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REAL TIME NON LINEAR CONSTRAINED MODEL PREDICTIVE CONTROL OF A GREENHOUSE

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Abstract: This paper describes the application of predictive control to the temperature regulation in agricultural processes. The main aim is to achieve climatic control of a greenhouse built in the Institute for Horticultural and Agricultural Engineering (ITG) of the University of Hannover (Germany). The MPC controller implemented here has the characteristic to take in account constraints in both manipulated and controlled variables using on-line linearisation, with very low computational burden. By means of a real time experiment, important advantages of the MPC algorithm are demonstrated, performance and mainly saving energy, using a soft optimal control effort. This controller has been compared with an adaptive PID controller. *Copyright ©2000 IFAC*

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1. INTRODUCTION

Agriculture under greenhouses has a growing economic and social importance in the European countries, for that reason climate computer has become very common in a large part of these countries. The actual climate computers mainly resolve the task of greenhouse climate control, i.e. inside temperature, relative humidity and CO_2 level. The manipulated variables are the temperature of the heating system, the windows opening, and the CO_2 supply. In some cases, the irrigation control is included. Many of these systems use a conventional PID control for each control loop, but this control strategy has important disadvantages: (a) the performance is very low, due to the interactions between the different variables, (b) the constraints are not considered and (c) no guarantees of preservation of the used energy. The main objective of this work is to implement a real time model predictive controller able to solve these problems, and to compare it with a conventional PID controller with respect to energy saving, economical issues and transparency.

A greenhouse is a closed enclosure that creates a difference between the outside and the inside air, due to the confinement of the air, and to the absorption of the short wave solar radiation by the double glass cover. In addition the long wave radiation is interchanged between the different components of the greenhouse (ground, heating system, plants, cover, etc.).

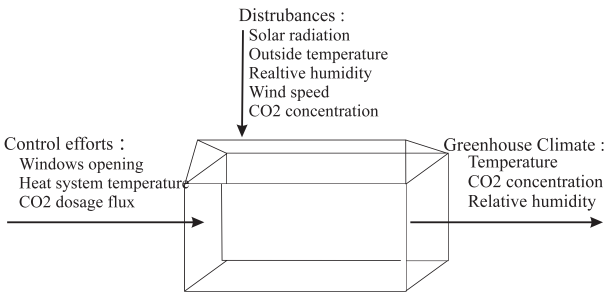

Fig. 1. Greenhouse system

The dynamic behaviour within the greenhouse is governed by the energy and mass balances. The energy balance is affected by the energy contribution by the heating system, the energy loses caused by the air exchange by transmission through the cover and the natural ventilation by means of the windows, and finally the energy contribution by the solar radiation (Bot, 1983).

The humidity balance is determined by the plants transpiration, and the air exchange due to the ventilation, finally the carbon dioxide balance is determined by the CO_2 supply, the plants consumption of CO_2, and the air exchange by ventilation.

Model Predictive Control (MPC) appears as a suitable control strategy to cope with the problems of controlling the climate and the growth processes. On the one hand, MPC can provide with high performance when models are accurate and, on the other hand, MPC is one of the very few strategies which guarantee the accomplishment of constraint specifications.

The main objective of this paper is to apply the techniques of the MPC in order to control the greenhouse temperature with two manipulated variables: heating and natural ventilation (windows opening). The greenhouse climatic control problem is tackled with an MPC algorithm which uses on-line linearised models (Oliveira and Morari, 1995; El Ghoumari, 1998; Megas *et al.*, 1999).

2. GREENHOUSE CLIMATE VALIDATION MODEL

In the greenhouse climate model used here, the state of greenhouse climate is represented by tree variables namely, inside air temperature T_g [C], carbon dioxide concentration C_i [Kg m^3], and absolute humidity V_i [Kg m^3]. Plant model was ignored for simplicity reasons.

