15th Triennial World Congress, Barcelona, Spain

ON–LINE IMPROVEMENT FOR THE DECENTRALIZED PREDICTIVE CONTROL OF THE HEAT DYNAMICS OF A GREENHOUSE

E.J. Kyriannakis[1], K.G. Arvanitis[2] and N. Sigrimis[2]

[1]*National Technical University of Athens, Dept. of Electrical and Computer Engineering, Intelligent Robotics and Automation Laboratory, Zographou 15773, Athens, GREECE, email: ekyrian@tee.gr*
[2]*Agricultural University of Athens, Department of Agricultural Engineering, Athens 11855, GREECE, email: karvan@.aua.gr, n.sigrimis@computer.org*

Abstract: A decentralized model-based predictive controller is used for the design of discrete-time control systems aiming at regulating the air temperature and heat supply in greenhouses. Moreover, alternative techniques are proposed for the approximation of the decentralized part of the control and the on-line improvement of the overall control problem. A state space model is used to predict the corresponding local indoor temperature over a long-range time-period and approximate models are used to predict the interactions among the subsystems. The sun radiation and outdoor temperature are treated as external disturbances that affect the overall system dynamics. A series of energy fluxes consist the heating system and the predictive controllers have proved to be powerful in controlling the supply temperature. *Copyright ã 2002 IFAC*

Keywords: Decentralized control, predictive control, greenhouse heat dynamics.

1. INTRODUCTION

Optimal control strategies in greenhouse climate systems are nowadays of significant importance for researchers and practitioners (van Straten, 1999; van Stratten, *et al*., 2000; Lacroix and Kok, 2000; Linker *et al*., 2000; Sigrimis *et al*., 2000). The control algorithms usually designed in a heuristic way decide about heating and ventilation and produce temperature, humidity and carbon dioxide control actions (Arvanitis *et. al*., 2000; Albright *et al*., 2000, Linker *et al.*, 2000). Optimal cultivation control has also been considered towards the key idea of calculating a control sequence such that the difference between the revenues from the crop and the costs from the resources is maximized. Normally, the objective is not formulated as a direct goal function based on economic terms but in terms of controller performance or desired properties of the controlled system. In practice, optimal control techniques require a reasonable description of the dynamics of the system and are strongly depended on the model used.

In this paper, an alternative optimal approach that combines Model Based Predictive Control (MBPC) (Camacho and Bordons, 1994; Kouvaritakis *et al*., 2000; Rodrigues and Odloak, 2000) and decentralized control (DC) issues (Tzafestas *et al*., 1997; Yang *et al*., 2001), is considered. The result is a *decentralized model based predictive control scheme* (DMBPC), which is achieved by a suitable estimation of the interactions at each control station. The approach takes advantage from the weighted robustness against modeling errors and parameter variations of the model used due to the features of MBPC. Moreover, it takes advantage of the disturbances/interactions efficient handling and the low dependence of the model itself due to the decentralized way (DC) of computing and feeding the control actions. The combined optimal approach is implemented and evaluated in a new model that consists of interconnected subsystems describing the overall heat dynamics of a greenhouse. The model is based on the general principles of a previous work (Nielsen and Madsen, 1998). The present paper describes how to identify an approximate model of interconnected submodels for the heat dynamics of a greenhouse by parameters of physical interpretation using the heat supplies of an N-node heating system, the global radiation and the outdoor air temperature as input variables (Fig. 1). The model predicts the air temperature at each node by a number of coupled linear differential equations and an associated discrete time model is derived for the need of the digital predictive algorithm used to control the system.

2. GREENHOUSE HEAT DYNAMICS.

The solution of the heat diffusion equation for heat conduction in all parts of a greenhouse and additionally the calculation of the heat transfer between the outer air and all the surfaces becomes a problem of high complexity and low practical importance. A common simplification implied by Nielsen and Madsen (1998) is the lumped capacitance method. The main assumption is that the heat capacities of the greenhouse are lumped in certain nodes where the temperature in each node is spatially uniform (see Fig. 1).

