Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Discrete Model-Based Greenhouse Environmental Control using the Branch & Bound Algorithm [⋆]

Ferreira, P.M. [1] **Ruano, A.E.**

Centre for Intelligent Systems, Faculty of Sciences and Technology,
University of Algarve, 8000-139 Faro, Portugal
(e-mail: {pfrazao,aruano}@ualg.pt).

Abstract: In this paper we propose the application of the Branch-and-Bound search algorithm to discrete model-based predictive control of greenhouses. The temperature control strategy is a mixture of temperature integration and difference between day and night temperatures. The general approach is presented and strategies are proposed in order to achieve a faster coverage of the solutions search space with reduced probability of loosing the optimal solution. The control energy requirements depend largely on the cost function coefficients and the evolution of the external climate. Fixed coefficients do not fully exploit the external climate predicted evolution in order to reduce energy consumption. A simple method is proposed to adapt on-line the cost function coefficients in a way that reduces energy consumption without significantly affecting control accuracy. The methods are briefly described and a subset of experimental and simulation results are presented.

Keywords: Model predictive control; Greenhouse environmental control; Optimisation problems; Search methods.

1. INTRODUCTION

Greenhouse environmental control (GEC) provides the means to improve the conditions in which plants are grown, in order to optimise the plant production process. GEC methods must take into account the influences of the outside weather, the actuators and the crop, which is achieved by the use of models. These are used by control and optimisation systems in order to compensate and exploit the external climate characteristics so that crop production and yield are favoured. An efficient approach consists in applying model-based predictive control (MBPC). In this paper we report results, obtained in a greenhouse and by means of simulations, regarding a MBPC and production optimisation system herein proposed, using radial basis function neural network (RBFNN) models and the branch-and-bound (B&B) optimisation algorithm. For the experiments carried out a tomato crop was considered. The greenhouse has a floor area of 180 m^2, a height of 3.5 m, a 200 μm thick polyethylene cover and concrete floor. It is equipped with motorised lateral windows for ventilation, a motorised zenital window, a diesel heating system, two cooling systems, a water fogging system, and an air extracting ventilator. The latter is actuated simultaneously with the coolers in order to extract hotter air which accumulates in the greenhouse ceiling. The culture type is hydroponic where the roots of plants are placed in a substrate container.

2. PROBLEM FORMULATION

The temperature control strategy will be briefly discussed. In our formulation humidity will only be controlled by preventing it from becoming smaller or larger than prescribed day and night lower and upper boundaries. The way this is accomplished is similar to what is going to be described regarding temperature, hence will not be further discussed in this paper.

The notion that the crop integrates temperature, and its growth and production are insensitive to instant variations, led to the concept of temperature integration (TI) [Liebig, 1988], where temperature is allowed to fluctuate within certain limits as long as its average over the integration period is maintained. Another factor which has an impact on plant growth, production, and fruit quality, is the temperature difference between day and night (TDIF) Seginer et al. [1994], Willits and Peet [1998]. Given the average climate conditions in the south of Portugal, which always impose a certain level of TDIF within the greenhouse, and the conclusions by Willits and Peet [1998] for a similar warm climate, the temperature control strategy herein proposed is a mixture of TDIF and TI. The former is desirable by its positive impact on crop production and fruit quality, the latter is needed to maximise yield by reduction of energy consumption. The basic idea is to employ TI over a long-term period (several days) and TDIF on a short-term (one day) basis. Two allowed temperature bands, $[Tn_{min}, Tn_{max}]$ and $[Td_{min}, Td_{max}]$, are

[⋆] The authors thank the *Fundação para a Ciência e a Tecnologia* for funding this work with a PhD grant (BD/1236/2000) and a research project (MGS/33906/99-00). The first author acknowledges partial support by the European Commission through the Marie Curie ToK project BRIDGET (MKTD-CD 2005029961).

[1] Current address: Unilever R&D Port Sunlight, Quarry Road East, Bebington, Wirral CH63 3JW, United Kingdom

978-1-1234-7890-2/08/$20.00 © 2008 IFAC 10.3182/20080706-5-KR-1001.3461

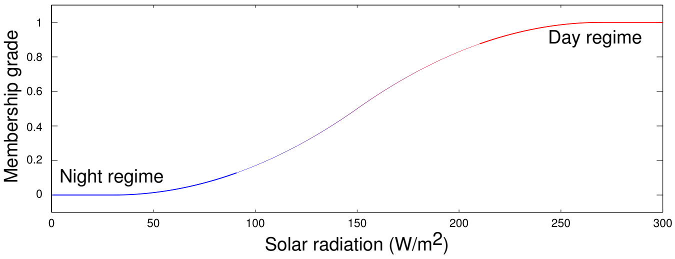

Fig. 1. Day-night regimes membership function

defined for night and day regimes, respectively. The bands limits define the range of values allowed for TDIF, from $Td_{min} - Tn_{max}$ to $Td_{max} - Tn_{min}$. This strategy can be thought as the TI method restricted by a range of allowed daily temperature patterns imposed by TDIF. The day-night and night-day transitions are required to be smooth in order to prevent excessive energy consumption due to an abrupt change in the temperature regime. An approach, with potential benefits regarding energy saving, consists in dynamically make the transition as a function of solar radiation. Using a common s-shaped function, a regime membership function, μ, may be defined whose range is from 0 (night regime) to 1 (day regime). Figure 1 shows the function $\mu(SR, 30, 270)$ considering SR in the interval $[0, 300]$ W/m^2. In practice the average SR over a few past samples should be provided to μ in order to avoid high frequency variations which would be reflected in the computed boundaries. By itself the method will not take into account the crop source/sinks relation, which may require higher or lower temperature boundary settings than those computed from SR. With this in mind, the boundary values are further corrected using a simple set of rules in the form of a Mandani type [Mamdani and Assilian, 1975] fuzzy inference system (FIS) as outlined in figure 2. μ_{TE} and μ_{SR} are functions to estimate the crop sink and source activities over the TI period. The FIS will output a value from -1 (lower the boundaries) to 1 (raise the boundaries) accordingly to the situation leading to an improper source/sinks relation, without specifying the amplitude to lower or raise, (mc), which is simply multiplied by this value. The corrected temperature lower (T_{lb}) and upper (T_{ub}) boundaries are thus given by:

