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The significance of crop co-states for receding horizon optimal control of greenhouse climate

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Abstract

While a tomato crop grows on the time-scale of weeks, the greenhouse climate changes on a time-scale of minutes. The economic optimal control problem of producing good quality crops against minimum input of resources is tackled by a two time-scale decomposition. First, the sub-problem associated to the slow crop evolution is solved off-line, leading to a seasonal pattern for the co-states of the amount of assimilates produced by photosynthesis, and the fruit and leaf weights. These co-states can be interpreted as the marginal prices of a unit of assimilate, leaf and fruit. Next, they are used in the goal function of an on-line receding horizon control (RHOC) of the greenhouse climate, thus balancing costs of heating and CO_2-dosage against predicted benefits from harvesting, while profiting as much as possible from the available solar radiation. Simulations using the time-varying co-states are compared to experimental results obtained with fixed co-states. It appears that the on-line control is sensitive to the time evolution of the co-states, suggesting that it is advantageous to repeat the seasonal optimisation from time to time to adjust the co-states to the past weather and realised crop state.

Keywords: Dynamic optimisation; Receding horizon optimal control; Greenhouse climate control; Crop cultivation control

1. Introduction

In the case of greenhouse climate control, the scientific knowledge on plant and greenhouse behaviour can be exploited in the most economical way by applying the methods of optimal control. Optimal control is based on a dynamic model describing the system behaviour and a criterion to be optimised (Bryson & Ho, 1975; Lewis, 1986). The grower's overall objective to obtain maximum profit can be implemented directly through a proper choice of the criterion (e.g. Seginer & Sher, 1993). A brief review of optimal control literature for greenhouse cultivation and a discussion of possible causes for reluctant acceptance in practice is given by van Straten, Challa, and Buwalda (2000).

Direct application of optimal control is hampered by the lack of knowledge of the exogenous inputs, which, in contrast to many other control problems, do not just constitute a disturbance but are, in any case with respect to the solar irradiance, essential resources for crop growth. In addition, feedback is needed to cope with the actual weather and unavoidable errors in the models.

This paper is based on the approach by which this problem is solved by first calculating a seasonal pattern of the crop adjoint variables, assuming a pseudo-static greenhouse and a selected weather pattern, and then using this information in a short-term receding horizon controller (van Henten, 1994). In this way, a link is provided between the relatively slow crop behaviour and the on-line control, exploiting the weather variability as much as possible.

The problem addressed in this paper is to see to what extent the crop adjoint variables, which act as marginal values for increment in crop biomass during the on-line control, influence the behaviour of the optimal controller algorithm.

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Nomenclature

Greenhouse states **z**:

T_g	greenhouse air temperature, °C
T_s	virtual greenhouse soil temperature, °C
T_p	heating pipe temperature, °C
V_i	air moisture content, kg m^{-3}
C_i	CO_2 concentration in the air, g m^{-3}

Crop states **x**:

D	development stage
B	assimilate buffer, g m^{-2} [soil]
W_L	leaf dry weight, g m^{-2} [soil]
W_F	fruit dry weight g m^{-2} [soil]

Co-states $\boldsymbol{\lambda}_s$:

λ_B	co-state for pool (buffer) of assimilates, Dfl g^{-1}
λ_{WL}	co-state for leaf dry weight, Dfl g^{-1}
λ_{WF}	co-states for fruit dry weight, Dfl g^{-1}

Controls **u**:

r_{wl}, r_{ww}	window opening on lee-side and windward side, respectively
r_h	relative heating valve opening
φ_{inj}	CO_2-dosage flux, g s^{-1} m^{-2} [soil]

Exogenous inputs **v**:

G	global radiation, W m^{-2}
T_o	outside temperature, °C
w	wind speed, m s^{-1}
C_o	outside CO_2 concentration, g m^{-3}
RH_o	outside relative humidity, %

Other variables:

