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Receding horizon optimal control of greenhouse climate based on the lazy man weather prediction

R.F. Tap, L.G. Van Willigenburg, G. Van Straten

Wageningen Agricultural University
Department of Agricultural Engineering and Physics
Bomenweg 4, 6703 HD Wageningen, The Netherlands
phone: +31 (0)317 484953, e-mail: frank.tap@user.aenf.wau.nl

Abstract: In greenhouse climate control a long term control strategy can be computed based on a model describing plant behaviour in relation to indoor climate and outdoor weather and a criterion reflecting maximum profit. In these computations the greenhouse climate dynamics, which are fast compared to those of the plant, are usually ignored. In the actual short term implementation of the control strategy, however, neglect of the greenhouse dynamics leads to serious loss of performance in case of fast changing weather. In order to maximally exploit the variability in external disturbances short term weather forecasts are needed. In this paper we demonstrate that the so called 'lazy man' weather prediction in combination with a receding horizon controller gives satisfactory results. In our application to lettuce cultivation a control horizon of one hour is shown to be the best choice. The horizon length of one hour is convenient for real time implementation of the algorithm.

Keywords: Dynamic optimization, receding horizon optimal control, greenhouse climate control, disturbance exploitation.

1. INTRODUCTION

At present climate control in greenhouses is performed by climate computers that use setpoint controllers to control temperature, humidity and CO_2 concentration. A setpoint controller tries to follow the course of the setpoint of an individual climate variable. The setpoints generated by the computer are based on "experience" of the individual grower and the computer manufacturer. This "experience" is reflected in many (in the order of 300) climate computer settings which have to be tuned individually for every single application. The "experience" is largely based on rules of thumb. This approach to greenhouse climate control has many drawbacks. Setpoint controllers do not properly account for interactions and also the influence of the outside weather and the costs associated to maintaining a favourable greenhouse climate are not properly accounted for. The "experience" of growers and manufacturers turns out to be very diverse and usually is not based on scientific knowledge of plant and greenhouse climate behaviour. Therefore one can state that at present greenhouse climate control is not performed in the most predictable, scientific and economic manner. This is unsatisfactory, both from the point of view of the growers, who seek maximal profitability, as well as from the point of view of the government, which desires to reduce environmental pollution and energy consumption through legislation.

Optimal control is based on a dynamic model describing the system behaviour and a criterion which is maximised (minimised) (Bryson and Ho 1975, Lewis 1986). The scientific knowledge on plant and greenhouse behaviour can be implemented directly through proper construction of a dynamic model. This model accounts for all types of interaction within the system, as well as the influence of the weather as major external disturbance. The growers' overall goal to obtain maximum profit can be implemented directly through a proper choice of the criterion (Seginer 1992). Given a choice of the model and the criterion there are, in theory, no computer settings that have to be tuned while the control, which is computed directly, is performed in a known, scientific and economic manner.

A major problem in the development of numerical algorithms for optimal greenhouse climate control is the fact that the system contains both fast dynamics representing the greenhouse climate behaviour and slow dynamics describing the plant behaviour (stiff system). It has been demonstrated that ignoring the fast dynamics results in serious loss of performance in case of fast changing weather (Tap *et. al.* 1993) . One could state that in order to be able to exploit the effect of the external disturbances - something rather unusual in regulator or tracking problems, but highly relevant here - the fast dynamics should be taken into account. The fast changing weather disturbances prevent the application of "standard" singular perturbation methods for optimal control of stiff systems (Van Henten 1994a). However, in the context of greenhouse climate control, Van Henten's work suggests that it is still possible to decompose the optimal control problem and algorithm into two parts (Van Straten, 1994). The first part deals with the slow dynamics and disturbances, the second with the fast dynamics and disturbances. This paper focuses on the second part. To benefit most from the incorporation of the greenhouse dynamics in this framework it should be accompanied by proper short term weather predictions (cf. Ioslovich *et al.*, 1995). In this paper we demonstrate that the lazy man weather prediction, which simply assumes the weather to stay equal to the last measurement, is a proper short term weather prediction when used in conjunction with a receding horizon optimal controller. The choice of the horizon length of the controller is based on an analysis of the loss of performance compared to the situation where we have perfect weather predictions. In our examples, which concern different days in the development of lettuce in a greenhouse without a heat storage tank, the best horizon length is shown to be 1 hour. Also we show that the use of commercially available short term weather predictions leads to very poor results because these regional predictions turn out to be very inaccurate locally.