In the present approach a main different issue is considered in regard to the original work by Nielsen and Madsen (1998): the heating system and all external inputs (outer temperature, solar flux) affect directly and independently all nodes instead of only the 1st one. For such a model, the energy balance at each node in the greenhouse is:

$$\frac{dq_{st}}{dt} = \frac{dq_{in}}{dt} - \frac{dq_{out}}{dt}$$

which result to:

$$C_i \frac{dT_i}{dt} = \frac{dq_{in,i}}{dt} \quad \frac{dq_{out,i}}{dt}$$

where q_{st}, q_{in}, q_{out} are the stored input and output energy (J), C_i is heating capacity (J/K) of node i, and T_i (^oK) is the temperature of node i. Thus, the energy balance of the i-th node is:

$$C_i \frac{dT_i}{dt} = a_i \frac{T_{i+1} - T_i}{R_i} + b_i \frac{T_{i-1} - T_i}{R_{i-1}} + \frac{T_0 - T_i}{R_{o,i}} + \\ + Q_i + A_i \Phi \qquad \text{for } i = 1,2,..., N \tag{1a}$$

where for the factors a_i and b_i holds:

$$a_i = \begin{cases} 1 & 1 \le i < N \\ 0 & i = N \end{cases} \text{ and } b_i = \begin{cases} 0 & i = 1 \\ 1 & 1 < i \le N \end{cases} \tag{1b}$$

In equation (1a-b), T_0 is the temperatures of the outdoor air, $R_{0,i}$ ($^oK/W$) is the resistance to heat transfer between the i-th node and the outside; R_i (in K/W) is the resistance to heat transfer between nodes I and i+1. The energy Q_i (W) is the heat input from the heating system to the i-th node. The heat flux from solar radiation Ö (W/m^2) and A_i (m^2) describes the effective horizontal glass area exposed to the global radiation, i.e. the area corrected for reflection, shading, dust, etc. respective to the i-th node.

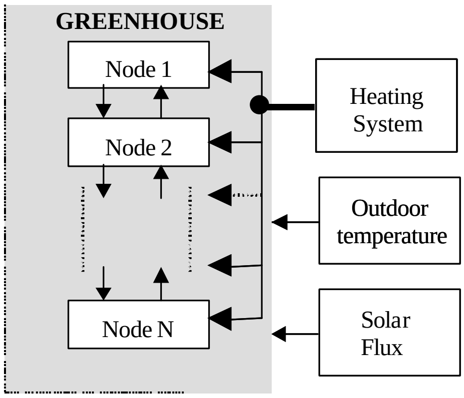

Fig.1. Energy fluxes in a greenhouse with N nodes.

Equation (1a-1b) can be written in the matrix notation a linear differential equation:

$$\frac{d\mathbf{T}}{dt} = \mathbf{AT} + \mathbf{BU} \tag{2}$$

where:

$$\mathbf{T} = [T_1 \quad T_2 \quad \cdots \quad T_N]^T$$
$$\mathbf{U} = [T_0 \quad Q_1 \quad Q_2 \quad \cdots \quad Q_N \quad \Phi]^T$$

and the matrices **A**, **B** are given in the Appendix.

The system of equation (2) can easily be converted to a discrete time system for the needs of the digital predictive control algorithm. The resultant discrete time, linear, possibly time-varying system, which consists of N-interconnected subsystems, each of which has the following state space description:

$$\begin{aligned} &T_i(t+1) = C_i T_i(t) + D_i Q_i(t) + E_i z_i(t) \\ &T_i(0) = T_{i,o} \qquad \text{for } i = 1,2,..., N \end{aligned} \tag{3}$$

where $z_i(t)$ is the interconnection input which describes the influence of all other subsystems upon the i-th one. The vector $z_i(t)$ is a linear combination of the states (temperatures) of all other subsystems and the non – locally controllable inputs T_o and Ö, i.e.

$$z_i(t) = \sum_{j=1}^{N} \lambda_{ij} T_j(t) + \gamma_i T_o + \delta_i \Phi \quad \text{with } \lambda_{ii} = 0 \tag{4}$$

for i=1,2,…,N, where ë$_{ij}$ are parameters assumed to be known to every control station. It is accentuated that the output $T_i(t)$ of the model may generally have a small difference from the real (or the measured) output $T_{r,i}(t)$ because of modeling errors or noise, which affect the whole system or parts of it.

