Optimal Control Design for a Solar Greenhouse

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Abstract: An optimal climate control has been designed for a solar greenhouse to achieve optimal crop production with sustainable instead of fossil energy. The solar greenhouse extends a conventional greenhouse with an improved roof cover, ventilation with heat recovery, a heat pump, a heat exchanger and an aquifer.
It was found that in the optimal controlled solar greenhouse, gas use can be seriously reduced (by 52%), while the crop production is significantly increased (by 39%), as compared to an optimal controlled conventional greenhouse without the solar greenhouse elements.

Keywords: horticulture, greenhouse, solar greenhouse, optimal control

1. INTRODUCTION

A novel advanced greenhouse design is used, called the solar greenhouse. In this greenhouse surplus solar heat is collected and stored in an aquifer [‡] using a heat exchanger, and retrieved using a heat pump. Ventilation with heat recovery is used at times of heat demand. These new elements in the greenhouse are called the solar greenhouse elements. Furthermore materials with better light transmittance and heat insulation properties are used for the roof cover.

The optimal control design consists of a dynamic model for greenhouse and crop, a cost function, and a solution method. With scientific knowledge (physics and physiology) concerning the greenhouse and the crop, and a clear quantitative goal, the best possible control is computed. The control objectives are to minimize gas use and to maximize crop yield, development and quality.

It is expected that the solar greenhouse will be operated in a wider range of temperature and humidity conditions as compared to conventional greenhouses. It is therefore vital that the greenhouse and the crop processes are correctly described for these wider ranges. Therefore a comprehensive dynamic model of the greenhouse-with-crop system has been developed in a form that is suitable for optimal control purposes.

The model describes the temperature, the carbondioxide and the water vapour balance in the greenhouse as a function of the external inputs (i.e. the outdoor weather conditions) and the control inputs (e.g. valve positions and window apertures). Part of the model is calibrated against experimental data for a conventional greenhouse. The parameters for the new elements such as the heat exchanger and the heat pump are derived by design. Crop growth is described by models for photosynthesis and crop evapotranspiration, while temperature integration is used to describe crop development.

For the optimal control a receding horizon optimal controller has been designed, which includes an efficient solution technique. First the degrees of freedom for the control actions are restricted to avoid actions that are unlikely to be optimal (e.g. heating *and* cooling). To avoid local minima, a *grid search* is performed to obtain a crude optimal trajectory, and finally a *gradient method* is used for fine-tuning. These modifications significantly reduce the computation time, a prerequisite for on-line application.

Results have been obtained by *year round* simulations, thus allowing the assessment of the savings of the solar greenhouse as compared to a conventional greenhouse. The effects of the temperature integral and the predicted weather on the expected benefits (before the control actions are invoked) and the real benefits (with the realized control) are investigated.

2. THE SOLAR GREENHOUSE

2.1 Solar greenhouse configuration

The solar greenhouse configuration is given in Fig. 1. The heating system consists of a boiler, a condenser and a heat pump. The lower heating net can be heated to 90℃ with the boiler and to about 33℃ with the heat pump. A condenser heated by flue gas from the boiler can heat the upper heating net to 45℃. The cooling system consists of a heat exchanger, which can cool the upper cooling net to about 10℃.

The heat insulation and the transmission of solar radiation are maximized by using a double layer zigzag roof cover. A warm- and a cold-water aquifer layer ($T_{aq}^{warm} = 16$℃ and $T_{aq}^{cold} = 10$℃ respectively) are used to store and retrieve the surplus solar energy. At times of heat surplus, the

[‡] An aquifer is a formation of water-bearing sand material in the soil that can contain and transmit water. Wells can be drilled into the aquifers and water can be pumped into and out of the water layers.