The paper is organised as follows. In section 2 we state the optimal control problem given an arbitrary fixed horizon length. In section 3 we describe the receding horizon optimal controller and the numerical algorithm to solve the successive optimal control problems involved in it. Results obtained with the receding horizon optimal controller for several horizon lengths and three types of weather predictions are also presented. Perfect weather predictions, the lazy man weather predictions and commercially available short term weather predictions are considered. In section 4 the results as well as possibilities for future research are discussed.

2. THE OPTIMAL GREENHOUSE CLIMATE CONTROL PROBLEM

A general optimal control problem is formulated as follows. Given a (non-linear) system described by n first order differential equations,

$$\dot{x} = f(x,u,t),\ x \in R^n,\ u \in R^m \quad (2.1)$$

where u is a vector of m control variables and given the initial state of this system,

$$x(t_0) = x_0 \quad (2.2)$$

maximise (minimise) the criterion,

$$J\big(u(t),x(t_o),t_o,t_f\big) = \Phi(x(t_f)) + \int_{t_o}^{t_f} L(x(t),u(t),t)dt \quad (2.3)$$

The optimal greenhouse climate control problem consists of a dynamic model describing both the greenhouse climate behaviour, i.e. the fast part of the dynamics, and the plant behaviour i.e. the slow part of the dynamics and a criterion representing maximum profit over the control horizon $[t_o,t_f]$. The model equations are given in the appendix. For a list of symbols and the list of parameter values one is referred to (Tap *et. al.* 1995). The model is almost the same as presented in (Tap *et.al.* 1993) except for an additional equation describing the dynamics of the heating tube temperature (Eqn. *A.3*). Altogether there are seven state variables.

Equations *(A.1-A.2, A.4)* for the dynamics of the greenhouse temperature and CO_2 concentration have been taken from Tchamitchian *et. al.* (1992) and are mainly based on the model of Udink ten Cate (1985). Equation *(A.7)* which describes the dynamics of the water vapour concentration is based on Van Henten (1994b). Finally, equations *(A.5,A.6)* which describe the lettuce crop growth are taken from Van Henten (1994b).

Given the decomposition of the control problem based on singular perturbation theory the criterion needed to compute the short term control action model would be given by

$$J = \int_{t_o}^{t_f}\big(\lambda_n\dot{W}_n + \lambda_s\dot{W}_s - \alpha_2\phi_i - \alpha_3 H_u - P_R\big)dt \quad (2.4)$$

where φ_i is the CO_2 injection rate, with an associated price α_2, H_u the heat input to the pipe system, with price α_3, P_R a penalty function on humidity constraints, to be explained below. The variables λ_n and λ_s represent the marginal value of the rate of increase of non-structural dry weight W_n and structural dry weight W_s, resp. These variables are co-states that should be computed from the solution of a seasonal optimization, assuming average seasonal weather and a static greenhouse assumption. The co-states act as a marginal price. Note that the price is a time variable part of the criterion and is different from the price of lettuce received at the end of the growing season (van Henten 1994a). Since both structural and non-structural dry weight are sold on the market, the difference vanishes at the end of the crop growth period (Van Henten, 1994a). We have assumed the crop to be 40 days old. Therefore, in this study, the distinction between the two variables was dropped. Moreover, for the time being, it has been assumed that the costates do not vary significantly within the horizon of the short term optimization, which is a couple of hours here as will be shown later. So λ_n and λ_s are assumed to be equal to the price of lettuce at the end of the growing season. With these assumptions the criterion reduces to

$$J = \alpha_1(1-\tau)(\Delta W_n + \Delta W_s) - \int_{t_0}^{t_f} (\alpha_2\phi_i + \alpha_3 H_u + P_R)dt \qquad (2.5)$$

where,

$$P_R = \begin{cases} 5\bullet 10^{-7}(70-R_i) & R_i \le 70 \\ 0 & 70 < R_i < 90. \\ 5\bullet 10^{-7}(R_i - 90) & R_i \ge 90 \end{cases} \qquad (2.6)$$