The problem is to find at every time t the best control

$Q_i(t)$ for the i-th subsystem, which leads the output current value $T_i(t)$ to its set-point $w_i(t)$. The control must be "the best" in the sense of minimizing a cost function, which will be described later. Moreover the control laws must be specified in a decentralized way, i.e. the control laws are assumed to be of the form $Q_i(t)=f_i(I_i(t))$, i=1,..., N, where $f_i(t)$ is a function of the available information set $I_i(t)$ of the i-th subsystem defined as follows: $I_i(t)=\{T_{r,i}(0)\ T_{r,i}(1), T_{r,i}(2), T_{r,i}(t); Q_i(1), \dots Q_i(t-1)\}$, $I_i(0)=\varnothing$. This means that $I_i(t)$ consists not only of the measurement of the current output $T_{r,i}(t)$ but also of the past outputs $T_{r,i}(r)$, $Q_i(r)$ r<t. The information set $I_i(t)$ does not contain $z_i(t)$, which is necessary for the computation of $Q_i(t)$ but not available at the i-th control station because it depends on the non-available states of the other subsystems $T_j(t)$, $j \neq i$.

In the following, predictive control techniques will be used to satisfy the problem requirements. It will be shown that the control laws are of the form :

$$Q_i(t)=Q_i^c(t)+Q_i^d(t),\ i=1,2,...,N \quad (5)$$

where $Q_i^c(t)$ is the centralized part of the control, i.e. the part that is available to the i-th control station, and $Q_i^d(t)$ is the decentralized part of the control law, which depends on information not available to the i-th control station, and more especially depends on $z_i(t)$ and predictions of it.

3. MBPC ALGORITHM IMPLEMENTATION

MBPC is a control algorithm, which uses a model for open-loop predictions, optimizing the control inputs on a moving horizon and updating the outputs of the model by closed loop predictions. Especially, at each time t, the output of the i-th subsystem $T_i(t+k/t)$ is predicted over a future period of time k=1,2,...,L_T where L_T is the prediction horizon. The predictions are determined by means of a model, for example state-space model. The predictions $T_{pi}(t+k/t)$, k= 1,2,...,L_T depend on future control values $Q_i(t+k/t)$, k=0,1,...,L_Q-1, where L_Q is the control horizon ($L_Q \le L_T$). In the control horizon we have:

$$Q_i(t+L_Q+k/t)=Q_i(t+L_Q-1),\ k>0 \quad (5)$$

The output predictions can be calculated as:

$$T_{p,i}(t+k/t)=T_i(t+k/t)+q_i(t+k/t) \quad (6)$$

where,

$$T_i(t+k/t)=C_i^k T_i(t)+\sum_{J=1}^{K} C_i^{j-1} D_i Q_i(t+k-j/t)+ \sum_{J=1}^{K} C_i^{j-1} E_i z_i(t+k-j/t),\quad k=1,2,...,L_T \quad (7)$$

and $q_i(t+k/t)$ is the closed-loop correction vector

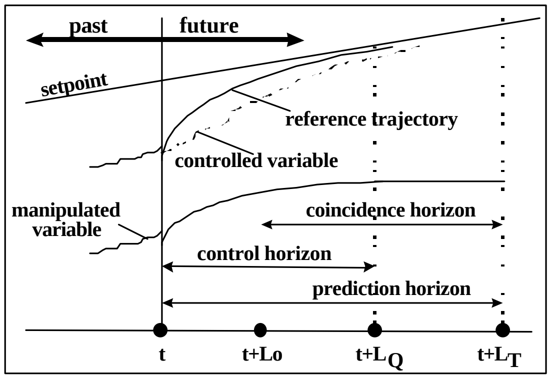

Fig.2. The characteristics of MBPC: reference trajectory; set-point trajectory; prediction, control and coincidence horizon.