RH_i	inside relative humidity, %
P_C	penalty function for excess CO_2, Dfl m^{-2} [soil] s^{-1}
P_T	penalty function violation of temperature bounds, Dfl m^{-2} [soil] s^{-1}
P_V	penalty function for violation of humidity bounds, Dfl m^{-2} [soil] s^{-1}
J	goal function, Dfl m^{-2} [soil]
H_u	heat input, W m^{-2} [soil]
p_F	price value for fruits (auction tomato price), Dfl g^{-1}
p_H	price of heat input energy, Dfl W^{-1}
p_C	price of CO_2 input, Dfl g^{-1}
t_c, t_f	current and final time, s
t_h	horizon length, s

2. Behaviour of crops

In order to understand the results presented later in this paper, a brief discussion is given on the major processes that govern crop behaviour. Tomato is used as an example. Under the influence of solar radiation, the plant assimilates CO_2 and water into primary carbohydrates by photosynthesis. Photosynthesis is mainly dependent upon light and CO_2 concentration. The produced carbohydrates are then used to grow new plant organs, such as stems, leaves, roots, and buds. Growth as well as distribution over various organs is mainly influenced by temperature. If over a prolonged period of time there is more light relative to the integral of the temperature, then assimilates will accumulate, and some of it will be directed to storage organs. It is said that the plant is 'sink limited', because increasing the temperature would increase the rate of drainage of the assimilates from the assimilate buffer. Conversely, at high temperatures relative to light, the assimilate buffer is low, and the plant is said to be 'source limited'. Crop cultivation control by the grower is mainly concerned with steering the balance between source and sink, and by steering the distribution over organs such as leaf and fruit. The major crop state variables are the assimilate pool, and the leaf and fruit weights. In addition, a development stage is often defined, which is no more than a temperature integral over time, in order to model the onset of bud formation and other phyto-morphological changes.

3. Greenhouse crop cultivation

Crops are grown in greenhouses because the enclosure allows control over environmental factors such that crop quality and yield can be enhanced as compared to open field cultivation. Moreover, the enclosure allows cultivation of crops at a wider range of geographical latitudes. State variables that are subject to control in a typical greenhouse are the air temperature, the humidity of the air and the CO_2 concentration in the air. The available actuators are the heating system, the windows or ventilators, a CO_2-dosing unit, and thermal screens. Sometimes, in hot climates, active cooling can be achieved by evaporation of water, in conjunction with air transport by fans. In cold climate, the CO_2 dosage may be realised by using flue gas from burning the heater.

A classical greenhouse climate controller consists of a computer that is programmed to act on the actuators by feedback, according to certain rules. The grower can enter the settings of the rules. Usually, for any specific crop, blue prints are available which help the grower to make these settings. Examples are the so-called heating line, which specifies below which temperature the heating should start to work, and a ventilation line, which specifies above which temperature or humidity the ventilators should be opened. The latter is an example of a situation where the same actuator—the window opening—is used to control two variables. It is clear that the system represents a multivariable control problem, with a strong interaction between the various control loops. In addition, unlike usual control situations, there is a 'disturbance' that must not be rejected but rather should be exploited: the solar radiation.

The grower, to actively influence his crop, uses the climate controller's settings. In fact, by manipulating the temperature, the grower knows how to influence the morphological and other plant-specific properties of the crop, as outlined in the previous section.

Although this system has shown to work very well, it is rather intuitive, and has several drawbacks. Due to its many settings the system is prone to error. In addition, the multivariable nature of the control has hardly been acknowledged in the rule-based design. This is partly reflected in large differences in the yield between growers who have the same radiation conditions in the same area. Also, the energy efficiency, i.e. the energy use per unit of crop, shows large variations among growers.

In order to improve the situation an optimal control scheme has been developed. Such a scheme requires: (i) a model of the system's behaviour, (ii) the specification of a goal function, preferably in economic terms, and taking into account constraints to accommodate non modelled issues, and (iii) a solution method.