The first term on the right of equation *(2.5)* represents the money obtained from growing lettuce from $t=t_0$ until $t=t_f$. The first term of the integrand represents the costs associated with CO_2 dosage, where we assumed a fixed price for CO_2. The second term of the integrand represents costs associated with heating. The remaining term of the integrand represents penalties associated with the violation of humidity constraints. These constraints provide a means to prevent the system from moving into regions where effects occur that have not been incorporated into the model. The humidity, for instance, influences the vulnerability to diseases, which is not described in our relatively simple model. In effect, a grower can use the humidity constraints to express his willingness to take risks.

The criterion, representing a mix of direct profit and a 'risk insurance premium', is maximized by searching for optimal control sequences of CO_2 dosage $\varphi_i(t)$, and of heating input $r_h(t)$, hidden in the term H_u, and window opening $r_w(t)$.

The initial state of the system is,

$$x(t_0) = \left(T_g(t_0) \;\; T_t(t_0) \;\; T_i(t_0) \;\; C_i(t_0) \;\; V_i(t_0) \;\; W_n(t_0) \;\; W_c(t_0)\right)^T$$
$$= (13 \;\; 14 \;\; 15 \;\; 0.65 \;\; 0.0085 \;\; 16 \;\; 74)^T \qquad (2.7)$$

The controls have technical bounds given by

$$0 \le r_h \le 100\,\%,\; 0 \le r_w \le 100\%,\; 0 \le \varphi_i \le 5\bullet 10^{-3}\, gs^{-1}m^{-2} \qquad (2.8)$$

3. RECEDING HORIZON OPTIMAL CONTROL ALGORITHM AND RESULTS

After each sampling instant s_i, $i=0,1,2,...$ at which all measurements and controls are updated a receding horizon optimal controller computes the solution to a new optimal control problem. The initial time t_0 of each problem equals the last sampling instant i.e.,

$$t_0 = s_i,\, i = 0,1,2,... \qquad (3.1)$$

The initial state $x(s_i)$, $i=0,1,2,...$ of each problem is adjusted using the measurements at s_i and the model. The final time t_f of each problem is adjusted according to,

$$t_f = s_i + t_h \qquad (3.2)$$

where t_h is the fixed horizon length of the receding horizon optimal controller. Our controller uses a fixed sampling period of 1 minute i.e.,

$$s_{i+1} - s_i = T = 60s,\, i = 0,1,2,... \qquad (3.3)$$

so measurements and controls are updated every one minute. This implies that every one minute an optimal control problem has to be solved on-line. To compute numerical solutions to optimal control problems a discretization in time has to be performed. In our case the discrete time step in the computation was also one minute i.e.,

$$\Delta t = T = 60s. \qquad (3.4)$$

So each numerical solution consists of controls for every one minute within $[s_i, s_i+t_h]$, $i=0,1,2,...$ i.e.

$$u(s_i + k\Delta t),\; k = 0,1,2,..,\frac{t_h}{\Delta t}-1,\; i = 0,1,2,... \qquad (3.5)$$

However these controls, which have to be computed on-line, become available only at the next sampling instant $s_{i+1}=s_i+T=s_i+\Delta t$. So from each optimal control sequence *(3.5)* only the value for which $k=1$ is actually applied to the system. The algorithm used to compute the optimal control sequences *(3.5)* was of the first order gradient type (Bryson and Ho 1975 pp.221) where the successive improvements of each optimal control sequence

$\delta u(s_i + k\Delta t), k = 0,1,2,...,t_h / \Delta t - 1$ are computed according to,

$$\delta u(t_0 + k\Delta t) = \vartheta \left.\frac{\partial H}{\partial u}\right|_{t_0+k\Delta t}, \quad k = 0,1,2,\ldots,\frac{t_h}{\Delta t}-1 \qquad (3.6)$$

where H is the hamiltonian, defined by

$$H = (\alpha_2\varphi_i + \alpha_3 H_u + P_k) + \lambda^T f \qquad (3.7)$$

with λ a vector of co-states, and f the right hand side of Eqn. *(2.1)*, and where ϑ is chosen to minimize the criterion which constitutes a line search. All controls are bounded from above and below so equation *(3.6)* only holds for each control variable if its bounds *(2.8)* are not violated.

