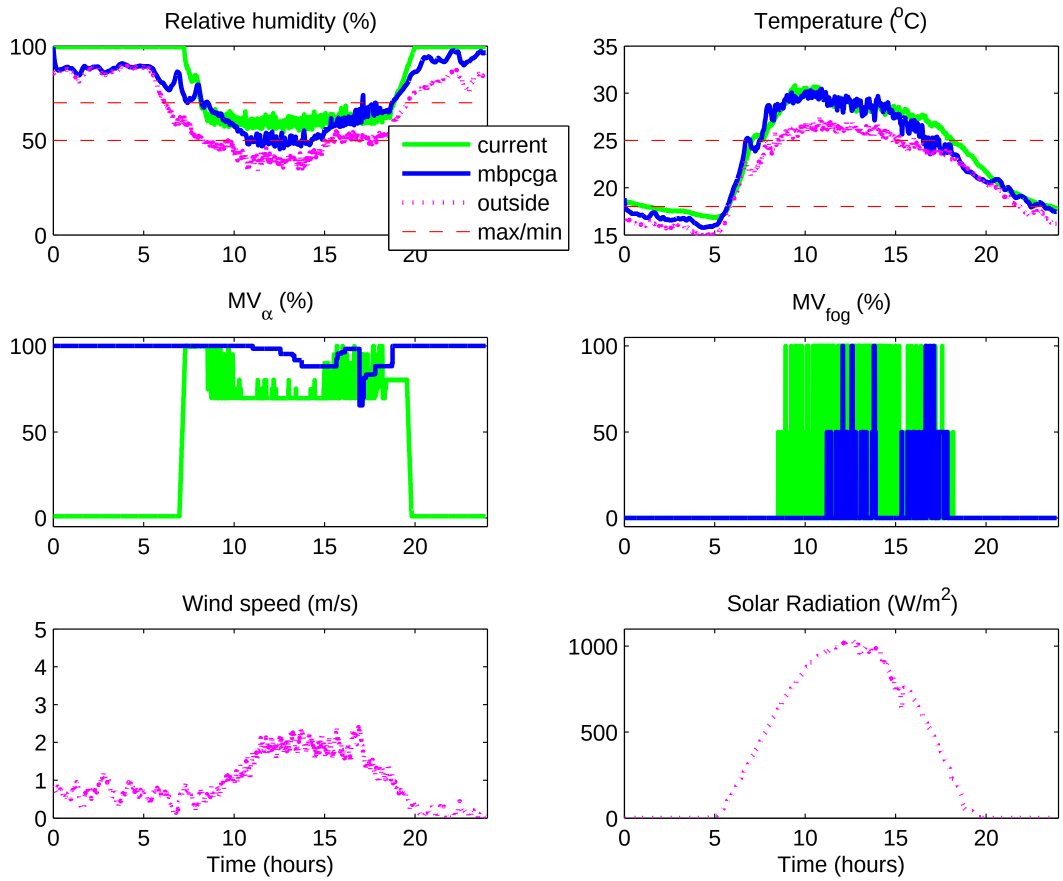

Fig. B.7. Control results: June 11, 2004.