4. The idealised optimal control problem

The system can be described by the following set of differential equations:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{z}, \mathbf{v}, t),$$
$$\dot{\mathbf{z}} = \mathbf{g}(\mathbf{x}, \mathbf{z}, \mathbf{u}, \mathbf{v}, t), \tag{1}$$

where $\mathbf{z}$ represents the greenhouse states, $\mathbf{x}$ the crop states, $\mathbf{u}$ the controls, $\mathbf{v}$ the measurable exogenous inputs, and t the time. The controls do not directly affect the crop states, but exert their influence via the greenhouse state variables. The models $\mathbf{f}$ and $\mathbf{g}$ used in this paper are described in detail by Tap (2000).

If the models were exact, and the exogenous inputs from the weather were perfectly known in advance, then the optimal control policy would be obtained by finding the control sequence that minimises the difference between the costs for heating and CO_2 dosage, and the benefits obtained by selling the harvested tomatoes. The crop model used describes the increase of the assimilate buffer by photosynthesis under influence of light, and the use of assimilates for growth and maintaining respiration, and the distribution over fruits and leaves under the influence of temperature. However, other developmental effects such as leaf stretching, bud formation, etc. are not described explicitly, nor are the risks of diseases due to, e.g., condensation. Consequently, it is necessary to modify the criterion function to give the grower the possibility to abate adverse effects that might occur in practice. So, the optimal control problem can be formulated as

$$\mathbf{u}^* = \arg\min J$$

$$J = \int_{t_0}^{t_f} L\,\mathrm{d}t = \int_{t_0}^{t_f} (-p_F \dot{W}_{HF} + p_C \phi_{inj} + p_H H_u + P_C + P_T + P_V)\,\mathrm{d}t, \tag{2}$$

where t_0 is the beginning and t_f the end of the production season. Two of the three inputs appear explicitly at the right-hand side, namely the heat supply H_u and the CO_2-dosage ϕ_{inj}. The remaining input, being the window opening r, exerts its influence via the greenhouse temperature and humidity. The temperature in turn affects the fruit growth, and both temperature as well as humidity have constraints and therefore, influence the penalty functions. The general form of the penalty functions used here is

$$P_x = \begin{cases} \alpha_x(x_{low} - x) & \text{if } x \leqslant x_{low}, \\ 0 & \text{if } x_{low} < x < x_{high}, \\ \alpha_x(x - x_{high}) & \text{if } x \geqslant x_{high}. \end{cases}$$

The term $\mathrm{d}W_{HF}/\mathrm{d}t$ represents the harvest rate of fruits. The harvest process is part of the model and is described as a function of the total fruit weight. The penalties are zero within the ranges specified, and simple linearly increasing functions outside.

5. Seasonal optimisation

The optimal control problem defined by Eqs. (1) and (2) has two time-scales and requires knowledge of the exogenous variables $\mathbf{v}$ on these scales. The problem is separated into two sub-problems (Tap, van Willigenburg, van Straten, & van Henten, 1993). First, using an assumed weather pattern $\hat{\mathbf{v}}$, derived from averaged weather, and the assumption that the greenhouse is in quasi-steady state, i.e.

$$\mathbf{g}(\mathbf{x}, \mathbf{z}, \mathbf{u}, \hat{\mathbf{v}}, t) = \mathbf{0} \quad \Rightarrow \quad \mathbf{z} = \mathbf{h}(\mathbf{x}, \mathbf{u}, \hat{\mathbf{v}}, t) \tag{3}$$

the quasi-optimal trajectories of the crop states are computed. This problem is solved by forming the Hamiltonian:

$$H = L + \boldsymbol{\lambda}_s \mathbf{f}(\mathbf{x}, \mathbf{z}, \mathbf{u}, \hat{\mathbf{v}}, t). \tag{4}$$

In this expression, L is the part under the integral of Eq. (2), and $\mathbf{z}$ follows from Eq. (3). Next, the optimal