The receding horizon optimal controller just described was simulated during 24 hours using weather data of several selected days out of a season in which lettuce was grown in a greenhouse. In these optimization calculations the non differentiable nature of the penalty function *(2.6)* did not cause any numerical problems. Figure 1 shows the performance using three different types of weather predictions for different values of the fixed control horizon t_h. The line at the top represents the outcome of the receding horizon optimization using perfect weather predictions. The middle line is obtained when the assumption is made that the actually observed weather remains the same over the specified horizon. Since the control is updated every minute, also this 'lazy man weather forecast' is updated every minute. The lower line is obtained by using commercially available hourly weather predictions over the next 24 hours, which become available at 7 am and 11 am. These forecasts were used without looking at the actual weather.

From Figure 1 a number of things can be concluded. All results can be compared to the theoretical best solution which is obtained by computing the optimization over the complete day using perfect weather predictions, i.e. when in Eqn. *(2.5)* $t_o=0$ h and $t_f=24$ h. In this situation a criterion value is found of $1.405\cdot10^{-2}$. By comparing this with the value obtained with the receding horizon controller using perfect weather forecasts it can be seen that the loss due to the use of a receding horizon controller in stead of the open loop solution is only 1% if a two hour horizon is taken. One could say that the control action needed at time t is hardly influenced by the weather at time $t+2$ hours or more. The converse is also true: the loss increases as shorter control horizons are used, indicating the significance of anticipating the weather in view of the dynamics of the system.

Both the optimal (open loop) solution and the perfect weather receding horizon solution represent a theoretical condition not achievable in practice because the weather cannot be known in advance. Therefore it is interesting to look at the loss in performance when the lazy man prediction is used. When the control horizon is relatively long, apparently the deviations from the actual weather become so large that they have a marked effect upon the computed control action. The criterion value drops from $1.4\cdot10^{-2}$ to $0.84\cdot10^{-2}$. There is, however, an optimum choice for the control horizon in this case. Using a receding horizon controller with a control horizon of 1 hour in combination with the lazy man weather prediction results in a loss of performance of about 15% with respect to the unachievable optimal solution, and of only 6 % with respect to the receding horizon solution using perfect weather. A control horizon of 1 hour is the best choice in case the lazy man weather prediction is used. Furthermore a control horizon of 1 hour results in real-time implementable control algorithms on a PC Pentium/60 if the sampling interval T is 1 minute.

Using just commercially available weather predictions without looking at the actual weather results in serious loss of performance which increases with an increasing control horizon. Of course, it can be expected that improvements will be possible if such forecasts are combined with actual measurements, for instance by modifying the lazy man prediction on the basis of the trend in the forecasts. However, the results of the lazy man optimization show that the maximum gain in performance that can be achieved when the lazy man weather prediction is replaced by other types of weather prediction and/or measurements is in the order of 10% only.

4. Discussion and future research

Several questions as to the results presented in section 3 arise. Results have been presented for one selected day, where fair variations in weather occurred. Repetition of the computation for other days showed about the same or smaller loss in performance. It can be expected that the differences are smaller when the weather behaves in a more predictable way. This underlines the feasibility of the receding horizon optimal control.

In the computations we assumed a constant price for lettuce during the day. As said before, this price should follow from an optimization of the slow problem resulting from the decomposition according to singular perturbation theory. Van Henten (1994a) reports co-state patterns of lettuce over the season suggesting that the variations within a day are small, as compared to variations over the season. So, the assumption of constant process over 24 hours is not unreasonable. The final implementation of the receding horizon controller requires that first the seasonal optimization is solved. This can be done beforehand, using average weather data.

All our results are based on simulation and optimization using the model *(A.1-A.7)*. The results are therefore conditional on the assumption that the model is a reasonable approximation of the real system. The crop model is validated in a field experiment (Van Henten, 1994b). Yet future work should include a series of comparative tests between the proposed controller, and the best available commercial control systems, over a whole growing season. Another subject of future research will be to investigate to what extent the optimal control is affected by uncertainties in model parameters and structure. Because the model had to be used in a control context, the order was kept as low as possible. The choice of model order should be guided by its computational complexity and accuracy. The advantage of an economic criterion is that this decision can be made in direct economic terms. Furthermore the robustness of this controller is a subject that needs more attention.