The greenhouse climate model describes the dynamic behaviour of the state variables with the following differential equations (Henten, 1994; Tap, 2000):

$$\begin{aligned}
\frac{dT_g}{dt} &= \frac{1}{c_{cap,q}}(Q_{pi,ai} - Q_{ai,ou} + Q_{rad} + Q_{soil}) \\
\frac{V_g}{A_g}\frac{dC_i}{dt} &= \phi_v(C_0 - C_i) + \varphi_i nj + R - \mu P \\
\frac{dV_i}{dt} &= \frac{1}{c_{cap,h}}(\Phi_{h,pi,ai} - \Phi_{h,ai,ou})
\end{aligned} \tag{1}$$

where $c_{cap,q}$ [J m^{-2} C^{-1}], $c_{cap,c}$ [m], $c_{cap,h}$ [m] are the heat and mass capacities of the greenhouse air respectively. In this model, the heat and mass transfer in the greenhouse are described per square metre soil.

The convective energy transport from the heating pipes to the greenhouse is described by:

$$Q_{pi,ai} = c_{pi,ai}(T_p - T_g)$$

were:

$c_{pi,ai}$ is the pipe air heat transfer coefficient [W m^{-2} C^{-1}]
T_p is the heating pipe temperature [C](**Manipulated variable**)
T_g is the inside temperature [C](**Controlled variable**)

The energy loss to the outside air can be described by:

$$Q_{ai,ou} = (\Phi_{vent} c_{cap,q,v} + c_{ai,ou})(T_g - T_{out})$$

were:

Φ_{vent} is the natural ventilation flux [m s^{-1}]
$c_{cap,q,v}$ is the heat capacity per volume [J m^{-3}C^{-1}]
$c_{ai,ou}$ is the heat transfer coefficient through the greenhouse cover [W m^{-2} C^{-1}]

The natural ventilation flux is calculated from the wind speed and the windows opening (de Jong, 1994; Baytorun, 1986).

$$\Phi_{vent} = \kappa + \lambda w + \gamma w r_w$$

were:

κ is the ventilation rate parameter [m s^{-1}]
λ is the ventilation rate parameter [-]
w is the outside wind speed [m s^{-1}]
γ is the ventilation rate parameter [-]
r_w is the relative windows opening [%](**Manipulated variable**)

The heat load from the sun is given by:

$$Q_{rad} = C_{rad} G$$

were:

C_{rad} is the radiation conversion factor [-]
G is the outside solar radiation [Wm^{-2}]

Finally the heat load from the soil is given by:

$$Q_{soil} = k_s(T_s - T_g)$$

were:

k_s is the soil heat transfer coefficient [W C^{-1} m^2]
T_s is the soil temperature [C]

The greenhouse air CO_2 concentration is described by the second line in the eqn.1 where $\frac{V_g}{A_g}$ is the average greenhouse height [m], C_0 is the outside CO_2 concentration [g m^{-3}], φ_{inj} is the CO_2 injection flux (**Manipulated variable**) [g s^{-1} m^{-2}], R is the respiration of the crop [g s^{-1} m^{-2}], P is the crop photosynthesis [g s^{-1} m^{-2}] and μ is the fraction of molar weight of CO_2 and CH_2O [-]. (These two last terms are neglected because no plants have been considered in this model).

Finally the greenhouse air vapour contents is described by the last line of eqn.1 where: $\phi_{h,pi,ai}$ is the canopy transpiration rate [kg m^{-2} s^{-1}], and $\phi_{h,ai,ou}$ is the humidity losses to outside air due to the ventilation [kg m^{-2} s^{-1}].