$u^*, \mathbf{x}^*$ and the co-states $\boldsymbol{\lambda}_s^*$ are calculated that fulfil the necessary optimality conditions, according to the theory of optimal control (Bryson & Ho, 1975; Bryson, 1999). At first, a first-order gradient algorithm was used. Using an initial guess of the control sequence at a series of discrete time instances, first the state equations are solved forward. Next, the co-state equations are computed backwards. From this, the derivative of the Hamiltonian to $\boldsymbol{u}$ can be computed. If these are non-zero, a new control sequence is generated in the direction of the gradient, and the computation is repeated until convergence. It appeared that in this case convergence was difficult to achieve. Therefore, the results of the gradient algorithm were used as initial guess for a sequential search algorithm according to Seginer and Sher (1993). In this algorithm, the permissible control is quantised to a limited number of discrete levels, and the optimal control is found by enumeration, starting at the last control instant, and working backward in time, in a sequence of iterations. The co-states or adjoint variables $\boldsymbol{\lambda}_s$ obey the following:

$$\dot{\lambda}_s^{\mathrm{T}}(t) = -\frac{\partial J(t)}{\partial \mathbf{x}_s}. \tag{5}$$

According to Stengel (1986), the co-states can be interpreted by defining the following value function V:

$$V^*(\mathbf{x}^*(t_c), t_c) = \int_{t_c}^{t_f} L(\mathbf{x}^*(t), \mathbf{u}^*(t), t)\,\mathrm{d}t.$$

This value function represents the cost that will be made from the current time t_c to the final time t_f under optimal control conditions. It appears that

$$\lambda_s^{*\mathrm{T}}(t) = \frac{\partial V^*(t)}{\partial \mathbf{x}_s}$$

i.e. the co-states can be seen as the sensitivity of the remaining future costs to perturbations in the current state. In the present application, where the effect of perturbations appears on the short-time scale, they can be viewed as the marginal benefits (negative costs) of producing an additional unit of assimilate buffer, leaf and fruit.

Problem (4) was solved by taking for $\hat{\mathbf{v}}$ the observed hourly averaged weather inputs of the experiment year 1995. The starting time of the calculation was when the plant had matured and started to produce fruits. Fig. 1 shows the result of the adjoint variables of the leaf and the fruits. As expected, initially, the marginal benefit of assimilates is negative at night (positive costs), and positive during the day. The marginal benefit of the leaf is negative in the beginning of the harvesting period (Fig. 2). Instead, it makes sense to put as much as possible of the assimilates into fruits. Between day 80 and 160 leaf production is profitable, because leaf area is needed to guarantee enough assimilate production in autumn when the global radiation decreases. The

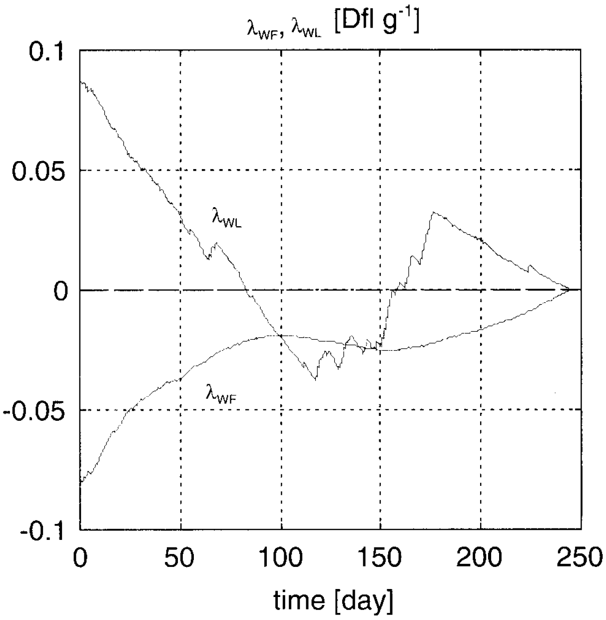

Fig. 1. Marginal costs over the harvesting season (1 March–31 October) for leaves (λ_{WL}) and fruits (λ_{WF}) assuming 1995 weather. Fruit auction price $p_F = 0.02$ Dfl/g.