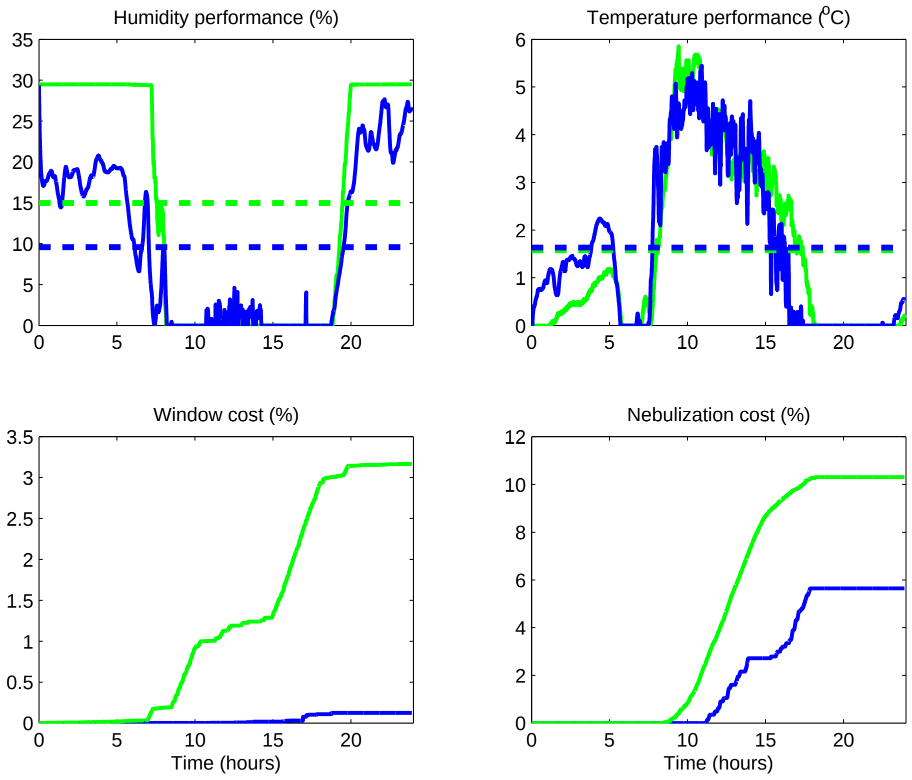

Fig. B.8. Results analysis: June 11, 2004.

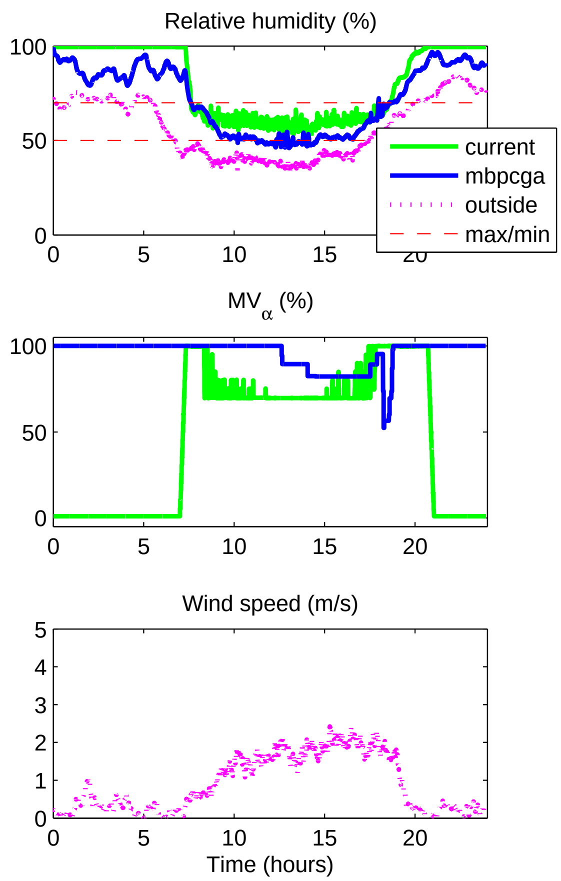

Fig. B.9. Control results: June 15, 2004.