based on the available information set at time t. A recommended form for $q_i(t+k/t)$ is the following:

$$q_i(t+k/t)=T_{r,i}(t)-T_i(t) \quad (8)$$

A reference trajectory $r_i(t+k/t)$, k=1,2,...,L_T is defined over the prediction horizon, which describes how the output $T_i(t)$ is guided to its set-point $w_i(t)$, i.e.

$$r_i(t+k/t)=w_i(t+k/t)+\upsilon_i(t+k/t) \quad (9)$$

where $\tilde{o}_i(t+k)$ is a correction vector based on the previous error information set $\{w_i(t)-T_{r,i}(t), w_i(t-1)-T_{r,i}(t-1),..., w_i(1)-T_{r,i}(1)\}$. A simple form that gives good results is the following:

$$\upsilon_i(t+k/t)=a^k[w_i(t)-T_{r,i}(t)] \quad (10)$$

where $0<a\le 1$ is a tuning parameter that specifies the desired closed-loop dynamic ($a\to 0$:fast control; $a\to 1$:slow control).

The reference trajectory is initiated at the current measured output i.e. $r_i(t/t)=T_{r,i}(t)$. It is noted that if the future set-point values $w_i(t+k/t)$, k=1,2,...,L_T are unknown at time t, one can assume that:

$$w_i(t+k/t)=w_i(t),\ k=1,2,...,L_T \quad (11)$$

All the above are illustrated in Fig.2.

The cost function of the i-th control station is :

$$\min_{Q_i(t+k/t)} J_i(t)= =\frac{1}{2}[\sum_{k=L_o}^{L_T}\left\| r_i(t+k/t)-T_{p,i}(t+k/t)\right\|^2_{S_i(k)}+ +\sum_{k=0}^{L_Q-1}\left\| Q_i(t+k/t)\right\|^2_{R_i(k)}] \quad (12)$$

where $S_i(k)\ge 0$, for k=L_0,…,L_T and $R_i(k)>0$ for k=0,…,L_Q-1.

Since $J_i(t)$ varies with t and has a moving optimization horizon, only the first term in the optimal solution is implemented to control the i-th subsystem.

The optimization parameter L_o determines, together

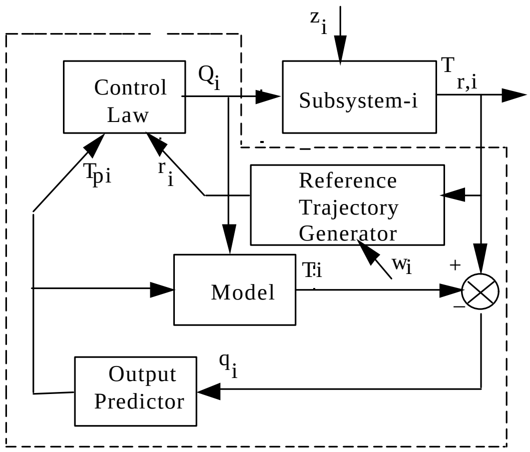

Fig.3. The local MBPC controller as it is applied to the i-th subsystem

with L_T, the “coincidence horizon” how the predicted output follows the reference trajectory over the time interval $[t+L_o,\dots,t+L_T]$. The basic concept of the MBPC structure as it is applied at the i-th subsystem is shown in the Fig.3.

In computing the optimal control in the i-th control station the following notation is introduced:

$$\hat{\mathbf{T}}_{p,i}(t) = [T_{p,i}(t+1/t),\dots,T_{p,i}(t+L_T/t)]^T \quad (13a)$$