$$\begin{gathered} T_{lb}(k) = Tn_{min}(k) + \\ + \left[Td_{min}(k) - Tn_{min}(k)\right] \mu\left(SR(k), SR_{p0}, SR_{p1}\right) + \\ + \mu_{BC}\left(\mu_{T_\varepsilon}(k, \rho), \mu_{SR}(k)\right) mc \qquad (1) \end{gathered}$$

$$\begin{gathered} T_{ub}(k) = Tn_{max}(k) + \\ + \left[Td_{max}(k) - Tn_{max}(k)\right] \mu\left(SR(k), SR_{p0}, SR_{p1}\right) + \\ + \mu_{BC}\left(\mu_{T_\varepsilon}(k, \rho), \mu_{SR}(k)\right) mc \qquad (2) \end{gathered}$$

The dependence of the boundaries on k has been made explicit to emphasise that these values should be set accordingly to the crop developmental stage, possibly determined with the aid of crop growth and production models.

The GEC system manipulates the greenhouse climate in order to achieve the following goals: maintain an average temperature considered ideal for the crop over the integration period; limit temperature and humidity to the intervals $[T_{lb}(k), T_{ub}(k)]$ and $[H_{lb}(k), H_{ub}(k)]$, respectively; minimise energy consumption and actuator wear off; and maximise crop growth and production or yield. As a consequence of the characteristics of some actuators, the control input space was discretised and a set of allowed actuating combinations $\{A_i\}_{i=1}^{9}$ was specified. Windows may be fully opened or closed, the remaining actuators are turned on or off during the complete sampling interval. Given the contradictory nature of some of the goals and the discrete nature of the control input space, the control problem can be characterised as a discrete optimisation problem. At each time instant k, the controller must find the best A_i, which optimises the goals and/or restrictions. Considering a TI period having NP_{TI} data points, the average temperature and the TI error over that period at time instant k are given by,

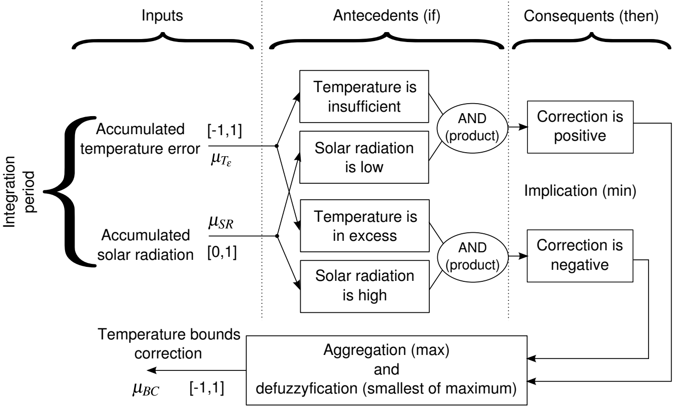

Fig. 2. Fuzzy inference system to perform temperature boundaries correction

$$\overline{T}(k) = \frac{1}{NP_{TI}} \sum_{i=k-NP_{TI}+1}^{k} T(i) \qquad (3)$$

$$\overline{T}_\varepsilon(k) = \overline{T}(k) - R\overline{T}(k) \qquad (4)$$

where $R\overline{T}(k)$ is the reference value for $\overline{T}(k)$. The absolute value of $\overline{T}_\varepsilon(k)$ is to be minimised, considering the restrictions imposed by the temperature and humidity boundaries mentioned above. The goals and restrictions are articulated in an objective function reflecting the cost of choosing the j^{th} control profile, $\mathbf{u}(k) = A_j$, at time instant k:

$$\begin{aligned} J(k) = {} & \lambda_1 \left|\mu_T\left(\overline{T}_\varepsilon(k), T_{\varepsilon 1}, T_{\varepsilon 2}\right)\right| + \\ & + \frac{\lambda_2}{N_{AT}} \sum_{i=1}^{NA} \left[\mathbf{u}_i(k-1) - \mathbf{u}_i(k-2)\right] + \\ & + \frac{\lambda_3}{N_{AC}} \sum_{i=1}^{NA} \mathbf{u}_i(k-1)\,\omega_i + \\ & + \lambda_4 \mu_{TV}\left(V_T(k), T_{\varepsilon v}\right) + \\ & + \lambda_5 \mu_{HV}\left(V_H(k), H_{\varepsilon v}\right) \qquad (5) \end{aligned}$$