Several aspects such as the occurrence and influence of plant diseases are not described by the model. In particular, condensation on the leaves, which is most likely to occur in the early morning hours, is known to increase the vulnerability to diseases. Therefore the violation of bounds on humidity are punished in the criterion *(2.5)*. The optimization will then naturally be constrained. The stricter the bounds are specified, the less room there is for economic optimization. The choice of these bounds is up to the grower, but in a practical implementation the effect of these choices could be presented to the grower as a means of influencing the control by weighing of risk against profit.

The modelling of lettuce growth is relatively easy as compared to other crops. The economic importance of lettuce in our region, however, is limited in contrast to, for instance, tomatoes. Therefore, further research is directed to the growth of tomatoes in greenhouses. Yet, the adopted approach to optimal control using a decomposition into a slow seasonal problem and a fast short term problem in combination with feed-back by a receding horizon optimal controller remains the same. We expect that also in case of tomatoes and other products the lazy man weather prediction will serve as an easy and appropriate short term weather prediction. It has to be noted that the assumption was made that CO_2 was freely available. In cases where CO_2 is generated by gas burning combined with heat storage, there is an additional constraint due to the restricted capacity of the heat storage.

Finally the real-time implementable numerical algorithm to compute successive optimal controls can be improved. Many algorithms for solving optimal control problems are known (Bryson and Ho 1975, Sage and White 1977) so there are possibilities for improvement of the numerical efficiency of the algorithm. This allows for the use of smaller sampling intervals or slower computers. The accuracy of the time discretization performed within the numerical algorithm can be improved which also allows for application of more general sampling schemes (Van Willigenburg 1994) and larger sampling intervals. The optimal control algorithm usually computes a local minimum where we actually desire a global minimum. In practice, this may be less serious than it seems, because performance in any case improves as compared to setpoint control. Yet, by enforcing proper initial conditions we may be able to guarantee the computation of global minima.

References

Bryson A.E., Ho Y. (1975). Applied optimal control. Hemisphere.

Ioslovich, I., Seginer, I. Gutman, P.-O., Borshchevsky, M. (1995). Sub-optimal CO_2 enrichment of greenhouses. *J. agric. Engng. Res.* **60**, 117-136.

Lewis F.L. (1986). Optimal Control. Wiley.

Sage A.P., White A. (1977). Optimum Systems Control, Prentice Hall, Englewood Cliffs.

Seginer I. (1992). Optimal dynamic management of the greenhouse environment. In: *The Greenhouse Ecosystem* (G. Stanhill and H.Z. Enoch, Eds.), chap. 16, Elsevier.

Tap R.F., Van Willigenburg L.G., Van Straten G., Van Henten E.J. (1993). Optimal control of greenhouse climate: computation of the influence of fast and slow dynamics. *Proceedings 12th IFAC World Congress 18-23 July 1993, Sydney, Australia* Vol. 10, 321-324.

Tap R.F., Van Willigenburg L.G., Van Straten G. (1995). Receding horizon optimal control of greenhouse climate based on the lazy man weather prediction, *MRS report 95-11, University of Wageningen, The Netherlands.*

Tchamitchian M., Van Willigenburg L.G., Van Straten G. (1993). Optimal control applied to tomato crop production in a greenhouse. *Proceedings ECC'93, 26-28 June, Groningen, The Netherlands*, Vol. 3, 1348-1351.

Udink ten Cate A.J. (1985). Modelling and simulation in greenhouse climate control. *Acta Horticulturae*, **147** (Greenhouse climate and its control), 461-467.

Van Henten E.J. (1994a). Greenhouse climate management: An optimal control approach, Ph.D. Thesis, Wageningen University, Department of Agricultural Engineering and Physics, The Netherlands.

Van Henten E.J. (1994b). Validation of a dynamic lettuce growth model for greenhouse climate control, *Agricultural Systems* **45**, 55-72.