Three calibration parameters are chosen, and they have been identified using a Sequential Quadratic Programming (SQP) method, minimising the error between the measured and calculated data during 14 days, subject to the constraints of the limits of calibration parameters which can be found in the literature (Baytorun, 1986). These parameters are the heat capacity of greenhouse air $c_{cap,q}$, the heat transfer coefficient $c_{pi,ai}$, and the energy transfer through greenhouse cover $c_{ai,ou}$. The optimal values of these parameters are as follows:

$$\begin{aligned} c_{cap,q} &= 20000[\mathrm{J\,m^{-2}C^{-1}}]\,, \\ c_{pi,ai} &= 9[\mathrm{W\,m^{-2}\,C^{-1}}]\,, \\ c_{ai,ou} &= 50[\mathrm{W\,m^{-2}\,C^{-1}}]\,. \end{aligned}$$

3. MPC ALGORITHM DESCRIPTION

In this paper, the climatic variables in the greenhouse are controlled using the *Modified Extended Linearised Predictive Controller* (MELPC) described in (El Ghoumari, 1998; Megas *et al.*, 1999). The MELPC is aimed to control non-linear MIMO systems with a low computational burden. This algorithm exploits the idea of obtaining on-line linearised models *at each sampling instant*, an alternative which has been shown to improve the performance achieved using a single (off-line) linear approximation of the process. A similar approach can be found in (Oliveira and Morari, 1995) and in (De Keyser, 1998), which formalises the idea of on-line linearisation by means of an iterative formulation.

The complexity of the greenhouse system, the large interaction between different variables, and the strong external disturbances stand out among the reasons for choosing MELPC. In addition, the controller is expected not only to control the climatic variables, but also to satisfy constraints in the manipulated variables (heating and opening of the windows). Because of this, the controller is formulated so as to take *hard input constraints* into account.

The MELPC works as follows. Let the process be described by the following autonomous non-linear ODE system:

$$\begin{cases} \dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x},\boldsymbol{u}), \\ \boldsymbol{y} = \boldsymbol{g}(\boldsymbol{x}), \end{cases} \tag{2}$$

with n states ($\boldsymbol{x}$), m inputs ($\boldsymbol{u}$) and p outputs ($\boldsymbol{y}$). In addition, let the incremental variable $\boldsymbol{v}$ be defined as $\boldsymbol{v} \doteq \boldsymbol{u} - \boldsymbol{u}(t_s - 1)$, where t_s denotes the current sampling instant. A vector of output predictions is given by

$$\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{y}_f(t_s+N_1) + \boldsymbol{y}_u(t_s+N_1) \\ \boldsymbol{y}_f(t_s+N_1+1) + \boldsymbol{y}_u(t_s+N_1+1) \\ \vdots \\ \boldsymbol{y}_f(t_s+N_2) + \boldsymbol{y}_u(t_s+N_2) \end{bmatrix},$$

where $\boldsymbol{y}_f(t_s+j)$ are the *free responses* (computed taking the future control moves to be zero) and $\boldsymbol{y}_u(t+j)$ are the *forced responses*, which depend on $\boldsymbol{\Delta v}(t_s+j)$ for $j = 1, \ldots, N_u$. Furthermore, N_1 and N_2 are, respectively, the lower and upper costing (or prediction) horizons, and N_u is called the control horizon [1]. As usual, a receding-horizon strategy is applied, *i.e.* only the first control move $\boldsymbol{\Delta v}(t_s)$ is used, whereas the rest are discarded.

The free responses $\boldsymbol{y}_f(t_s+j)$ are computed by integrating the non-linear model of eqn.2 at each sampling instant. This leads to predictions which are quite close to the behaviour of the true system. The output predictions are then computed as $\boldsymbol{Y} = \widetilde{\boldsymbol{Y}}_f + \widetilde{\boldsymbol{H}}\boldsymbol{\Delta V}$, where $\widetilde{\boldsymbol{Y}}_f$ is a vector of free responses, and $\widetilde{\boldsymbol{H}}$ is a matrix formed with the step-response coefficients of the on-line linearised model. As pointed out in (Megas *et al.*, 1999), there are several ways to obtain the matrix $\widetilde{\boldsymbol{H}}$. Here, the step-response coefficients which yield $\widetilde{\boldsymbol{H}}$ are obtained linearising the ODE system numerically about the current point $[\boldsymbol{x}(t_s), \boldsymbol{u}(t_s-1)]$ and then using the Jacobian. Δ is the differential operator (1-q^{-1}) and $\boldsymbol{\Delta V}$ is a vector of future control moves, defined as