The values of the λ_i parameters weigh the corresponding normalised (to the unit interval) terms, hence determining their relative contribution to $J(k)$. The first term includes μ_T to map $\overline{T}_\varepsilon(k)$ into the $[-1, 1]$ interval: values smaller than $T_{\varepsilon 1}$ and larger than $T_{\varepsilon 2}$ are mapped to -1 and 1, respectively; values between these thresholds may be mapped linearly or by means of any convenient smooth function, to $[-1,1]$. The second and third terms account for energy consumption and actuator wear-off. NA is the number of actuators, N_{AT} and N_{AC} are scaling factors allowing for normalisation. The last two terms describe penalties for the violation of temperature and humidity boundaries. μ_{TV} and μ_{TH} are defined in a similar way to μ_T, mapping the absolute values of the violations in the intervals $[0, T_{\varepsilon v}]$ and $[0, H_{\varepsilon v}]$ to $[0,1]$. Values larger than $T_{\varepsilon v}$ or $H_{\varepsilon v}$ are mapped to 1. The cost function may be simplified by removing these two penalty terms which may be used as restrictions to the optimisation problem. $\overline{RT}(k)$ should be obtained by optimising the crop production model or a formulation of the crop yield.

Considering the application of MBPC, a sequence of control actions must therefore be determined over the prediction horizon PH,

$$\mathbf{U}(k) = [\mathbf{u}(k), \mathbf{u}(k+1), \cdots, \mathbf{u}(k+PH-1)], \quad (6)$$
$$\mathbf{U}(k) \in \mathcal{U}_{PH}$$

where $\mathcal{U}_{PH}$ is the set of all sequences of size PH formed as combinations of the control alternatives. The accumulated cost from time instant k to $k+PH-1$, due to a particular choice of $\mathbf{U}(k)$ is given by $\mathcal{J}_{1:PH}(k)$. The GEC problem may be formulated as in equation 8, that is, as the search for the particular sequence $\mathbf{U}(k)$ that minimises the cost function $\mathcal{J}_{1:PH}(k)$:

$$\mathcal{J}_{1:PH}(k) = \left. \left(\sum_{i=k+1}^{k+PH} \hat{J}(i) \right) \right|_{\mathbf{U}(k)} \quad (7)$$

$$\min_{\mathbf{U}(k) \in \mathcal{U}_{PH}} \mathcal{J}_{1:PH}(k) \quad (8)$$

As the system operates, a new optimisation problem is solved at every iteration k and only the first component of $\mathbf{U}(k)$, $\mathbf{u}(k)$, is actually applied to the actuators, following the receding horizon principle. The computation of $\mathcal{J}_{1:PH}(k)$ requires the use of predictive models in order to estimate the quantities involved in the calculus of $\hat{J}(i)$. The climate and greenhouse environment models are non-linear auto-regressive (NAR) and NAR with exogenous inputs on-line adapted RBFNN models. Details about the neural network training and structure identification methods, and partially about the identification of these models may be found in Ferreira and Ruano [2000], Ferreira et al. [2002, 2003], Ruano et al. [2005]. A complete publication regarding the climate, environmental, and crop modelling aspect of this work, is currently in preparation.

3. APPLICATION OF BAB MBPC TO GEC

The application of MBPC to GEC problems usually focus air temperature regulation problems [Tap et al., 1996, Gonzalez and Leyris, 1996, Tzafestas et al., 2001, Piñón et al., 2002, Ghoumari et al., 2005, Piñón et al., 2005, Coelho et al., 2005] and less frequently multivariable control, for example temperature, CO_2 and relative humidity [Cunha et al., 2000]. The combination of a particular cost function and model(s) type define the optimisation problem to be solved. In the studies referred above, the minimisation of the cost functions employed is accomplished by means of sequential quadratic programming methods, linear matrix inequalities methods, gradient descent methods and the particle swarm optimisation method. When the control input space is discrete or has been discretised, the optimisation problem may be solved by means of discrete optimisation methods. BaB methods have been proposed [Sousa et al., 1997] and applied in practice to discrete (or discretised) non-linear MBPC problems [Roubos et al., 1999, Berenguel et al., 2004, Mendonça et al., 2004]. In summary, this method implements a structured search over a tree structure, using bounds to restrict branching thus preventing an exhaustive search to occur. For further details on this technique please consult any of the referred studies above and the references therein. These studies point out some advantages of the BaB method over other non-linear optimisation techniques when applied to MBPC:

- The optimal solution is always found. This guarantees that the controller is optimal in the discrete space of control alternatives. No assumptions need to be made on the formulation of the cost function.
- The method implicitly deals with constraints without being negatively affected. Constraints may even improve the efficiency of bounding by eliminating those alternatives that lead to constraint violation.
- As opposed to other iterative optimisation methods, the algorithm outcome is not negatively influenced by a poor initialisation, although the time spent to find the optimum may be greater.

As formulated in Sousa et al. [1997], two bounds are employed: an upper bound on the total cost from instant $k+1$ to $k+PH$, and a lower bound on the cost from instant $k+i$ to $k+PH$. Before the minimisation problem is solved by the BaB method, the upper bound on the cumulative cost is computed by successive minimisation of (5) from $i=1$ to $i=PH$:

$$\mathcal{J}^U_{1:PH}(k) = \sum_{i=k+1}^{k+PH} \min_{u(i-1)=A_j} \left\{ \hat{J}(i) \right\}_{j=1}^{nao} \quad (9)$$