Van Straten, G. (1994). On-line optimal control of greenhouse crop cultivation. IFAC Workshop on Modelling and control in agriculture, Silsoe, September 1994. Submitted to Acta Horticulturae.

Van Willigenburg, L.G. (1995). Digital optimal control and LQG compensation of asynchronous and aperiodically sampled non-linear systems. Proc. 3rd European Control Conference , Rome, 5-8 sept. 1995 (ECC'95), Vol. 1, 496-500.

Appendix.

$$\frac{dT_g}{dt}=\frac{1}{C_g}[(k_v+k_r)(T_o-T_g)+k_s(T_s-T_g)+H_s+\eta G] \quad (A.1)$$

$$\frac{dT_s}{dt}=\frac{1}{C_s}[k_s(T_g-T_s)+k_d(T_d-T_s)] \quad (A.2)$$

$$\frac{dT_t}{dt} = c_l(H_s+H_u) \quad (A.3)$$

$$\frac{dC_i}{dt}=\frac{A_g}{V_g}[\Phi_v(C_o-C_i)+\varphi_i-f_{gc}+f_{rc}] \quad (A.4)$$

$$\frac{dV_i}{dt}=\frac{A_g}{V_g}[E-\Phi_v(V_i-V_o)] \quad (A.5)$$

$$\frac{dW_n}{dt}=\alpha f_{gc}-f_{mr}-\frac{r_g}{\beta}W_s \quad (A.6)$$

$$\frac{dW_s}{dt}=r_g W_s \quad (A.7)$$

where,

$$k_v = M_a\Phi_v \quad (B.1)$$

$$\Phi_v=\kappa+\lambda w+\gamma\, w r_w \quad (B.2)$$

$$H_s=c_2\sqrt{3.0+\sqrt{|T_g-T_t|}}\bullet(T_g-T_t) \quad (B.3)$$

$$H_u=c_3\frac{r_h}{200-r_h}(T_h-T_t) \quad (B.4)$$

$$R_p=t_g pG \quad (B.5)$$

$$A_p=1-e^{-K g_{lai}(1-\tau)W_s} \quad (B.6)$$

$$f_{gc} = A_p\frac{\varepsilon R_p\mu\omega(C_{ip}-\Gamma)}{\varepsilon R_p+\mu\omega(C_{ip}-\Gamma)},$$

$$\varepsilon=\varepsilon_0\frac{C_{ip}-\Gamma}{C_{ip}+2\Gamma} \quad (B.7)$$

$$\frac{1}{\mu}=\frac{1}{g_s}+\frac{1}{g_b}+\frac{1}{g_x},$$

$$g_x=\frac{g_{x_1}}{(T_g+g_{x_2})^2+g_{x_3}} \quad (B.8)$$

$$C_{ip} = C_i a_c(T_g+273.15) \quad (B.9)$$

$$\Gamma=\Gamma_0 Q_\Gamma^{\frac{T_g-20}{10}} \quad (B.10)$$

$$r_g=r_{gm}Q_g^{\frac{T_g-20}{10}}\frac{W_n}{W_s+W_n} \quad (B.11)$$

$$f_{mr}=(r_s(1-\tau)W_s+r_r\tau W_s)Q_r^{\frac{T_g-25}{10}} \quad (B.12)$$

$$f_{rc}=\frac{1}{\alpha}\left(f_{mr}+\frac{1-\beta}{\beta}r_g W_s\right) \quad (B.13)$$

$$T_p=\begin{cases}T_g & G<250\\ T_g+2.5 & G\geq 250\end{cases} \quad (B.14)$$

$$V_o=\frac{a_v R_o}{100(T_o+273.15)}e^{\frac{17.4T_o}{239+T_o}} \quad (B.15)$$

$$R_i=\frac{100}{a_v}V_i(T_g+273.15)e^{\frac{-17.4T_g}{239+T_g}} \quad (B.16)$$

$$E = A_p C_{pa}\left(\frac{a_v e^{\frac{17.4T_p}{239+T_p}}}{273.15+T_p}-V_i\right) \quad (B.17)$$

Figure 1 : Criterion value in Dutch Guilders (fl) against the optimization horizon.