$$\hat{\mathbf{T}}_i(t) = [T_i(t+1/t),\dots,T_i(t+L_T/t)]^T \quad (13b)$$

$$\hat{\mathbf{r}}_i(t) = [r_i(t+1/t),\dots,r_i(t+L_T/t)]^T \quad (13c)$$

$$\hat{\mathbf{q}}_i(t) = [q_i(t+1/t),\dots,q_i(t+L_T/t)]^T \quad (13d)$$

$$\hat{\mathbf{Q}}_i(t) = [Q_i(t/t),\dots,Q_i(t+L_Q-1/t)]^T \quad (13e)$$

$$\hat{\mathbf{w}}_i(t) = [w_i(t+1/t),\dots,w_i(t+L_T/t)]^T \quad (13f)$$

$$\hat{\mathbf{o}}_i(t) = [\upsilon_i(t+1/t),\dots,\upsilon_i(t+L_T/t)]^T \quad (13g)$$

$$\hat{\mathbf{d}}_i(t) = [C_i T_i(t+1/t),\dots,C_i^{L_T}(t+L_T/t)]^T \quad (13h)$$

$$\hat{\mathbf{z}}_i(t) = [z_i(t/t),\dots,z_i(t+L_T-1/t)]^T \quad (13i)$$

Then, equation (7) can be formulated as:

$$\hat{\mathbf{T}}_i(t) = \hat{\mathbf{d}}_i(t) + \mathbf{S}_i^*\hat{\mathbf{Q}}_i(t) + \mathbf{R}_i^*\hat{\mathbf{z}}_i(t) \quad (14)$$

where for the matrices S_i^* and R_i^* holds:

$$S_i^* = \begin{bmatrix} C_i^0 D_i & 0 & \cdots & 0 & 0 \\ C_i^1 D_i & C_i^0 D_i & \cdots & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ C_i^{L_Q-1} D_i & C_i^{L_Q-2} D_i & \cdots & C_i^1 D_i & F_i^0 \\ C_i^{L_Q} D_i & C_i^{L_Q-1} D_i & \cdots & C_i^2 D_i & F_i^1 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ C_i^{L_T-1} D_i & C_i^{L_T-2} D_i & \cdots & C_i^{L_T-L_Q+1} D_i & F_i^{L_Y-L_Q} \end{bmatrix} \quad (15)$$

with $F_i^j = \left(\sum_{k=0}^{j} C_i^k\right) D_i$ and

$$R_i^* = \begin{bmatrix} C_i^0 D_i & 0 & \cdots & 0 \\ C_i^1 D_i & C_i^0 D_i & \cdots & 0 \\ \cdots & \cdots & \cdots & 0 \\ C_i^{L_T-1} D_i & C_i^{L_T-2} D_i & \cdots & C_i^0 D_i \end{bmatrix} \quad (16)$$

Moreover,

$$\hat{\mathbf{T}}_{p,i}(t) = \hat{\mathbf{T}}_i(t) + \hat{\mathbf{q}}_i(t), \quad \hat{\mathbf{r}}_{p,i}(t) = \hat{\mathbf{w}}_i(t) + \hat{\mathbf{o}}_i(t)$$

and the cost function (12) can be rewritten as:

$$J_i(t) = \frac{1}{2}\left\| \mathbf{S}_i^*\hat{\mathbf{Q}}_i(t) + \mathbf{K}_i(t) \right\|_{\hat{\mathbf{S}}_i}^2 + \frac{1}{2}\left\| \hat{\mathbf{Q}}_i \right\|_{\hat{\mathbf{R}}_i}^2 \quad (17)$$

$$\hat{\mathbf{S}}_i = \mathrm{diag}\left[0 \;\; \cdots \;\; 0 \;\; S_i(L_o) \;\; \cdots \;\; S_i(L_T+1)\right]$$

$$\hat{\mathbf{R}}_i = \mathrm{diag}\left[R_i(0) \;\; \cdots \;\; R_i(L_Q-1)\right]$$

$$\mathbf{K}_i(t) = \hat{\mathbf{d}}_i(t) + \hat{\mathbf{q}}_i(t) - \hat{\mathbf{r}}_i(t) + \mathbf{R}_i^*\hat{\mathbf{z}}_i(t)$$