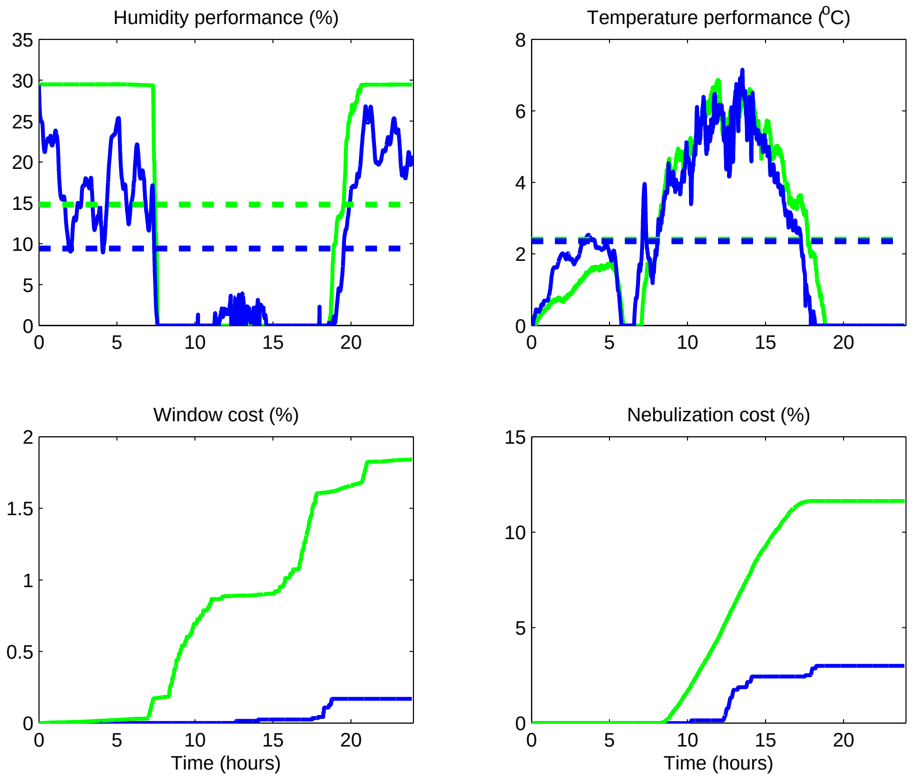

Fig. B.10. Results analysis: June 15, 2004.

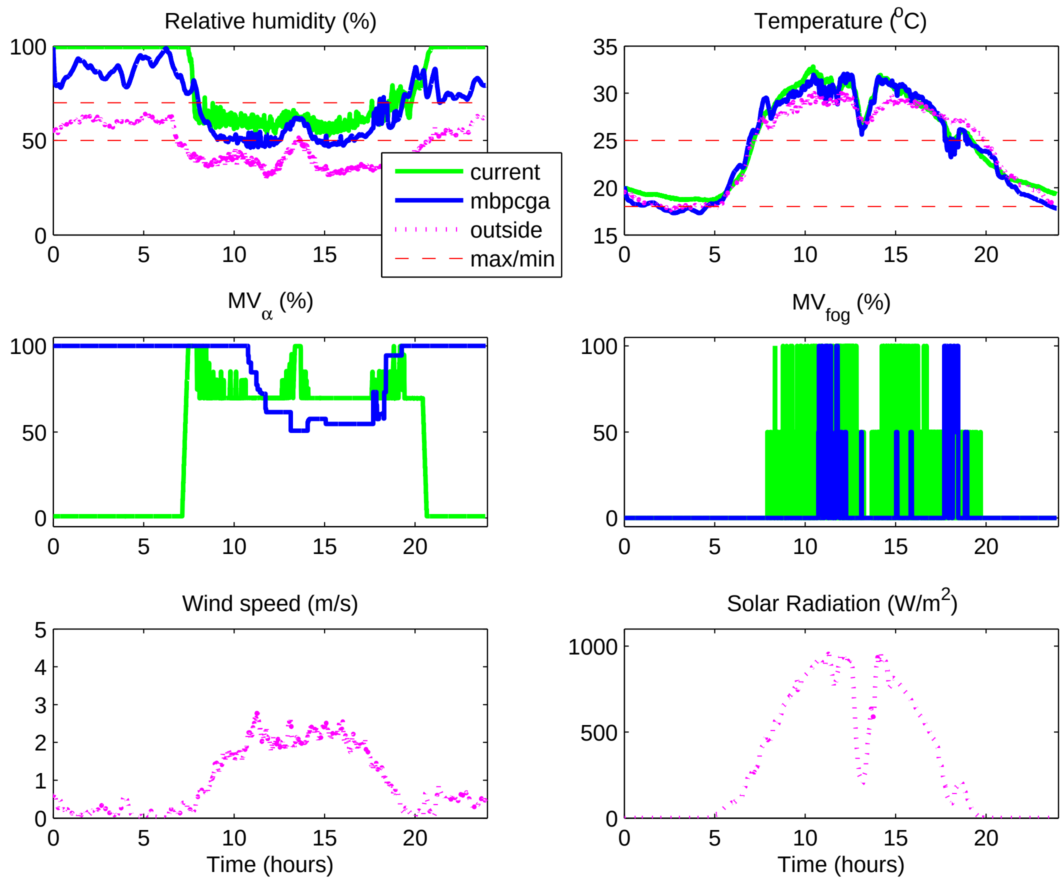

Fig. B.11. Control results: June 20, 2004.