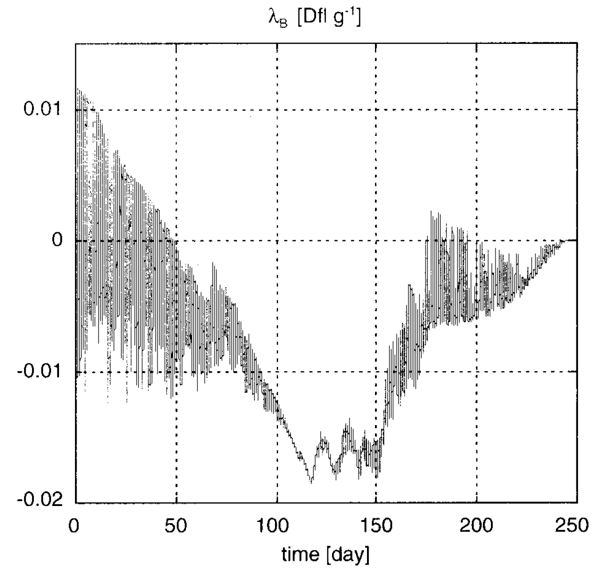

Fig. 2. Marginal costs over the harvesting season (1 March–31 October) for the assimilate buffer (λ_B) assuming 1995 weather. Fruit auction price $p_F = 0.02$ Dfl/g.

observed dynamics in the co-states is the result of the complex interplay of varying environmental conditions and conditions in the greenhouse. In particular, in the middle range of production it appeared difficult to comply with the humidity constraint, and hence, the cost component invoked by the associated penalty function influences the marginal values of the crop states. At the end of the season, it is a waste to invest in leaves since there is not enough time to pay back. Both co-states approach to zero in the end.

Fig. 2 shows the result for the co-state of the assimilate buffer. Since the assimilate buffer is filled during day, and drawn during night, the co-state also shows a clear daily pattern. The sensitivity of the costs to perturbations in the assimilate buffer state are an order of magnitude smaller than those of leaves and fruits.

6. On-line optimal control

Once the marginal values of the crop (crop co-states) are known, they can be used to link the long-term optimisation to the short-term receding horizon optimal control, in order to accommodate fast changes in the weather. At each sampling instant t_c, the short-term receding horizon optimal controller solves an optimal control problem over 1 h, using the currently measured weather as hourly forecast, and the currently measured greenhouse states as initial conditions, i.e.

$$\mathbf{u}^*(t) = \arg\min J_f,$$
$$J_f = \int_{t_c}^{t_c+t_h} (L + \lambda_s^T \mathbf{f})\, dt \quad t \in [t_c, t_c + t_h], \tag{6}$$

where L is the term under the integral of Eq. (2), and the second term represents the benefits (negative costs) of an additional increment of assimilate buffer, leaf and fruits. The control horizon is denoted by t_h, and the current time by t_c. The sampling interval was equal to 2 min. The solution of Eq. (6) was constrained by the condition that the control is held piecewise constant over successive control intervals. The control interval in this case was chosen as 2 min as well. Only the first control is applied to the system, and a new optimisation problem is solved at the next sampling interval. Further details of the short-term RHOC procedure are described by Tap (2000).

A receding horizon optimal controller (RHOC) as used here belongs to the family of optimal controllers. The motivation to use RHOC rather than more common designs such as LQG and GPC is threefold: (i) the goal function is of an economic nature, rather than quadratic, (ii) the system is not affine in the controls, and (iii) some of the disturbances, such as solar radiation, are not small and must be exploited, rather than suppressed. RHOC is computationally expensive since it needs to solve an optimal control problem at each sampling interval. In a greenhouse, with present-day fast computers and a sampling interval of 2 min, there is enough time to perform this task.

