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CONSTRAINED PREDICTIVE CONTROL OF A GREENHOUSE

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Abstract: A scheme for temperature control of a greenhouse is presented. The present work proposes an approach based on a combination of two different control schemes: Feedback Linearization (FL) and standard linear Model Predictive Control (MPC), using their advantages. The treated greenhouse is considered a nonlinear Single-Input Single-Output process and subject to strong external disturbances. Since the methodology used for solving the MPC+FL approaches generally leads to an optimization problem subject to state-dependent nonlinear constraints, an alternative for its implementation is discussed. Two control techniques are compared, namely MPC+FL and Nonlinear Model Predictive Control (NLMPC).

Keywords: nonlinear control systems, predictive control, feedback linearization, constraints control, agriculture.

1. INTRODUCTION

In industrial applications a great number of practical control schemes have to deal with boundaries. These boundaries arise both from input physical constraints, such as actuator saturation, and from output constraints due to specific conditions of the process. Furthermore, if the plant to be controlled is nonlinear the problem becomes more complex and a nonlinear program must be solved. In general, this leads to a non-convex optimization problem and to an increase in computational demands.

As the system models in engineering are frequently nonlinear, several approaches have been developed to solve the constrained control problem by approximating the nonlinear model to a linear one. Since most practical control schemes have to deal with physical constraints, a controller that can handle these constraints is necessary, thus maintaining the linearity of the system to be controlled. One of the reasons for choosing Model Predictive Control (MPC) is its capability to handle the constraints explicitly.

In recent years, several approaches have been proposed to deal with the climate control problem in greenhouses (Boaventura *et al.* 1997; Wang and Wu, 1999), however most techniques provide only indirect constraint compensation.

This work deals with the problem of following a desired trajectory for the optimum temperature behavior inside a greenhouse, which has been modeled as a time-invariant nonlinear system, linearized by the Feedback Linearization (FL) approach. Model Predictive Control using Feedback Linearization problem (MPC+FL) can be explicitly solved only for some cases and the main difficulty of this configuration is that the MPC design must be made subject generally to nonlinear constraints. Here, the FL will be presented as the Input Output Linearization (IOL) of a greenhouse temperature control subject to constraints inherent to the actuator, as well as to inside temperature constraints.

The paper is organized as follows. Section 2 discusses some aspects of modeling greenhouse dynamics, taking into account the disturbances from climatic conditions to which the greenhouse is subjected. Section 3 gives a brief revision of system linearization and stability analysis of zero dynamics and a desired trajectory follow-up is discussed, in controlled variable. Section 4 deals with the

Table 1: List of symbols for model

Symbol	Definition
a_{bso}	Absorbtivity of the covering material [ND]
a_h	Average height of a greenhouse [m]
a_{rto}	Area ratio of total plant leaf area to floor area. a_{rto1}=1-a_{rto} [ND]
c_a	Volumetric heat capacity of air [KJ/m^3/ºC]
c_c	Heat capacity of cover [KJ/m^{3}ºC]
c_p	Heat capacity of a single plant [KJ/m^{3}ºC]
c_s,	Heat capacity of floor [KJ/m^{3}ºC]
d_{ex}	Thickness of covers [m]
γ	Water vapor resistance [h/m]
g_{si}	Dryness factor of the surface [ND]
h_i	Convective heat transfer in the inner cover [KJ/m^2h^oC]
h_o	Convective heat transfer in the outer cover [KJ/m^2h^oC]
h_{lg}	Latent heat for evaporation [KJ/Kg]
k_s	Soil thermal conductivity [KJ/hm^oC]
l_{ai}	Leaf area index [ND]
q_h	Air flow rate due to ventilation [m^3/m^2h]
r_{ad}	Direct solar radiation [W/m^2]
r_{ads}	Diffused solar radiation [W/m^2]
ρ	Density of air [kg/m^3]
r_{mc}	Reflectivity of the outer cover for long wave radiation [ND]
s_{ig}	Stefan-Boltzman constant [ND]
t_{lv}	Transmisivity of cover for long wave radiation
t_{bl}	Lower boundary of soil temperature. [^oC]
a_{lc}	Absorptivity of the inner cover for solar radiation [ND]
a_{lf}	Absorptivity of the floor for solar radiation [ND]
a_{lp}	Absorptivity of the plant for solar radiation [ND]
t_o	Outside air temperature [^oC]
w_o	Humidity ratio in the greenhouse [kg/kg Dray Air]
t_{ran}	Transmissivity of the covering material [ND]
z_0- z_1	Depth of soil layer [m]