Solving, derives the minimization of the cost defined by equation (17)

$$\frac{\partial J_i(t)}{\partial \hat{\mathbf{Q}}_i} = 0 \quad (18a)$$

provided that

$$\frac{\partial^2 J_i(t)}{[\partial \hat{\mathbf{Q}}_i]^2} > 0 \quad (18b)$$

After some simple calculations, (18a) yields:

$$\hat{\mathbf{Q}}_i(t) = -\mathbf{K}_i(t)[\mathbf{S}_i^{*T}\hat{\mathbf{S}}_i(t)\mathbf{S}_i^* + \hat{\mathbf{R}}_i(t)]^{-1}\mathbf{S}_i^{*T}\hat{\mathbf{S}}_i(t) \quad (19)$$

whereas, equation (18b) leads to:

$$\hat{\mathbf{R}}_i(t) + \mathbf{S}_i^{*T}\hat{\mathbf{S}}_i(t)\mathbf{S}_i^* > 0 \quad (20)$$

denying that the problem is always solvable with the criterion being minimized.

Equation (19) can be rewritten in the form:

$$\begin{aligned} \hat{\mathbf{Q}}_i(t) = &-\hat{\mathbf{Đ}}_i[\hat{\mathbf{d}}_i(t) + \hat{\mathbf{q}}_i(t) - \hat{\mathbf{w}}_i(t) - \hat{\mathbf{o}}_i(t)] \\ &-\hat{\mathbf{Đ}}_i\mathbf{R}_i^*\hat{\mathbf{z}}_i(t) \end{aligned} \quad (21)$$

where the first term of (21) is the centralized part of the control i.e.,

$$\hat{\mathbf{Q}}_i^c(t) = -\hat{\mathbf{Đ}}_i[\hat{\mathbf{d}}_i(t) + \hat{\mathbf{q}}_i(t) - \hat{\mathbf{w}}_i(t) - \hat{\mathbf{o}}_i(t)] \quad (22)$$

and the second part is the decentralized part, i.e.,

$$\hat{\mathbf{Q}}_i^d(t) = -\hat{\mathbf{Đ}}_i\mathbf{R}_i^*\hat{\mathbf{z}}_i(t) \quad (23)$$

Note that only the first element $Q_i(t/t)$ of the solution vector $\hat{\mathbf{Q}}_i(t)$ will be supplied to every subsystem. Then, a new measurement $T_{r,i}(t+1)$ will be available and the whole procedure will be repeated.

The centralized part of the control (equation (22)) depends on information, which is locally available at the i-th control station. The decentralized part of the control (equation (23)) depends on information, which is not available at the i-th control station. This information is the extended interaction vector which consists of present and future values of the interaction vectors $z_i(t+k/t)$, $k=0,1,\dots,L_T-1$. None of the previous vectors are available at the i-th control station because they all depend on the outputs (present and future) of the other subsystems. Approximating techniques using interaction models or model following controllers can be used to locally reconstruct the decentralized part of the control but that will higher the overall computational burden and complex the problem. Moreover, MBPC algorithm has proved robust enough to deal with uncontrollable inputs of systems in many cases. The suboptimal solution derived by only feeding the centralized part of the control at each subsystem has proved to be efficiently accepted (Tzafestas *et al.*, 1997).

4. APPROXIMATIONS FOR THE DECENTRALIZED PART OF THE CONTROL

It is well known that MBPC techniques can manage systems with unusual dynamical behavior efficiently and introduce in a natural way feedforward control action for compensating the disturbances. If we consider $z_i(t)$ in the dynamical equation (1a) as a disturbance for the i-th subsystem, then for the case of weakly coupled systems in which the elements of the matrices Ei, i=1,...,N, are small enough we can make the assumption that $u_i^d(t) \approx 0$, and let the centralized part $u_i^c(t)$ alone to control the system. Two different techniques for the case where this is not true are the following.

(a) *The case of problems with m-step delay sharing pattern and a linear model for the interconnections.*

A decentralized control problem is said to have an m-step delay-sharing pattern when it permits the spreading of its information through the subsystems but with delay of m time steps. Clearly each control station obtains instantaneously all information about its associated subsystem, and after a delay of m time steps all the information available to *all* control stations. For our problem this means that at time t in the i-th control station the vectors $T_j(t\text{-}m)$, $j \neq i$ and all the past values $T_j(t\text{-}m\text{-}k)$, k>0 are known.