In equation 9 $\hat{J}(i)$ denotes the fact that model predicted quantities are used to estimate $J(i)$. This value, also called the incumbent value, is the initial estimate of the minimum of $\mathcal{J}_{1:PH}(k)$. Taking into account that no branching will be performed beyond the control horizon CH, equation 9 may be decomposed and rearranged as,

$$\mathcal{J}^U_{CH+1:PH}(k) = \mathcal{J}^U_{1:PH}(k) - \mathcal{J}^U_{1:CH}(k) \quad (10)$$

which gives the initial estimate of the optimal cumulative cost from step $CH+1$ to PH. When the BaB algorithm is in one node at level $i < CH$ and it must decide if a particular branch j should be searched in more depth or not, the estimate of the lower bound on the cumulative cost from step i to PH, $\mathcal{J}^L_{i:PH}(k)$, must be computed. Using the result from equation 10 this estimate may be given by:

$$\mathcal{J}^L_{i:PH}(k) = \left. \hat{J}(k+i) \right|_{\mathbf{u}(k+i-1)=A_j} + \mathcal{J}^U_{CH+1:PH}(k) \quad (11)$$

This formulation equals the cost of creating the new branch corresponding to the control action A_j, plus the current estimate of the cumulative cost from step $CH+1$

to PH. An accurate lower bound estimate from step $i+1$ to CH is very hard to achieve and it is preferable to make it implicitly zero in equation 11 in order to prevent the search from not exploring parts of the tree, which may contain the optimal solution, due to a bad estimate. With the aim of saving some additional computing time when evaluating the branching rule, the first term in the right hand side of equation 11 may be further decomposed as,

$$\hat{J}\left(k+i\right)\Big|_{\mathbf{u}(k+i-1)=A_j} = \\ = \left(\hat{J}^e\left(k+i\right) + \hat{J}^m\left(k+i\right)\right)\Big|_{\mathbf{u}(k+i-1)=A_j} \qquad (12)$$

$\hat{J}^e\left(k+i\right)$ accounts only for the actuator wear-off and energy consumption terms in the cost function (5). $\hat{J}^m\left(k+i\right)$ accounts only for those terms of the cost functions that need the process models to be evaluated, which is the relevant time consuming task. Using this decomposition the branching rule at step i due to the control action A_j may be done in two steps by first computing the lower bound estimate of the cumulative cost from step $i=1$ to step $i=PH$ as,

$$\mathcal{J}^L_{1:PH}\left(k\right) = \mathcal{J}_{1:i-1}\left(k\right) + \hat{J}^e\left(k+i\right)\Big|_{\mathbf{u}(k+i-1)=A_j} + \\ +\mathcal{J}^U_{CH+1:PH}\left(k\right) \qquad (13)$$

and then evaluating the following conditions in the order presented:

$$\mathcal{J}^L_{1:PH}\left(k\right) < \mathcal{J}^U_{1:PH}\left(k\right) \quad (14)$$

$$\mathcal{J}^L_{1:PH}\left(k\right) + \hat{J}^m\left(k+i\right)\Big|_{\mathbf{u}(k+i-1)=A_j} < \mathcal{J}^U_{1:PH}\left(k\right) \quad (15)$$

In the first condition only the contribution of $\hat{J}^e\left(k+i\right)$ is accounted in $\mathcal{J}^L_{1:PH}\left(k\right)$. If the result of the evaluation of (14) is not true then the optimisation over branch j is stopped because this branch will not lead to a better solution than the current best. In this case the computing time needed to evaluate $\hat{J}^m\left(k+i\right)$ is spared, thus contributing to a faster traversal of the tree of solutions. If condition (14) evaluates to true then the second condition, given in (15), which adds the contribution of $\hat{J}^m\left(k+i\right)$, is evaluated in order to decide if the solution search will follow this particular branch.

When the BaB method is in one node at level $i=CH$, in order to choose the best control input $\mathbf{u}\left(k+CH-1\right)$ and a particular control alternative, A_j, is being tested, if the two branching conditions, (14) and (15), evaluate to true it means that a better solution than the current one has been found. Denoting the control trajectory corresponding to the particular path followed from $i=1$ to $i=CH$ by $\mathbf{U^*}_{1:CH}\left(k\right)$, the new value of the best solution is recomputed using,

$$\mathcal{J}^U_{1:PH}\left(k\right) = \mathcal{J}_{1:CH}\left(k\right)\big|_{\mathbf{U^*}_{1:CH}(k)} + \mathcal{J}^U_{CH+1:PH}\left(k\right) \quad (16)$$

where the second term in the sum is recomputed in a similar way as the initial estimate of $\mathcal{J}^U_{1:PH}\left(k\right)$ in equation 9, but starting from step $i=CH+1$ and assuming the newly found control solution, $\mathbf{U^*}_{1:CH}\left(k\right)$. At this stage the values of the best solution found (the incumbent), $\mathcal{J}^U_{1:PH}\left(k\right)$, and the upper bound on the cumulative cost from $i=CH+1$ to $i=PH$, $\mathcal{J}^U_{CH+1:PH}\left(k\right)$, are stored and the algorithm resumes its operation on the remaining branches of the current node and then on other nodes still unexplored. As better solutions are found by the BaB method the branching operation becomes more restrictive, thus having a higher probability of eliminating more branches from the search. When there are no branches to explore in the current node and no unexplored node remains, the optimisation stops and the best solution stored is the optimal one.