Table 2: Parameters used in the model

$c_1 = -h_i-h_o$	$c_2 = -(e_{psf}+1)$
$c_3 = s_{ig}.e_{psc}.e_{psf}$	$c_4 = h_o$
$c_5 = s_{ig}.e_{psc}.e_{psa}$	$c_6=a_{bso}+(1-a_{lf})t_{ran}.a_{lc}$
$c_7 = a_{lc}+a_{lc}(1-a_{lf})t_{ds}$	$c_8 = h_i$
$c_9 = -2h_i-c_a.q_h-2.h_i.a_{rto}.l_{ai}$	$c_{10} = 2h_i.a_{rto}.l_{ai}$
$c_{11} = c_a.q_h$	$c_{12} = s_{ig}.e_{psf}.e_{psc}$
$c_{13} = -2k_s/(z_0+z_1)-h_i$	$c_{14} = -s_{ig}.e_{psf}(1-r_{mc})$
$c_{15} = d_{lex}c_c$	$c_{16} = s_{ig}.e_{psf}.e_{psa}.t_{lv}$
$c_{17} = a_{lf}.t_{ran}.a_{rto1}$	$c_{18} = a_{lf}.t_{ds}.a_{rto1}$
$c_{19} = -h_{lg}.k_m.g_{si}$	$c_{20} = 2k_s/(z_0+z_1)$
$c_{21} = s_{ig}.e_{psp}.e_{psc}$	$c_{22} = 2l_{ai}.h_i$
$c_{23} = -2l_{ai}.h_i$	$c_{24} = -s_{ig}.e_{psp}(1-r_{mc})$
$c_{25} = c_a a_h$	$c_{26} = s_{ig}.e_{psp}.e_{psa}.t_{lv}$
$c_{27} = a_{lp}.t_{ran}$	$c_{28} = a_{lp}.t_{ds}$
$c_{29} = -2\rho/\gamma.h_{lg}.l_{ai}$	$c_{30} = c_s z_0$
c_{31}=-$a_{rto}/v_p c_p$	

MPpresence of constraints at both the control and w

MPC+FL structure. Section 5 shows several simulations and results obtained to evaluate the performance of the predictive control technique with a FL internal loop. This technique will be compared with the Nonlinear Model Predictive Control (NLMPC) and Section 6 presents the conclusions and possible future works.

2 NONLINEAR MODEL FOR GREENHOUSES

In the paper, a greenhouse model will be used with a single layer cover. Takakura (1993) previously discussed the selected greenhouse nonlinear model. The model takes into account absorbed solar radiation, radiation exchange between the sky and the cover and between the cover and the interior space of the greenhouse. Heat exchanges due to convection are also considered: between the inside air and the cover, between the cover and the outside air, and finally, the latent heat liberated by the condensed water vapor. The energy balance of the inside air includes the convective exchange with the cover, with the seedlings and with the floor, as well as the heat exchange with the outside air. For simplicity, the air mass inside the greenhouse is considered to have a homogenous temperature distribution.