Then one can calculate $z_i(t\text{-}m)$ using equation (4) as:

$$z_i(t-m) \approx \sum_{j=1}^{N} \ddot{e}_{ij} T_j(t-m) \quad \text{with } \ddot{e}_{ii} = 0 \qquad (24)$$

i.e. $z_i(t\text{-}m)$ is well known to the i-th control station at time t.

The presumption that the vector $z_i(t\text{-}m)$ is the output of a linear model having order p and coefficients a_{ij}, j=1,2,...,p, i.e.

$$\tilde{z}_i(t-m) = \sum_{j=1}^{p} a_{ij} z_i(t-m-j) \qquad (25)$$

where $\tilde{z}_i(t-m)$ is an estimate of $z_i(t\text{-}m)$, is now made.

The coefficients a_{ij} of the linear model (24) can be calculated on-line at every time t in the least squares sense by minimizing the norm of the error vector:

$$e_{z_i}(t) = z_i(t-m) - \tilde{z}_i(t-m)$$

After having calculated the coefficients a_{ij} one can use the model (23) to produce the predictions $z_i(t+k/t)$, k=1,2,...,L_y-1 that are needed in equation (23) in order to approximate the decentralized part of the control $u^d{}_i(t)$. The predictions are:

$$\tilde{z}_i(t-m+k/t) = \sum_{j=1}^{p} a_{ij} \tilde{z}_i(t-m+k-j/t), \qquad (26)$$
$$k = 1,2,\ldots, m, m+1,\ldots, L_T`+m-1$$

Then $\hat{z}_i(t) \approx \hat{z}_i'(t)$ implies

$$\begin{bmatrix} z_i(t/t) \\ z_i(t+1/t) \\ \ldots \\ z_i(t+L_T-1/t) \end{bmatrix} = \begin{bmatrix} \tilde{z}_i(t/t) \\ \tilde{z}_i(t+1/t) \\ \ldots \\ \tilde{z}_i(t+L_T-1/t) \end{bmatrix}$$

and so

$$\hat{\mathbf{Q}}_i^d(t) = -\hat{\mathbf{Đ}}_i \mathbf{R}_i^* \hat{\boldsymbol{z}}_i(t) .$$

(b) *On-line improvement for the predictions of the interconnections, based on a model for them*

In this approximation a method will be suggested which provides on-line improvement for the predictions of the interconnections. This method will reduce the dependence of the predictions from the original model used for them. Moreover, the case of problems that do not have m-step delay sharing patterns will be covered, where one cannot use a linear model for the interconnections with on-line computation of its parameters because of the non-spreading of the information. For this case one can use a model of the form

$$Z = A_{zi}(t-1) \qquad (27)$$

where A_{z_i} is the part of the whole system matrix C_g=C+EL (C=diag[C_i], E=diag[E_i], L=[$\ddot{e}_{ij}$]) that corresponds to the elements of the vector z_i (Singh, 1981). The predictions provided by (27):

$$z_i'(t+k/t) = A_{z_i} z_i'(t+k-1/t), k = 0,1,\ldots, L_T - 1 \qquad (28)$$

can be used to approximate the decentralized part of the control of equation (23).

5. CONCLUSIONS

A linear decentralized state space model of the heat dynamics of a greenhouse in continuous time is introduced and decomposed. The model is useful for predicting changes in the air temperature and the decomposed formulation of the model allows for the treatment of the generic case of multi – heating systems in a greenhouse. Although a greenhouse is a complex system, it is shown that approximately a few nodes can describe the heat dynamics. The optimal control $Q_i(t)=Q_i^c(t)+Q_i^d(t)$ is optimal in the sense of decentralization, but it remains sub-optimal in comparison with the solution that would be attainable if the whole information was available to every control station. The decentralized controller depends weakly on the initial conditions and strongly on the approximate model used for the interconnections $z_i(t)$. The last dependence seems to be reduced by the actions of the predictive controllers and the principle of the moving prediction horizon that enriches the robustness of the control algorithm against both parameter variations and external disturbances. An approximate calculation of the decentralized part of the control based on model following controllers and approximate interconnection models are used to improve the overall control performance.