$$\boldsymbol{\Delta V} = \left[\boldsymbol{\Delta v}(t_s)^{\mathrm{T}} \ldots \boldsymbol{\Delta v}(t_s+N_u-1)^{\mathrm{T}}\right]^{\mathrm{T}}$$

The output predictions are computed using the superposition principle, which is valid only for linear systems. However, if these predictions are performed over a “short enough” horizon, this property can very approximately hold, as remarked in (Megas *et al.*, 1999). Obviously, the quality of the solution depends on this approximation. The approach of (De Keyser, 1998) overcomes this difficulty and leads to an exact result, since the superposition principle is applied at each iteration until the forced response (called optimised response there) comes out to be zero, on-line application for this method can be impossible, due to the great computational burden which could be necessary until the optimised response converges.

[1] The control moves are taken to be zero for $j \geq N_u$.

Now, a standard quadratic cost function is defined as follows

$$J(t_s) = (\boldsymbol{W} - \boldsymbol{Y})^{\mathrm{T}} \boldsymbol{Q} (\boldsymbol{W} - \boldsymbol{Y}) + \boldsymbol{\Delta V}^{\mathrm{T}} \boldsymbol{R} \boldsymbol{\Delta V},$$

where $\boldsymbol{Q}$ and $\boldsymbol{R}$ are positive-semidefinite and positive-definite weighting matrices respectively, and $\boldsymbol{W}$ is a vector of future setpoints which are known at the current sampling instant t_s or, if not, taken to be constant and equal to the current values. Finally, the optimal control move vector is obtained solving the problem

$$\boldsymbol{\Delta V}^{\mathrm{opt}} = \arg\min_{\boldsymbol{\Delta V}} J(t_s) \text{ subject to } \boldsymbol{P}\boldsymbol{\Delta V} \leq \boldsymbol{r},$$

where the matrix $\boldsymbol{P}$ and the vector $\boldsymbol{r}$ specify input constraints. Details to build $\boldsymbol{P}$ and $\boldsymbol{r}$ are provided in (Kuznetsov and Clarke, 1996). This problem can be solved using standard optimisation tools, such as *Quadratic Programming* (QP).

In the climate control problem presented in the next section the state, input and output variables considered are

$$\begin{aligned} \boldsymbol{x} &= \left[\, T_g \,\right]^{\mathrm{T}}, \\ \boldsymbol{u} &= \left[\, T_p \ r_w \,\right]^{\mathrm{T}}, \\ \boldsymbol{y} &= \left[\, T_g \,\right]^{\mathrm{T}}, \end{aligned}$$

as defined in Section 2.

4. EXPERIMENTAL RESULTS

The experiments have been performed in real double glass greenhouse built in the Institute for Horticultural and Agricultural Engineering (ITG) of the university of Hannover (Germany), the dimensions of which are 200 m^2 of surface, and 3 m of average height.

The aim of these experiments is to control the inside temperature of greenhouse. The setpoints are chosen so that at night they are 18C, and by the day they are 23C until the 20 hours of the night. These setpoints can vary depending on the type of plants inside greenhouse (in this experiment, there were no plants in the greenhouse).

The tuning parameters have been chosen as $N_u = 3$ (control horizon), $N_2 = 15$ (prediction horizon), $\boldsymbol{R} = [10^{-8} 10^{-2}]\boldsymbol{I}$ (control effort for heating system and window opening respectively) and $\boldsymbol{Q} = 30\boldsymbol{I}$ (tracking error weighting matrix). These values have been obtained in order to achieve a convenient solution for both the setpoint tracking and the regulatory problems. The sampling time is of 1 minute.