The system has been established as a SISO system discretized by the Euler method each one being 3 min long (ΔT= 0.01 hours) and several real disturbances are considered. The state vector $x(k)$=[t_c t_i t_f t_p] is formed of: greenhouse cover temperature t_c, temperature of the inside air t_i, floor t_f and plant temperature t_p. The complete dynamics of the temperature inside the greenhouse take into account some perturbations such as: direct solar radiation r_{ad}, diffuse solar radiation r_{ads}, external temperature t_o and the temperature under a 10 cm-deep soil layer t_{bl}. These five variables make up the perturbation vector $d(x)$ of (1). Temperatures t_c, t_i, t_f are measured variables. The seedling temperature is not directly measured, it is estimated by an Extended Kalman Filter. The details of its implementation are shown in a previous work (Piñón *et al.* 1998b). Tables 1 and 2 show the parameters and symbols used.

The discrete greenhouse model can be expressed as in the following mathematical equations:

$$\begin{aligned} t_c(k+1) = (&c_1 t_c(k) + c_2 t_c{}^4(k) + c_3 t_f{}^4(k) \\ &+ c_8 t_i(k) + c_6 r_{ad} + c_7 r_{ads} + c_4 t_o \\ &+ c_5 t_o^4)\Delta T / c_{15} + t_c(k) \end{aligned}$$

$$\begin{aligned} t_i(k+1) = (&c_8 t_c(k) + c_9 t_i(k) + c_8 t_f(k) + c_{10} t_p(k) \\ &+ c_{11} t_o + Q_{cal})\Delta T / c_{25} + t_i(k) \end{aligned}$$

$$\begin{aligned} t_f(k+1) = (&c_{12} t_c{}^4(k) + c_8 t_i(k) + c_{13} t_f(k) + c_{14} t_f{}^4(k) \\ &+ c_{19} ws_{t_f}(t_f(k)) + c_{17} r_{ad} + c_{18} r_{ads} \\ &+ c_{16} t_o^4 + c_{20} t_{bl})\Delta T / c_{30} + t_f(k) \end{aligned}$$

$$
\begin{aligned}
t_p(k+1) = (&c_{21} t_c{}^4(k) + c_{22} t_i(k) + c_{23} t_p(k) \\
&+ c_{24} t_p{}^4(k) + c_{29} w_{st_p}(t_p(k)) + c_{27} r_{ad} \\
&+ c_{28} r_{ads} + c_{26} t_o^4)\Delta T / c_{31} + t_p(k)
\end{aligned}
$$

and the terms for latent heat from solid surfaces are,

$$
w_{st_f}(k) = \frac{0.62 e^{\beta(t_f(k))}}{1.10^5 - e^{\beta(t_f(k))}}
$$

$$
w_{st_p}(k) = \frac{0.62 e^{\beta(t_p(k))}}{1.10^5 - e^{\beta(t_p(k))}}
$$

β is a empirical factor which depends on the nonlinear shape of the temperature profile. The system can be formulated by

$$
\begin{aligned}
x(k+1) &= f(x(k)) + g(x(k))u + p_d(x(k))d(k) \\
y &= h_c(x(k))
\end{aligned}
\qquad (1)
$$

where $x \in \Re^4$ is the state vector, $u \in \Re$ is the input, $d \in \Re^4$ is the disturbance vector and $y \in \Re$ is the output. $f: \Re^4 \to \Re^{4x1}$, $g: \Re^4 \to \Re^{4\times 1}$, p: $\Re^4 \to \Re^{4\times 4}$ are smooth vector fields, and h_c: $\Re^4 \to \Re$ is a smooth function

$$
x(k+1) = \begin{bmatrix} t_c(k+1) & t_i(k+1) & t_f(k+1) & t_p(k+1) \end{bmatrix}^T
$$

and

$$
f(x) = \begin{bmatrix} f_1(x(k)) & f_2(x(k)) & f_3(x(k)) & f_4(x(k)) \end{bmatrix}^T
$$