REFERENCES

Albright L.D., A.-J. Both and A.J. Chiu (2000). Controlling greenhouse light to a consistent daily integral. *Trans. ASAE,* **43**, 421-431.

Arvanitis K.G., P.N.Paraskevopoulos and A.A. Vernardos, (2000). Multirate adaptive temperature control of greenhouses. *Comp. Electr. Agricul*., **26**, 303-320.

Camacho E.F. and C. Bordons (1994). *Model Predictive Control in the Process Industry*. Springer, London/Berlin.

Kouvaritakis B., J.A. Rossiter and J. Schuurmans (2000). Efficient robust predictive control. *IEEE Tran. Autom. Control*, **45**, 1545-1549.

Lacroix R. and R. Kok (2000). Simulation-based control of enclosed ecosystems - a case study: Determination of greenhouse heating setpoints. *Can. Agricul. Engg*., **41**, 175-183.

Linker R., P.O. Gutman and I. Seginer (1999). Robust controllers for simultaneous control of temperature and CO_2 concentration in greenhouses. *Control Eng. Pract*., **7**, 851-862.

Nielsen, B. and H. Madsen (1998). Identification of a linear continuous time stochastic model of the heat dynamics of a greenhouse. *J. Agr. Eng. Res*, **71**, 249-256.

Rodrigues M.A. and D. Odloak (2000). Output feedback MPC with guaranteed robust stability. *J. Process Contr.,* **10**, 557-572.

Singh, M.G. (1981), *Decentralized Control*, North Holland: Amsterdam.

Sigrimis N.A., A. Anastasiou and N. Rerras (2000). Energy saving in greenhouses using temperature integration: a simulation survey. *Comp. Electr. Agricul*., **26**, 321-341.

Tzafestas S.G., E.J. Kyriannakis and G. Kapsiotis (1997). Decentralized model based predictive control of large scale systems. *Syst. Anal. Modeling Simul.* , **29**, 1-25.

van Straten, G. (1999). Acceptance of optimal operation and control methods for greenhouse cultivation. *Ann. Reviews in Contr*., **23**, 83-90.

van Straten, G., H. Challa and F. Buwalda (2000). Towards user accepted optimal control of greenhouse climate. *Comp. Electr. Agricul*., **26**, 221-238.

Yang G.-H., J.L. Wang and Y.C. Soh (2001). Decentralized control of symmetric systems. *Syst. Control Lett*., **42**, 145-149.

APPENDIX

$$\mathbf{A}=\begin{bmatrix} -\frac{1}{R_1C_1}-\frac{1}{R_{0,1}C_1} & \frac{1}{R_1C_1} & 0 & \vdots & \vdots & \vdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \vdots & -\frac{1}{R_{i-1}C_i} & -\frac{1}{R_iC_i}-\frac{1}{R_{i-1}C_i}-\frac{1}{R_{0,i}C_i} & \frac{1}{R_iC_i} & \vdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \vdots & \vdots & \vdots & \vdots & \frac{1}{R_{N-1}C_N} & -\frac{1}{R_{N-1}C_N}-\frac{1}{R_{0,N}C_N} \end{bmatrix}$$

$$\mathbf{B}=\begin{bmatrix} \frac{1}{C_1R_{0,1}} & \frac{1}{C_1} & \cdots\ 0\ \cdots & \vdots & \frac{A_1}{C_1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{1}{C_iR_{0,i}} & 0 & \cdots\ \frac{1}{C_i}\ \cdots & 0 & \frac{A_i}{C_i} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{1}{C_NR_{0,N}} & 0 & \cdots\ 0\ \cdots & \frac{1}{C_N} & \frac{A_N}{C_N} \end{bmatrix}$$