7. Experiments

Experiments were conducted in a real-sized experimental greenhouse compartment at the former Department of Horticulture in Wageningen, The Netherlands. The greenhouse was equipped with a heating pipe system for heating, and with lee-side and windward-side windows for ventilation. Also, there was an equipment to dose pure CO_2. The greenhouse climate was observed using commercially available horticultural sensors for relative humidity (RH), wet and dry bulb temperature, and CO_2 concentration. For the purpose of this research, displacement sensors were mounted to measure the position of the window openings. Heat input could be reconstructed from the readings taken from the equipment to measure pipe flow and incoming and outgoing temperature. Despite emphasis on energy savings, such an equipment is not common in commercial greenhouses, and had to be installed specially for this research. Outside conditions of diffuse and total global radiation, RH, CO_2, temperature, wind speed and direction, and a rain indicator were also measured. All the data were recorded at 1-min intervals. Controls were computed with the RHOC technique at the department, and sent to the greenhouse over an Internet link. All data were logged locally, and transferred to the central server once a day. Inside the greenhouse, tomato plants were grown using the high wire technique. Harvesting started on March 1 and production lasted until the end of October. Leaf and fruit harvest was recorded at weekly intervals.

8. Experimental results with fixed crop co-states

At the time the experiments were performed (Tap, van Willigenburg, & van Straten, 1996) the slow sub-problem had not yet been solved. Instead, fixed marginal values were assumed, being $-\lambda_B = p_B = 0$, $-\lambda_{WF} = -\lambda_{WL} = p_F = p_L = 0.02$ Dfl/g. The marginal values were set equal to the auction price of tomatoes. The leaves were given the same value, in order to make sure that the short-term optimal controller did not ignore the production of leaves. Fig. 3 shows the exogenous variables (top row), the important greenhouse states (second row) and the controls (third row) for 1 September 1995.

During nighttime, the heating is turned on ($r_{h,exp}$ in Fig. 3) in order to satisfy the lower temperature constraint (15°C at night and 17°C during the day). During daytime, the heating is turned off, as the temperature stays above its lower boundary (cf. $T_{g,exp}$ in Fig. 3) and the upper relative humidity constraint (set at 95%) is satisfied as well ($RH_{g,exp}$). During the night, when the humidity is not expected to be a problem, the windows are closed to save energy ($r_{w,exp}$). During the