The column vector $g(x(k))$ can be formulated as

$$
g(x(k)) = \begin{bmatrix} 0 & \Delta T / c_{25} & 0 & 0 & 0 \end{bmatrix}^T \qquad (2)
$$

and the control variable is the heat flow given off by the heater/cooler

$$
u(k) = Q_{cal}(k) \qquad (3)
$$

For the present case, the inside temperature has been chosen as the controllable variable of the system $h_c(x(k)) = t_i(k)$ and the heat flow Q_{cal} as the control variable and the matrix $p_d(x)$ is given by

$$
p_d(x(k)) = \begin{bmatrix}
\dfrac{c_6 \Delta T}{c_{15}} & \dfrac{c_7 \Delta T}{c_{15}} & \dfrac{(c_4 + c_5 t_o^3)\Delta T}{c_{15}} & 0 \\
0 & 0 & \dfrac{c_{11} \Delta T}{c_{25}} & 0 \\
\dfrac{c_{17} \Delta T}{c_{30}} & \dfrac{c_{18} \Delta T}{c_{30}} & \dfrac{c_{16} t_o^3 \Delta T}{c_{30}} & 0 \\
\dfrac{c_{27} \Delta T}{c_{31}} & \dfrac{c_{28} \Delta T}{c_{31}} & \dfrac{c_{26} t_o^3 \Delta T}{c_{31}} & 0
\end{bmatrix}
$$

The perturbations vector is formulated as

$$
d(k) = \begin{bmatrix} rad(k) & rad_s(k) & t_o(k) & t_{bl} \end{bmatrix}^T
$$

This work use measurements collected by the commercial Davis Weather Station (© David Instruments Corporation) over 21 consecutive days in July-August. This station is situated in San Juan, Argentina (31º32 lat., 68º31 long.) Fig. 1 shows the external climate recorder. Temperature [*ºC*], outside humidity ratio [*kg/kg Dry Air*] and wind speed [*Km/h*] are some of the collected data that have been introduced in to the system at each control time. It should be noted that in this zone the climate is very unstable.

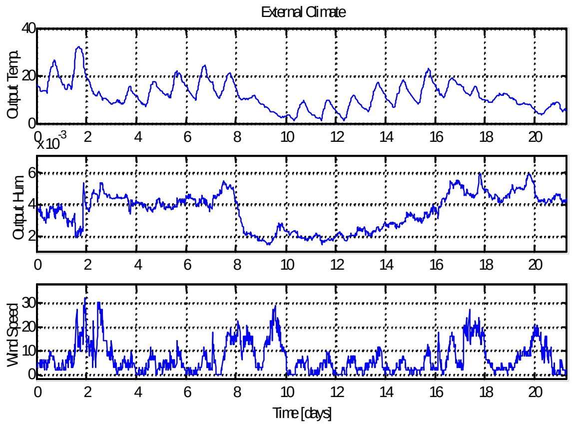

Fig. 1: Climate of the INAUT weather station

FEEDBACK LINEARIZATION OF A GREENHOUSE

The Input Output Linearization (IOL) is summarized in (Henson 1997). The linearization of the greenhouse system adopted here may be referred to for details in Piñón *et al.* (1998a). In said work, a relative degree of the greenhouse system r=1 was obtained, disturbances were decoupled and a diffeomorphism $[\xi(k)^T, \eta(k)^T] = \Phi^T[x(k)]$ where $\xi_1(k) = t_i(k)$, $\eta(k) = [t_c(k) \quad t_f(k) \quad t_p(k)]$ was also defined. Therefore, the transformed system can be expressed in a normal form as

$$
\xi_1(k+1) = A_d \xi(k) + B_d v(k) \qquad (4a)
$$

$$
\eta(k+1) = \bar{q}(\xi(k), \eta(k)) + \bar{k}(\xi(k), \eta(k))d(k) \qquad (4b)
$$

$$
y(k) = \xi_1(k) \qquad (4c)
$$

where A_d=1, B_d=ΔT. We have introduced here the smooth functions $\bar{q}$ and $\bar{k}$. The details of how these functions depend on *f, g, p* and *h* can be seen in Henson (1997). To make the system of eq. (4a) be linear, the feedback should be shaped as

$$u(k) = -(c_8 t_c(k) + c_9 t_i(k) + c_8 t_f(k) + c_{10} c_{25} t_p(k)) \\ + c_{25} v(k) - c_{11} t_o(k)$$

Thus, the control law exactly linearizes the map between the transformed input v and the output y. Consequently, a linear controller can be designed to satisfy control objectives such as setpoint tracking. It is important to note that the η dynamics remain nonlinear.