Considering the GEC problem formulation using the cost function defined in equation 5 but with the last two terms implemented as restrictions, the implementation requires some minor changes. During algorithm initialisation, when computing the upper bound of the optimum solution, and when a new best solution is found and $\mathcal{J}^U_{CH+1:PH}$ needs to be recomputed, violations to the restrictions should be checked and predefined control alternatives should be enforced when restrictions are predicted to be violated irregardless of the control alternative applied. When some of the control options do not violate restrictions, than the one that minimises the cost function is chosen among these in the usual way. When the BaB algorithm is in one node of the tree of solutions, no branching is performed for those control alternatives that lead to the violation of at least one restriction, thus pruning the sub-tree that would originate from the candidate branch. Due to this reason, it may be expected that the restricted problem formulation will be computationally cheaper when compared to the unrestricted formulation.

Reduction of the control inputs space Another approach to reduce the search space, thus reducing the time needed to find the optimal control input, consists in dynamically adapting the matrix of control alternatives, A, so that only a reduced number of alternatives need to be tested for branching. This may be accomplished by specifying a set of *if-then* rules that will decide for the removal of certain control alternatives provided certain requirements are met. Four rules were implemented that allow the reduction of A from 22.2% to 66.6%. In order not to loose the optimal solution in a removed branch, the only requirement is that the predicted average greenhouse temperature should be above or below its set-point during the complete prediction horizon.

On-line adaptation of the λ parameters Assume a formulation involving the cost function (5) having the last two terms implemented as restrictions. It may be desirable to have the coefficients, λ_1, λ_2 and λ_3, changing as the system evolves in time. When $\overline{T}$ is considerably far away from $R\overline{T}$, it is desirable to let the control system spend more energy in order to decrease $\overline{T}_\varepsilon$ by decreasing the values of λ_2 and λ_3. In this situation, if λ_2 and λ_3 are too high, the reduction of $\overline{T}_\varepsilon$ becomes highly dependent on the future weather conditions. When $\overline{T}_\varepsilon$ is small enough, λ_2 and λ_3 may have larger values to prevent the control system from controlling $\overline{T}$ in a tight way and spending possibly unnecessary energy. In this case it might be worth to let the control system depend on the outside weather, and, if it is favourable, sparing some energy. Let λ_1, λ_2 and λ_3, be such that,

$$\lambda_1 + \lambda_2 + \lambda_3 = 1.0 \qquad (17)$$

By reflecting the different nature of the first three terms in the cost function (5), from equation 17 λ_1 may be expressed as:

$$\lambda_1 = 1 - \lambda e \tag{18}$$

$$\lambda e = \lambda_2 + \lambda_3 \tag{19}$$

$$\lambda_2 = \lambda e \lambda e_t, \ \lambda e_t \in [0,1] \tag{20}$$

$$\lambda_3 = 1 - \lambda_2 \tag{21}$$

Given a value of λe, λe_t establishes a trade-off between actuator wear-off (λ_2) and energy consumption (λ_3). The value of $\lambda e\,(k+i)$ is given by:

$$\lambda e\,(k+i) = \begin{cases} \lambda e_{max} \ , \left|\overline{T}_{\varepsilon}\,(k+i-1)\right| \leq \overline{T}_{\varepsilon 2} \\ \lambda e_{min} \ , \left|\overline{T}_{\varepsilon}\,(k+i-1)\right| \geq \overline{T}_{\varepsilon 1} \\ \dfrac{\lambda e_{min} - \lambda e_{max}}{\overline{T}_{\varepsilon 1} - \overline{T}_{\varepsilon 2}} \left(\left|\overline{T}_{\varepsilon}\,(k+i-1)\right| - \overline{T}_{\varepsilon 2}\right) + \\ +\lambda e_{max} \ , \text{otherwise} \end{cases}$$

λe_{min} and λe_{max} are, respectively, the minimum and maximum values that λe can take at any given instant $k+i$. λe_{min} should be attained when the absolute value of $\overline{T}_{\varepsilon}\,(k+i-1)$ reaches a specified threshold, $\overline{T}_{\varepsilon 1}$, reflecting that $\overline{T}\,(k+i-1)$ is sufficiently far away from $R\overline{T}\,(k+i-1)$, and corresponds to the value of λe that enforces the highest energy consuming regime of the control system. λe_{max} should be attained when the absolute value of $\overline{T}_{\varepsilon}\,(k+i-1)$ reaches a specified threshold, $\overline{T}_{\varepsilon 2}$, reflecting that $\overline{T}\,(k+i-1)$ is sufficiently close to $R\overline{T}\,(k+i-1)$, and corresponds to the value of λe that enforces the lowest energy consuming regime of the control system. Although not discussed here, it is possible to show that the contribution of the second and third terms in the cost function must be smaller than the reduction obtained by choosing a determined control alternative, otherwise that particular alternative may not be chosen. Using this result and the first term of the cost function, it is possible to estimate the required λ values in order to achieve different levels of actuation by the controller.