A reference trajectory based on a third-order polynomial was chosen, in order to provide a smooth control.

Fig.2 shows the result obtained by the constrained MELPC. By night the system is able to follow the setpoint, because there are no disturbances coming form the sun, however the solar radiation effect can

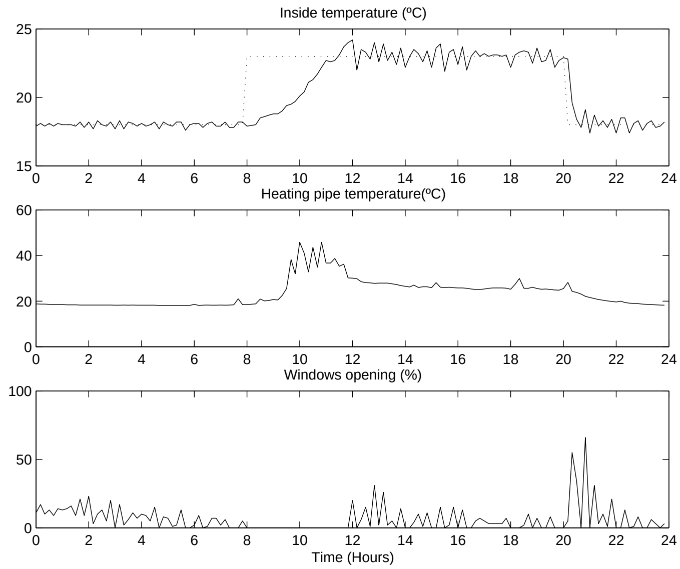

Fig. 2. MPC controller: closed loop response

observed by day, and some oscillations around the setpoint can be observed.

The most important result of this experiment is the fact that with the MPC controller there is no energy losses, since the heating system is off when the windows are opened. In Fig.2 it can be observed that the temperature increase between 9 and 12 hours what means that the valves are opened, when windows are closed completely, out of this time interval the valve remains closed because the heating pipe temperature is low. In the formulation of the MPC controller the constraints were the heating system temperature limits, and the energy loss quantity in (W/m^2) and can be described as follows: The energy loss Q due to the ventilation is a function of windows opening A:

$$\begin{aligned} \boldsymbol{Q} &= f(A)(T_i - T_{out}), \\ \boldsymbol{Q}_{limt} &= f(A_{limit})(T_i - T_{out}), \\ \boldsymbol{A}_{limit} &= \frac{g(Q_limit)}{T_i - T_{out}}, \end{aligned}$$

Then depending on the objectives of the control, we can decide about the energy losses quantities to achieve these objectives.

The MPC controller has been compared with the ITG control system (adaptive PI controllers) in a similar greenhouse (with no plants also), in the same day [2], and Fig.3 shows the output and the control signals. The system is not able to follow the setpoint, also the heating system is on when the windows are opened between 4:00 p.m. and 6:00 p.m.

The main advantages of the predictive controller can be summarized in the following points:

- MPC controller gives to better yield
- Exact formulation of the restrictions.
- Multivariable and easy to implement.

[2] The day setpoint is 22 C.