In this work the analysis is particularized to the tomato crop. Due to biological conditions the seedling temperature may not be above 37º*C* on below 10ºC with 3 leaves and $0.21 g/m^2$ of dry weight. The optimal reference and the inside temperature bounds for obtaining seedlings are recommended in a previous work (Sander *et al.* 1993 and Fullana et al. 1999). Such trajectory and bounds were found using experimental results from the National Institute for Agricultural and Livestock Technology and Research (INTA), San Juan, Argentina. Therefore, the output variable $t_i(k)$ is constrained so as not to surpass a 3ºC band around the optimal reference of day time temperature and in order to save energy during the night the inside temperature may reach 10ºC under this optimal reference of temperature.

4 THE MPC + FL APPROACH

The reason for introducing this combination approach is to increase computing efficiency by linearizing the plant and by reformulating the MPC problem on the new linearized coordinates. This is not easy to do solve, unless the nonlinear constraints and the objective function are convex. Thus, the originally nonlinear model used for the MPC prediction becomes linear, which leads to an easier implementation of the MPC algorithm and a significant reduction of the computations involved in the nonlinear optimization problem.

4.1 Statement of the problem

The MPC algorithm is formulated so as to solve (on-line and at every instant) an optimal control problem with finite horizon. The objective function (5) used here is given in terms of the new control variable *v*. In contrary to the NLMPC design, the criterion is in terms of the original inputs *u*, instead of the FL control variables. Details of the NLMPC have been deliberately excluded from this paper because of space limitations. Then, the objective function is,

$$J(k) = \sum_{i=1}^{NP} \left\| y_{(k+i|k)} - y_{r(k+i|k)} \right\|_Q^2 + \sum_{i=1}^{NC} \left\| v_{(k+i|k)} \right\|_R^2 \quad (5)$$

subjected to the linear system (4a) and the nonlinear constraints (7) and (8), where

$y_{(k+i\|k)}$:	Output predictive vector at *k*.
$y_{r\,(k+i\|k)}$:	Reference trajectory.
$v_{(k)}$:	Sequence of control computed at *k*; $v_{(k+i\|k)}=0$ for $i>NC$. $v_{(k\|k)}$ is the control move at *k*.
Q, *R*:	Positive definite matrices representing weights on the states and new control variables.
NP, *NC*:	Prediction and control horizon ($NC \le NP$.)

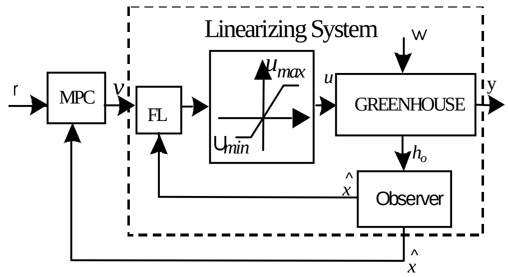

Fig. 2. MPC+ FL structure used

A main feature of MPC is that process constraints can be directly incorporated into the online optimization performed at each time step. The big advantage of MPC compared to the other control techniques is its multivariable constraint handling capability and it is therefore very successful in industrial applications.

Fig. 2 shows the proposed hybrid MPC+FL structure for controlling nonlinear systems with hard constraints at the input. An inner FL loop is embedded in an external predictive control loop, linearizing the greenhouse nonlinear plant and tracking its own reference input *v*, considering the constraints in the manipulated variable (heater/cooler) and in the controlled variable (inside temperature). The linear properties of the FL loop are preserved, i.e. the eq. (4a) holds, only if the original constraints on *u* are satisfied. This implies that MPC design in the external loop must be made subject to implicit constraints on the new input *v*. Hence, the real input is bounded $0 \le u_{heat} \le 300 W/m^2$ to the heater. Then, the new input *v* of the linearized plant, after the mapping, is,