4. RESULTS AND DISCUSSION

An experiment was carried out in the greenhouse in order to test the functionality and global behaviour of the proposed control system. The cost function (5) was employed and the results obtained constituted the motivation for the improvements presented in the previous section. Figure 3 illustrates the weather conditions to which the greenhouse and the control system were exposed to. The sampling frequency was 2.5 minutes, corresponding to 576 points per day. The temperature integration period was set to 6 days, the prediction horizon to 3 hours (72 points), and the control horizon to 10 minutes (4 points). A time limit of 20 seconds was established for the execution of the BaB algorithm in order to keep the time-delay between sensor reading and actuation small. If the 20 seconds limit is reached then the best solution found that far is applied to the greenhouse actuators. $R\overline{T}\,(k)$ was set to 16^oC, the day and night allowed temperature intervals were set to $[10^oC, 15^oC]$ and $[16^oC, 26^oC]$, and the day and night allowed relative humidity intervals were set to $[40\%, 95\%]$ and $[35\%, 80\%]$. In equations 1 and 2, SR_{p0}, SR_{p1}, and mc, were set to $30Wm^{-2}$, $250Wm^{-2}$, and 1^oC, respectively. The cost function parameters $T_{\varepsilon 1}$, $T_{\varepsilon 2}$, $T_{\varepsilon v}$, and $H_{\varepsilon v}$, were made equal to -4^oC, 4^oC, 5^oC, and 10%, respectively. $\{\omega_a\}_{a=1}^{6}$ and $\{\lambda_i\}_{i=1}^{5}$ were set to $\{0.5, 0.2, 0.15, 0.05, 0.05, 0.05\}$ and $\{0.8192, 9e^{-5}, 9e^{-5}, 9e^{-3}, 9e^{-3}\}$. The actuator cost parameters, ω_a, correspond to the cooler, heater, fog, lateral windows, and zenital window, respectively. The cost function λ parameters, correspond to those that were employed most of the time, although these were sometimes varied in order to analyse the control system response in view of the changes made.

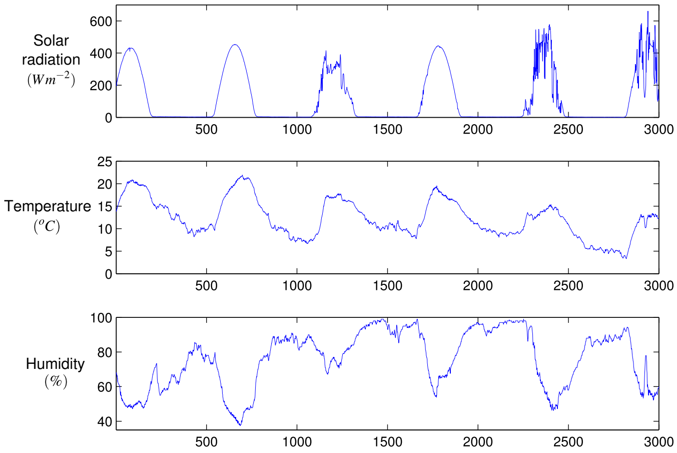

Fig. 3. Outside weather conditions

Due to an error in the parameterisation of the models on-line training set adaptation algorithm, the models had to be reset to their initial state a few times during the experiment. This fact is highlighted in figure 4 by means of red arrows pointing to those instants where the model should have responded to the heating device and blue arrows indicating the instants where the model reset occurred. In figure 4, two black solid lines in the upper part of the graph show the upper and lower temperature boundaries, the blue line corresponds to the greenhouse inside air temperature, the black dashed line shows the average temperature reference, and the solid red line depicts the average temperature over the integration period. In the lower part of the figure, three lines illustrate the actuation signals corresponding to the cooling, heating and fog systems, as indicated. At about time step 1750 the average temperature reaches its set-point and until the end of the experiment the system was able to maintain its value close to the reference. It is evident that the control effort is much larger before reaching the set point and clearly decreases after this. Once the temperature set-point has been reached, the unique situation where the heater is intensely actuated is during the last night period in order to keep the greenhouse temperature above its lower boundary. Approximately during the first 800 time steps, there is an excessive actuation on the cooling system due to the relation between the values of λ_2, λ_3 and λ_4. When the value of λ_4 (temperature boundary violation term weight) is large enough when compared to the sum of λ_2 and λ_3 and the greenhouse temperature is predicted to violate its upper boundary, the control system chooses to counteract the predicted violation by turning the cooling system on, because the reduction in the cost function value will be

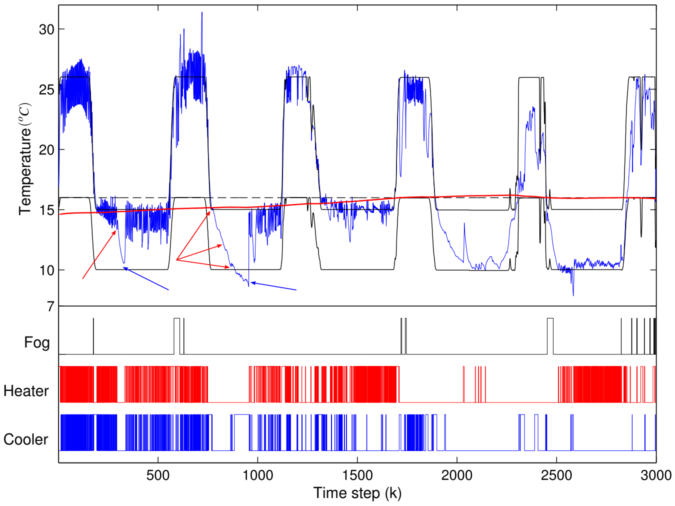

Fig. 4. Control signals, and greenhouse temperature

	S0	S1	S2	S3	S4
$\overline{t}$	13.7	8.9	8.6	5.2	4.1
$\overline{\text{nodes}}$	1374	717	624	513	365
$\overline{N_{ns}}$	1.9	1.1	0.8	0.9	0.6
$\overline{\overline{T}_{\varepsilon}(k)}$	0.13	0.14	0.14	0.14	0.15
$\sum_k \sum_i \mathbf{u}_i(k)$	8760 100%	7257 82.8%	6563 74.9%	6941 79.2%	6177 70.5%
$\lambda_1, \lambda_2 \left(\times 10^4\right)$		2.749	5.249	2.749	5.249

Table 1. Results from simulations of the restricted and unrestricted formulations

significant due to the large value of λ_4. After lowering the value of λ_4 ($k \approx 800$) this behaviour was corrected and the cooling system actuation was considerably decreased. This becomes apparent in the temperature response over the last four days which tends to stay close to its boundaries without showing an excessive ripple effect as in the first two days of operation. From this instant ($k \approx 800$) onwards the cooling system is actuated because it is really needed to maintain the greenhouse temperature below its upper boundary or due to temperature prediction errors which unnecessarily drive the control system to turn the coolers on.