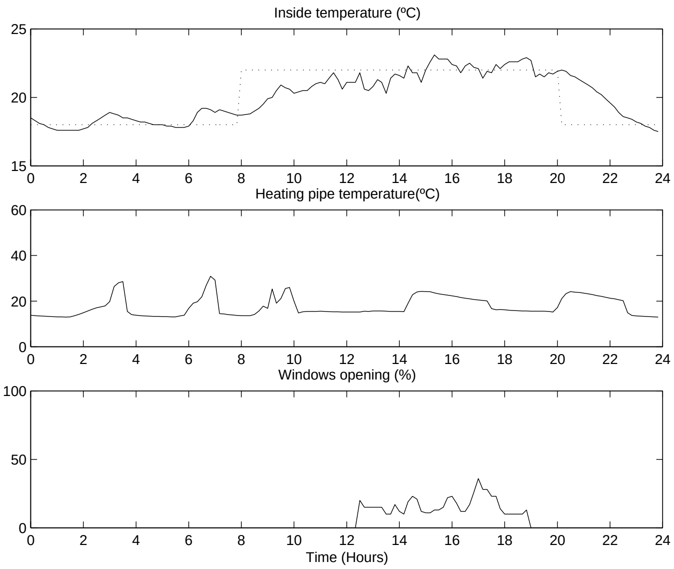

Fig. 3. PI controller: closed loop response

5. CONCLUDING REMARKS

Usually in greenhouses, PID controllers have been used for climate control. These controllers have the disadvantages that constraints are not considered, SISO loop are implemented, and performance is usually poor. In this work an MPC algorithm is presented and implemented in real time to resolve the problems found for the PID controllers application.

These experiments show the importance of the use of the new advanced control techniques to regulation of very complex processes with high non-linearities like the climate under greenhouse. Economic profitability, transparency and simplicity, stand out among the main advantages.

An MPC controller has been chosen to control a non-linear MIMO system, with constrained controlled variables. This controller has been compared with an adaptive PI controller. The linearised model is obtained at each sample instant, and an optimal control signal is computed. The free response is obtained directly from non-linear model, and linear approximation is only used to compute the forced response.

This algorithm can be used to control the second level for the hierarchical structure using a growth model for the plant. In this level, economical criteria can be optimised to achieve a production objective. This work is left for a future research (Tantau, 1993).

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6. REFERENCES

Baytorun, A.N: (1986). Bestimmung des Luftwechsels bei gelften Gewchshusern.. PhD thesis. Institute of Horticultural and Agricultural Engineering, University of Hannover, Germany.

Bot, GPA. (1983). Greenhouse Climate: from physical processes to a dynamic model.. PhD thesis. Institute of Agricultural and Environmental Engineering,Wageningen Agricultural University, The netherlands.

de Jong, T. (1994). Natural Ventilation of large multi-span greenhouse.. PhD thesis. Wageningen Agricultural University, The netherlands.

De Keyser, R. M. C. (1998). A gentle introduction to model based predictive control. Plenary paper.. In: *EC-PADI2 International Conference on Control Engineering and Signal Processing.*. Peru.

El Ghoumari, M. Y. (1998). Control predictivo no lineal de un robot de tres grados de libertad. Master’s thesis. Departament d’Informtica. Universitat Autnoma de Barcelona. (In Spanish).

Henten, E.J. Van (1994). Greenhouse Climate Management: An Optimal Control Approach.. PhD thesis. Institute of Agricultural and Environmental Engineering,Wageningen Agricultural University, The netherlands.

Kuznetsov, A. G. and D. W. Clarke (1996). The performance of generalised predictive control with interval constraints. *European J. Control* **2**, 260–277.

Megas, D., M. Y. El Ghoumari and J. Serrano (1999). Extended linearised predictive control: Practical control algorithms for non-linear systems. In: *Proc. of the European Control Conference*. Karlsruhe, Germany.

Oliveira, S. L. De and V. Nevistićand M. Morari (1995). Model predictive control for nonlinear systems subject to input constraints. Technical report. Automatic Control Laboratory, Swiss Federal Institute of Technology (ETH).

Tantau, H.-J. (1993). Optimal control for plant production in greenhouses. In: *The computerized Greenhouse* (Inc. Academic Press, Ed.). Chap. 6, pp. 139–152. 1250 sixth Avenue, San Diego, California 92101-4311.

Tap, F. (2000). Economics-based Optimal Control of Greenhouse Tomato Crop Production.. PhD thesis. Institute of Agricultural and Environmental Engineering,Wageningen Agricultural University, The netherlands.