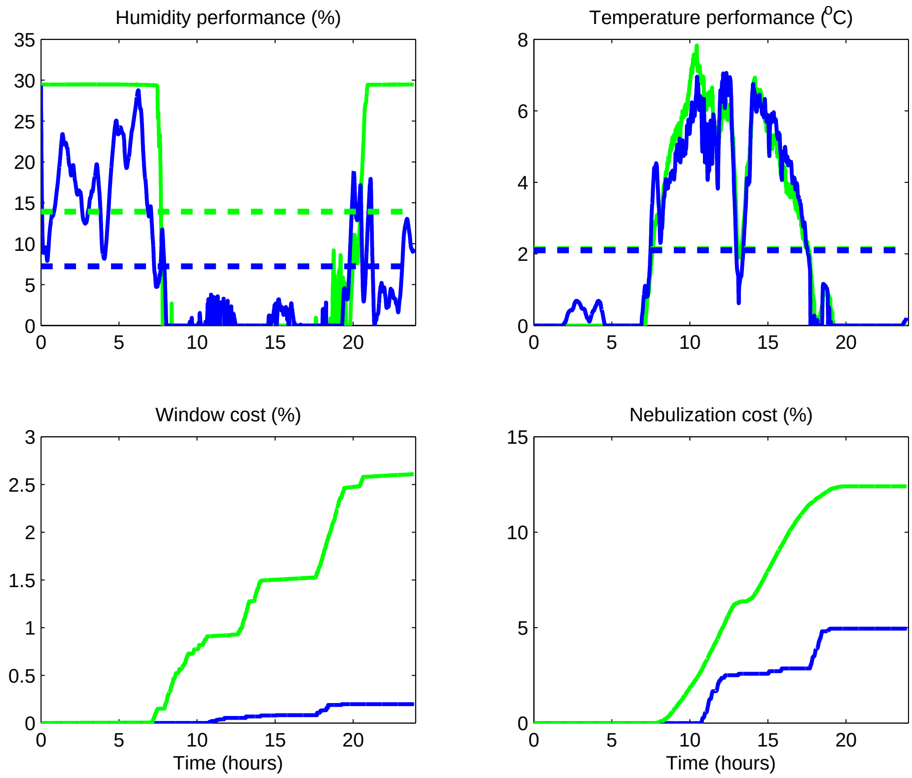

Fig. B.12. Results analysis: June 20, 2004.