Table 1 presents averaged results from a set of 5 simulations denoted from S0 to S4. An overline indicates the average operation. t denotes the computing time taken to find the optimal solution, nodes stands for the number of nodes visited, N_{ns} is the number of new solutions found when searching the tree, and $\overline{T}_{\varepsilon}(k)$ is the TI error. The following row shows a total sum of all the actuation during the simulation. The last row details the values of λ_2 and λ_3 for simulations S1 to S4 ($\lambda_1 = 1 - (\lambda_2 + \lambda_3)$. S0 corresponds to a simulation using the unrestricted formulation (equation 5), the remaining, S1 to S4, are all related to simulations employing the restricted cost function (equation 5 without the last two terms which have been implemented as restrictions). Different values of λ_2 and λ_3 were used for the pairs (S1,S3) and (S2,S4), setting a higher actuation cost on the latter. S3 and S4 also implement the rule-based reduction of the control inputs space (RRCIS) when $\left|\overline{T}_{\varepsilon}(k)\right| < 0.05^oC$, a value believed to guarantee that the sign of $\overline{T}_{\varepsilon}(k)$ will not change over the prediction horizon. When comparing the three types of simulations, it may be seen that both versions employing the restricted cost function present significant improvements, being the version using the RRCIS the best overall. The actuation results show that the restricted formulation has a high impact on the actuation profile, the RRCIS adding a further smaller improvement. Regarding the computing times and nodes visited, the restricted version with the RRCIS presents the best results. Even for S1, only in 6.5% of the iterations the 20 seconds limit was reached whereas for S0 the limit was reached in 32% of the simulation (not shown on the table). The different λ settings show the importance of these coefficients, given the significant difference in actuation at almost no expense in TI regulation. To this respect the results are similar, with S4 showing the biggest decrease (0.02^oC) in temperature regulation.

	S5	S6	S7	S8
$\overline{t}$	4.7	3.3	1.9	2.7
$\overline{\text{nodes}}$	382	258	168	217
$\overline{N_{ns}}$	0.7	0.5	0.4	0.4
$\overline{\overline{T}_{\varepsilon}(k)}$	0.14	0.16	0.34	0.21
$\sum_k \sum_i \mathbf{u}_i(k)$	6572 75.0%	5991 68.4%	4744 54.2%	5354 61.1%
$\lambda e_{min} \left(\times 10^4\right)$	5.498	10.498	12.998	10.498
$\lambda e_{max} \left(\times 10^4\right)$	10.498	15.498	17.998	17.998

Table 2. Results from simulations with on-line adaptation of the λ parameters

Table 2 presents the results from a series of four simulations, denoted by S5 to S8, where the on-line adaptation of the λ parameters has been included in addition to the restricted problem formulation and the RRCIS. The values of λe_t, $\overline{T}_{\varepsilon 1}$ and $\overline{T}_{\varepsilon 2}$ were set to 0.5, 0.5^oC and 0.05^oC, respectively. The values of λe_{min} and λe_{max} were varied and are shown at the bottom of the table. In S5, λe_{min} and λe_{max} have values corresponding to $\lambda_2 + \lambda_3$ in S3 and S4, respectively. As expected, the results may be found in the range from those of S4 to those of S3. For S6, the value of λe_{min} was set to that of λe_{max} in S5 and the value of λe_{max} to $\lambda e_{min} + 0.0005$, hence setting up the highest energy costs when compared to all previously presented simulations. $\overline{T}_{\varepsilon}$ is 0.16^oC, 0.02 and 0.03 higher than in S5 and S0, respectively. The actuation total is decreased almost by 9% when compared to S5 and almost 32% when compared to S0. Globally, the results show that the greenhouse MBPC algorithm is capable of displaying behaviours anywhere between two extremes, depending mostly on the values of the λ parameters. If these are made *extremely* small, the algorithm performs a tight control of the average temperature by compensating the temperature value at the beginning of the integration period with that achieved at time instant $k + 1$ resulting from the choice of control alternative that instantly minimises the error. In this situation the predicted climate over the integration period has little or none influence over the actions chosen, and the control system approximates a one-step-ahead average temperature pure tracking system. On the contrary, if the λ parameters are made *extremely* large, the solution that is always chosen is not to actuate at all unless at least one boundary restriction is violated. This results in a control scheme totally dependent on the course of the outside weather in what respects the greenhouse average air temperature. In fact it corresponds to the most frequently found in practice form of control, where actuation only occurs to counteract prespecified climate boundary violations. The S7 simulation demonstrates this last control behaviour by specifying higher λe_{min} and λe_{max} parameters, although not *extremely* high, resulting in a controller much more dependent on the outside weather (specially under the operation of λe_{max}) and where a larger proportion of actions taken serve only the purpose of maintaining the greenhouse temperature and/or humidity within the specified boundaries. In S8, λe_{min} and λe_{max} were set to the values adopted in S6 and S7, respectively. The aim is to bring together the best of two worlds: higher energy consumption profiles when needed and lower ones so that the external weather may be exploited while sparing energy. As expected the results are in between of those obtained by S6 and S7. When compared to S0 (highest consumption) a reduction of about 39% is achieved in the sum of actuations at the expense of an increase of 0.08^oC in $\overline{T}_\varepsilon$.