$$v(k) = a(\xi(k), \eta(k)) + b(\xi(k), \eta(k)) u(k) \\ + \gamma(\xi(k), \eta(k) w(k)$$

where

$$a(\xi(k), \eta(k)) = f_2(\xi(k), \eta(k)) / c_{25}$$
$$b(\xi(k), \eta(k)) = \Delta T / c_{25}$$
$$\gamma(\xi(k), \eta(k)) = c_{11} / c_{25}$$

one can derive the following expressions for a constraint set Ω_v ,

$$v_{min}(k) = a(\xi(k),\eta(k)) + b(\xi(k),\eta(k))u_{min}(k) + \gamma(\xi(k),\eta(k))w(k) \quad (7)$$

$$v_{max}(k) = a(\xi(k),\eta(k)) + b(\xi(k),\eta(k))u_{max}(k) + \gamma(\xi(k),\eta(k))w(k) \quad (8)$$

It is clear that, due to the FL, original hard constraints (u_{min},u_{max}) are mapped into the MPC constraints on *v*. In this case the new constraint represents the inside temperature rate.

5. SIMULATIONS RESULTS

Various simulation tests were applied to gain some insight on the performance property and efficiency of the MPC+FL approach as compared to the NLMPC. Both NLMPC and MPC+FL were implemented using Matlab 5.3 software. The model used for the prediction in NLMPC was defined by the original nonlinear greenhouse system (see eq. 1), whereas the constraints are hard for both the heat/cool flow and the output variable.

In our application, the error and the control are weighed in a different usy during the day and the night to get a great saving in energy. Q_d and Q_n are defined factors that weigh the error during the day and the night respectively. Whereas R_d and R_n denote the control weight for the day and the night.

Several experiments were simulated having *NC*=*NP*=4. In every case the control objective was achieved. The desired trajectory was correctly tracked and the imposed constraints were fulfilled. The difference between the MPC+FL implementation for different weights is shown in Fig. 4. The output temperature of the greenhouse during a two day experiment is shown by fine line. In this case, the following can be observed:

- In Experiment. 1: The dot dot-dashed line response was obtained with R_d=10, Q_d=1, R_n=Q_n=0. Here, the error between the desired reference trajectory and the output is noticed during the night, but it does not pose any hazards to the crop's growth as it is still within the allowed temperature range. During the day, the error is small and the energetic consumption is low.
- In Experiment 2: With R_d=0.001, Q_d=100; R_n=Q_n=0, the dot-dashed line response was obtained. Better performance is achieved due to a minimum-error follow-up, though the energy demands are greater than with the previous experiment (20 W/m^2 Vs. 17 W/m^2 in the previous experiment). The mean square errors obtained for these experiments were 0.5ºC and 0.2º C, respectively.
- In Experiment 3: (Represented in bold-line) With R_d=0, Q_d=10; R_n=Q_n=0, in this case the energy demand is less than in the other cases and the temperature error is within the permitted values. This last experiment was made only in order to later be compared with the non-linear controller response.

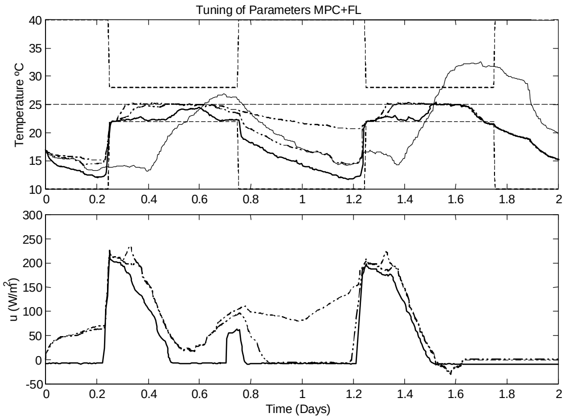

Fig. 3. MPC+FL, Experiment 1 (dot-dot-dashed line). Experiment 2 (dot-dashed-line). Experiment 3 (dashed line). Output temperature (fine line). Constraints and setpoint (dashed line)

Other simulations using the NLMPC method were performed. In all cases the objectives under restrictions were also reached.