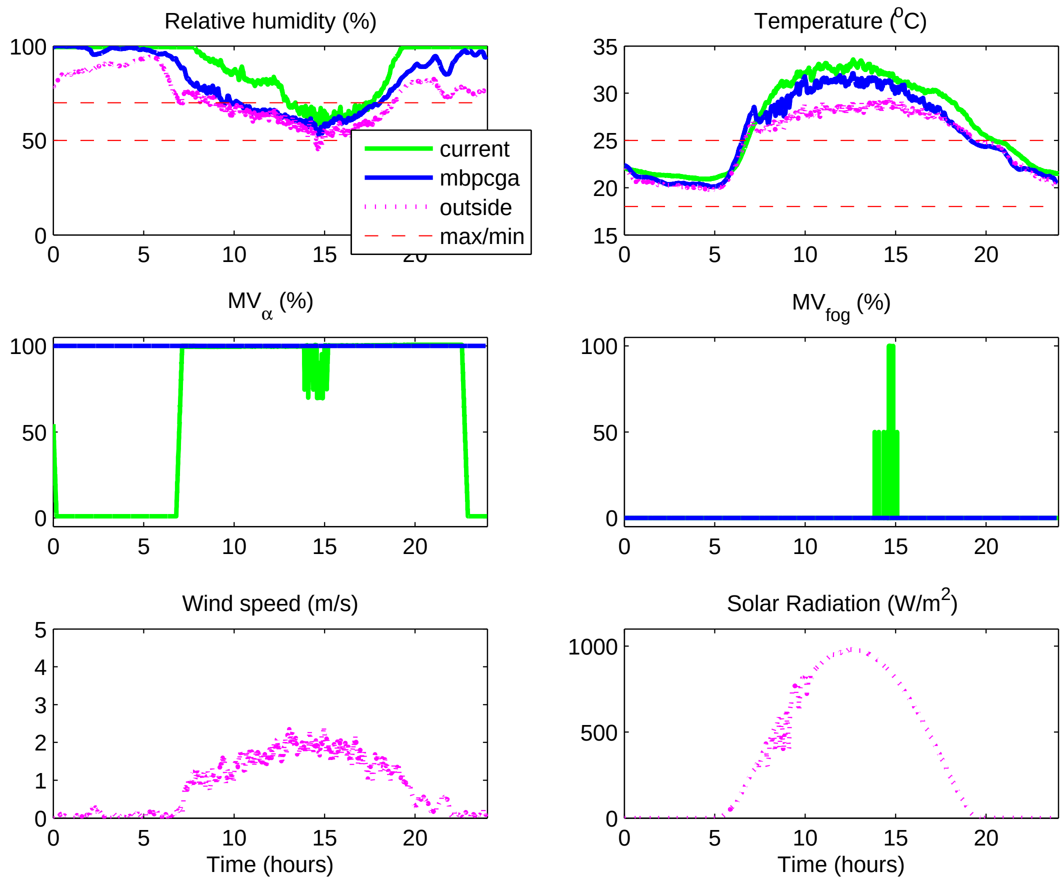

Fig. B.13. Control results: July 28, 2004.

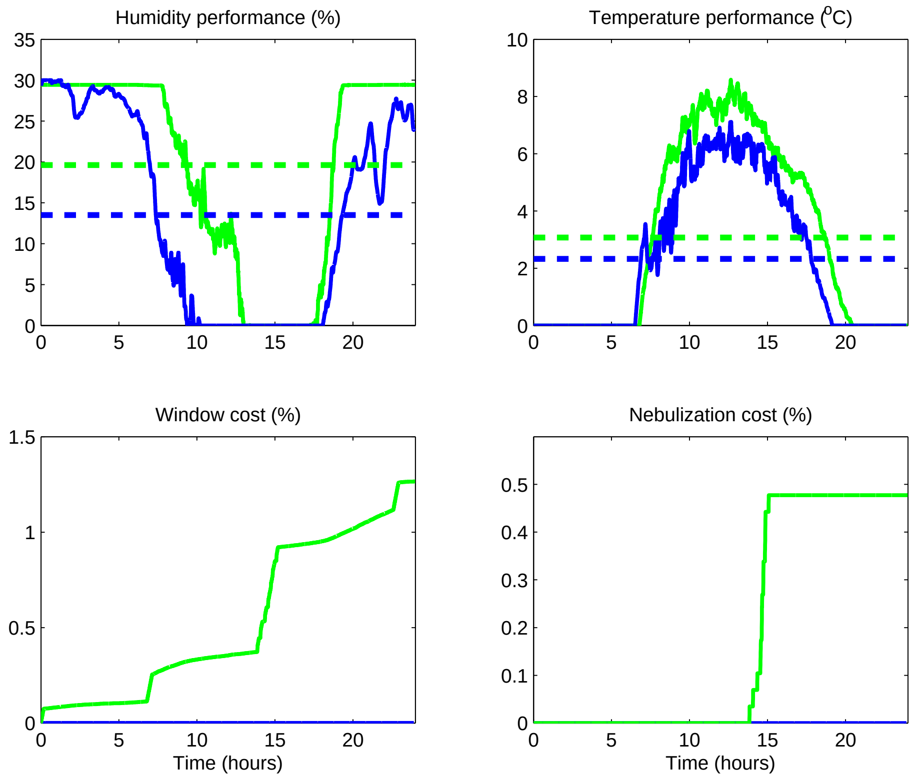

Fig. B.14. Results analysis: July 28, 2004.