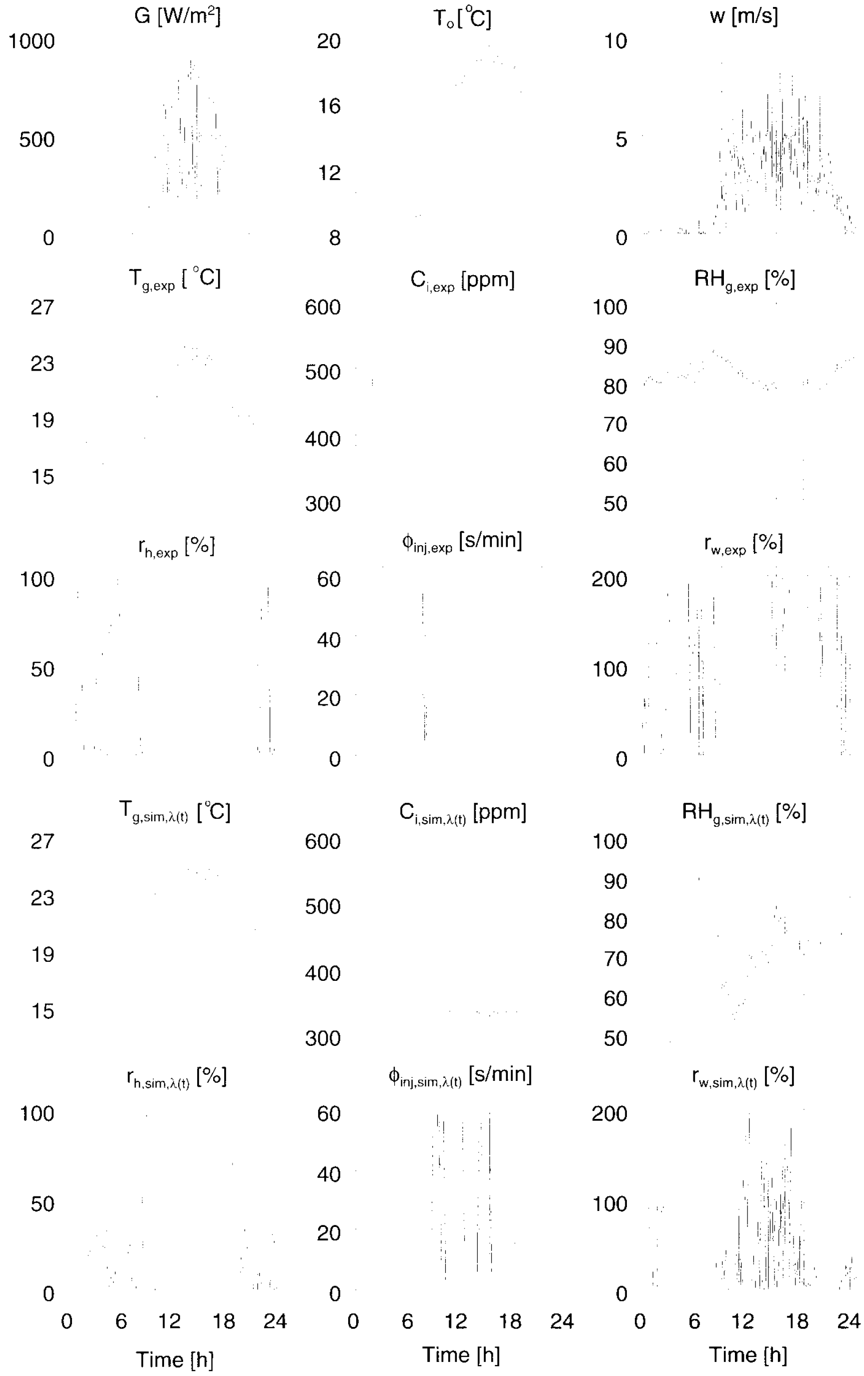

Fig. 3. Results for 1 September 1995. Top: first row: exogenous inputs, second row: state trajectories during the experiment, and third row: controls during the experiment. Fixed co-state marginal values (see text). Bottom: first row: state trajectories simulated with the co-state trajectories of Fig. 3, and second row: associated controls.

day the temperature is adjusted by opening the windows ($r_{w,exp}$; 200% means both wind-ward and lee-side windows are fully open) in order to economise on respiration losses, which maximises income as all biomass (fruits, leaves and harvested fruits) have the same assumed marginal value in the experiment. The windows stay closed until about 8 a.m. to benefit from the high CO_2 concentration at the end of the night ($C_{i,exp}$). During a short time when the sun is shining and the windows are still closed, CO_2 is dosed ($\Phi_{inj,exp}$). The dosage is suspended as soon as the windows open for humidity and temperature reasons.

Tap (2000) shows by simulation that the results are robust, i.e. deviations between the model and true system are effectively counteracted by the feedback provided by the receding horizon controller.

9. Simulation results with dynamic co-states

Knowing in retrospect the co-state trajectories, it is now possible to simulate the behaviour of the RHOC controller that would have been obtained had the co-state pattern been used rather than fixed values. The result of the RHOC simulation is shown in Fig. 3 (bottom two rows). Fig. 4 shows the co-state patterns for 1 September 1995. The buffer co-state is fluctuating. In the simulation it reaches its lowest values during daytime hours, from 7–19 h. The value is negative, meaning that a positive perturbation of the assimilate pool in the plant would depress the costs. Thus, in the simulation it makes more sense to invest in the assimilate buffer during the day, than in the experiment, where the marginal value was set to zero, but since the numerical values are small, the effect is probably limited. Since the marginal fruit price ($-\lambda_{WF}$ in Fig. 4) is practically the same as the fixed value in the experiment it will also have little effect. However, the leaf co-state at this day is positive (λ_{WL} in Fig. 4), meaning that it is more costly to produce leaves in the simulation than that assumed in the experiment. As a consequence, the temperature is increased, as can be seen by comparing $T_{g,sim,\lambda(t)}$ and $T_{g,exp}$ in Fig. 3, in order to produce as few leaves and as much fruits as possible. This can be achieved by closing the windows as much as possible; compare $r_{w,sim,\lambda(t)}$ with $r_{w,exp}$. Since the temperature is higher, the relative humidity ($RH_{g,sim,\lambda(t)}$) does not reach its limits as fast as that during the experiment ($RH_{g,exp}$). Apparently, the ventilation rate, though lower, is still sufficient to prevent moisture problems. The optimal control algorithm immediately tries to take advantage of this situation and starts to dose CO_2 when the windows are closed or almost closed ($\Phi_{inj,sim,\lambda(t)}$ in the lower pane in Fig. 3).