5. CONCLUSIONS

The application of the branch-&-bound algorithm to greenhouse model-based predictive control was proposed. It was shown how the algorithm may be efficiently implemented in order to decrease the computational time needed to find the optimal control inputs, by introducing a simpler restricted cost function and an adaptive control inputs space reduction methodology. The importance of the cost function coefficients was made clear, by showing its impact on energy consumption and average temperature regulation. By on-line adapting the the three coefficients as a function of the average temperature error over the integration period, the control system is able to exploit the external disturbances predictions, exhibiting significant reductions in energy consumption at the expense of a very small increase in the average temperature regulation error. Future work will focus on methodologies to increase the control and prediction horizons and to quantify the impact on crop yield.

REFERENCES

M. Berenguel, F. Rodríguez, F. G. Acién, and J. L. García. Model predictive control of ph in tubular photobioreactors. *Journal of Process Control*, 14:377–387, 2004.

J. P. Coelho, P. B. de Moura Oliveira, and J. Boaventura Cunha. Greenhouse air temperature predictive control using the particle swarm optimisation algorithm. *Computers and Electronics in Agriculture*, 49:330–344, 2005.

J. B. Cunha, C. Couto, and A. E. B. Ruano. A greenhouse climate multivariable predictive controller. In *Acta Horticulturae*, volume 534, pages 269–276. ISHS, 2000.

P. M. Ferreira and A. E. Ruano. Exploiting the separability of linear and nonlinear parameters in radial basis function networks. In *IEEE Symposium 2000: Adaptive Systems for Signal Processing, Communications, and Control*, pages 321–326, Lake Louise, Alberta, Canada, October 2000. ISBN 0-7803-5800-7.

P. M. Ferreira, E. A. Faria, and A. E. Ruano. Neural network models in greenhouse air temperature prediction. *Neurocomputing*, 43(1–4):51–75, 2002.

P. M. Ferreira, A. E. Ruano, and C. M. Fonseca. Genetic assisted selection of rbf model structures for greenhouse inside air temperature prediction. In *Proceedings of 2003 IEEE Conference on Control Applications*, volume 1, pages 576–581, Istanbul, Turkey, June 2003.

M. Y. El Ghoumari, H.-J. Tantau, and J. Serrano. Nonlinear constrained mpc: Real-time implementation of greenhouse air temperature control. *Computers and Electronics in Agriculture*, 49:345–356, 2005.

A. Gonzalez and J. P. Leyris. Application of generalized predictive control in mimo systems to greenhouse climate regulation. *International Journal of Systems Science*, 27(1):27–32, 1996.

H. P. Liebig. Temperature integration by kohlrabi growth. In *Acta Horticulturae*, volume 230, pages 371–380. ISHS, 1988.

E. H. Mamdani and S. Assilian. An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, 7(1):1–13, 1975.

L. F. Mendonça, J. M. Sousa, and J. M. G. Sá da Costa. Optimization problems in multivariable fuzzy predictive control. *International Journal of Approximate Reasoning*, 36:199–221, 2004.

S. Piñón, M. Peña, E. F. Camacho, and B. Kuchen. Robust predictive control for a greenhouse using input/output linearization and linear matrix inequalities. In *Proceedings of the 6^{t}h IFAC Symposium on Cost Oriented Automation*, pages 95–100, Berlin, Germany, October 2002.

S. Piñón, E. F. Camacho, B. Kuchen, and M. Peña. Constrained predictive control of a greenhouse. *Computers and Electronics in Agriculture*, 49:317–329, 2005.

J. A. Roubos, S. Mollov, R. Babuška, and H. B. Verbruggen. Fuzzy model-based predictive control using takagi-sugeno models. *International Journal of Approximate Reasoning*, 22:3–30, 1999.

A. E. Ruano, P. M. Ferreira, and C. M. Fonseca. An overview of nonlinear identification and control with neural networks. In A. E. Ruano, editor, *Intelligent control systems using computational intelligence techniques*, pages 37–87, London, UK, 2005. IEE - The Institution of Electrical Engineers.

Ido Seginer, Christian Garyb, and Marc Tchamitchian. Optimal temperature regimes for a greenhouse crop with a carbohydrate pool: A modelling study. *Scientia Horticulturae*, 60:55–80, December 1994.

J. M. Sousa, R. Babuška, and H. B. Verbruggen. Fuzzy predictive control applied to an air-conditioning system. *Control Engineering Parctice*, 5(10):1395–1406, 1997.

R. F. Tap, L. G. Van Willigenburg, and G. Van Straten. Receding horizon optimal control of greenhouse climate based on the lazy man weather prediction. Mrs report, Wageningen University, Department of Agricultural Engineering and Physics, The Netherlands, January 1996.

S. G. Tzafestas, E. J. Kyriannakis, K. G. Arvanitis, and N. Sigrimis. Decentralized predictive control of the heat dynamics of a greenhouse. In *Preprints of the 2nd IFAC-CIGR Workshop on Intelligent Control for Agricultural Applications*, pages 193–198, Bali, August 2001.

D. H. Willits and M. M. Peet. The effect of night temperature on greenhouse grown tomato yields in warm climates. *Agricultural and Forest Meteorology*, 92:191–202, 1998.