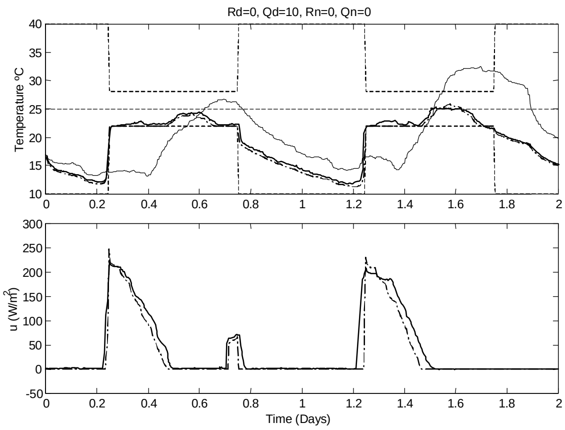

Fig. 4. Comparison of MPC+FL (bold line) Vs. NLMPC (dotted line). Constraints and setpoint (dashed line). Output temperature (fine line)

If NLMPC is compared to MPC+FL (see Fig. 4); with *NC* = *NP* = 2 and Q_d=10, Q_n=0, R_d=R_n=0, it can be stated that:

- Both the output (inside air temperature) and control variables (heat flow) obtained by the NLMPC and MPC+FL techniques show a similar behavior. Notice that for NLMPC design the criterion is described in terms of the original inputs *u*, instead of the FL control variables *v*.
- The control action to achieve such a follow-up is also very similar. This follow-up is kept within

the maximum and minimum bounds permitted by the heater capacity.

- For both techniques, a mean square error around 1:5 ºC is obtained to MPC+FL and 1:8 ºC to NLMPC. The mean values of the control signals were 16 W/m^2 and 13 W/m^2, respectively.
- It is noticeable that during the night both the MPC+FL and the NLMPC have obtained a temperature value smaller than the output temperature. This phenomenum is called thermal inversion and takes place in unheated greenhouses in clear sky zones. This has been amply studied in the literature and for more details refer to a (Takakura, 1993)

In all cases the sampling time was 3 min. Notice that MPC+FL and NLMPC methods can be compared only if there is no weight on the control variable, i.e., R=0. As has been mentioned above this accurs because NLMPC uses the original cost whereas the MPC+FL is based on the new cost given in terms of the new coordinates and the new control variable.

Although the performance for MPC+FL and NLMPC is very similar, the associated computational effort to optimization is very different (0.006 sec. Vs 13 sec respectively in a Pentium III 550 MHz, 128 Mbytes RAM). This arises from MPC+FL using linear models which avoid the computationally demanding prediction integrations, resulting in a significant decrease of computational load. It should be noticed that the NLMPC method allows direct weighting of the energy consumption whereas the MPC+FL method uses indirect weighting through a complex nonlinear function. Therefore, the second method is more suitable for any direct control implementation intended for incrementing the greenhouse profit due to its easy energetic consumption interpretation.

6. CONCLUSIONS

A nonlinear model of a greenhouse subject to constraints and real disturbances was analyzed. Using an observer, the complete state vector was obtained to carry out the I/O Linearization. By decreasing the computation burden and making the performance analysis easier, the discussed hybrid control structure, MPC+FL, enabling to offer a general approach to the solution of nonlinear control problems.

This approach produces nonlinear state dependent constraints. It means that an optimization problem for a nonlinear greenhouse system subject to hard constraints in the input has been transformed to a new optimization problem for a linear greenhouse system subject to nonlinear constraints in the new input.

Due to its relative computational efficiency, the MPC+FL strategy seems to be attractive for a class of feedback linearizable systems. This study is intended to be continued in a future practical implementation, where the physical limitations of the heater/cooler will be considered as well as the necessary restrictions for an optimal performance.

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