10. Conclusion

The separation of the optimal control problem of tomato cultivation in greenhouses into a long-term and a short-term optimisation problem leads to a feasible optimal control algorithm. It was shown that the behaviour of on-line receding horizon control is influenced by the adjoint variables for the crop states obtained from a seasonal optimisation. This suggests that it makes sense to repeat the seasonal optimisation from time to time, in order to adjust to the past weather and the realised state of the crop. Hence, the following can be concluded:

- Short-term economic-optimal control of greenhouse climate is feasible on-line using a receding horizon optimal controller. The RHOC ensures that the best use is made out of the available solar radiation.
- A receding horizon controller for short-term control is robust with respect to assumed crop value.
- The two time-scale decompositions allow the seasonal optimisation to be performed separately to

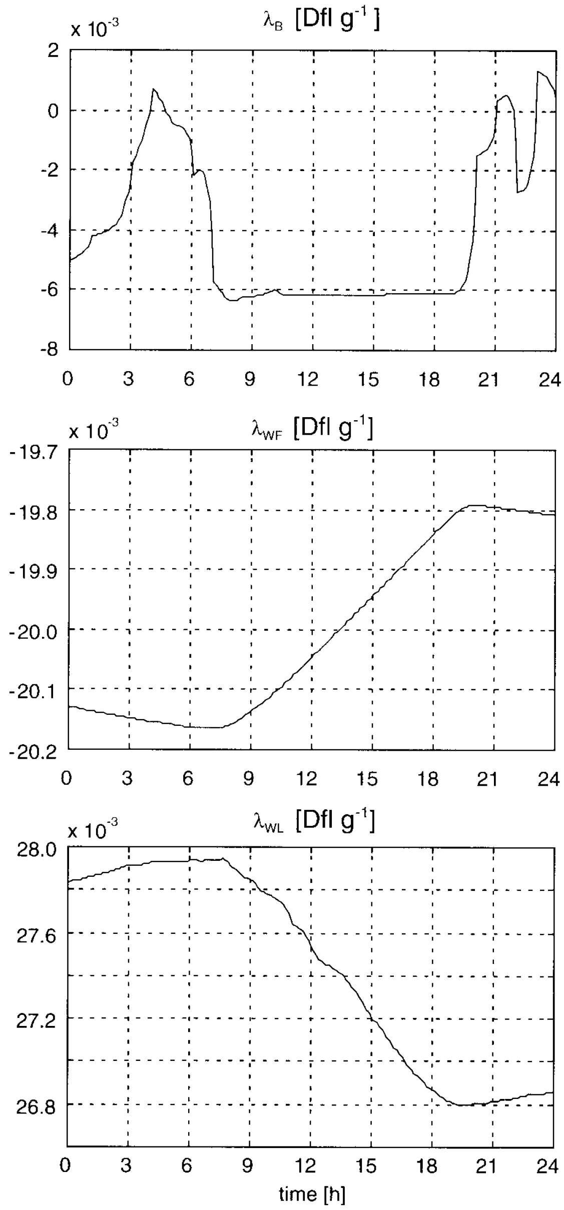

Fig. 4. Crop co-state patterns for 1 September 1995.

provide necessary information to the short-term optimal control.
- No short-term greenhouse controller can be truly optimal if due account is not given to the long-term behaviour of the crop.

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