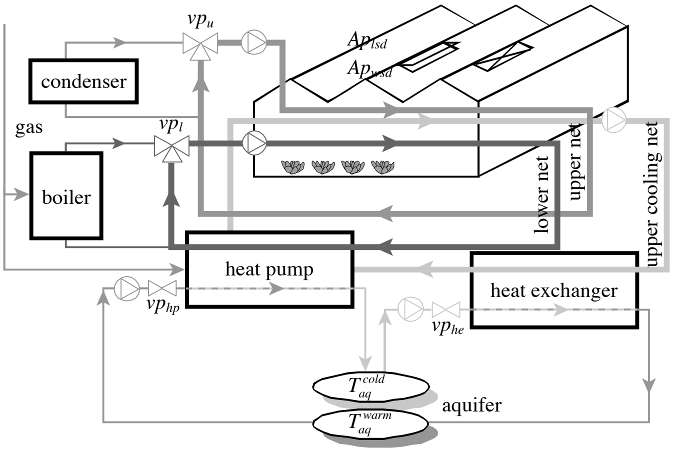


Fig. 1. Greenhouse configuration

greenhouse can be cooled with a heat exchanger and cold aquifer water, while energy is harvested. At times of heat demand, the greenhouse can be heated with little energy input with a heat pump and warm aquifer water that was harvested. The boiler can be used for additional heating if the heat pump cannot supply enough heat. It is assumed that the CO_2 supply can be acquired from a power plant, thus avoiding the need to use the boiler at times of CO_2 demand. The greenhouse is dehumidified by ventilation with heat recovery at times of heat demand, and by using the windows at times of heat surplus — as in normal greenhouse practice. A thermal screen, which is operated based on rules used in common practice, can be closed during the night to reduce the heat loss to the environment. To minimize fossil energy consumption, no lighting is used.

2.2 Solar greenhouse model

Based on a model and a mathematical description of the control objectives, the optimal controller finds the best solution. The successful application of optimal control depends critically on the accuracy of the model. Furthermore the model should be sufficiently small with respect to the number of differential equations, controls and external inputs to limit computation time. For the heat and mass transport the following elements are taken into account: air (above and below the screen), crop, heating and cooling net, roof, screen and soil. These elements are modelled as lumped parameter models, which are assumed homogeneous. Soil and roof are divided into two parts.

For the receding horizon optimal control concept used, a state space description of the system is needed

$$\dot{x} = f(t, x, u, d) \tag{1}$$

where f is a non-linear function of time t, states $x = x(t) \in \mathbb{R}^{n_x}$, control inputs $u = u(t) \in \mathbb{R}^{n_u}$, and external inputs $d = d(t) \in \mathbb{R}^{n_d}$. The description of these variables is given in table 1. The function f is integrated by a Runge-Kutta algorithm to obtain the states.

The dynamic behaviour of the states is described using first order differential equations based on the laws of conservation of enthalpy and matter. The conventional greenhouse model is based on research by van Henten (1994), de Zwart (1996), de Jong (1990) and Bot (1983). A crop model is used to describe the exchange of heat, CO_2 and water between crop and greenhouse. The main external input is the weather. This conventional greenhouse model with crop has been calibrated and validated with data, and was found to give a good description of reality (van Ooteghem 2007). To describe the solar greenhouse behaviour, this model has been extended with a thermal screen, a double layer zigzag roof cover, a cooling net, and the so-called solar greenhouse elements: heat pump, heat exchanger, and ventilation with heat recovery.

Table 1. States, control inputs and external inputs

symbol	description	unit
	States x	
B	total biomass (fresh weight)	kg[fw] m^{-2}
$C_{CO2,a}$, $C_{CO2,as}$	CO_2 concentration indoor air below/ above screen	kg[CO_2] m^{-3}
$C_{H2O,a}$, $C_{H2O,as}$	H_2O concentration indoor air below/ above screen	kg[H_2O] m^{-3}
E_{aq}	aquifer energy content	J m^{-2}
S_T	temperature integral	K day
T_a, T_{as}	temperature indoor air below/above screen	K
T_c	temperature crop	K
T_l, T_u	temperature lower/upper heating net	K
T_{ri}	temperature roof indoor side	K
T_s	temperature soil (upper layer)	K
T_{sc}	temperature thermal screen	K
T_{uc}	temperature upper cooling net	K
	Control inputs u	
Ap_{lsd}, Ap_{wsd}	window aperture lee-side/ windward-side	[0,1]
Cl_{sc}	thermal screen closure	[0,1]
op_{vhr}	option ventilation heat recovery	{0,1}
vp_{CO2}	valve position CO_2 supply	[0,1]
vp_{he}	valve position heat exchanger	[0,1]
vp_{hp}	valve position heat pump	[0,1]
vp_l, vp_u	valve position lower/upper net	[0,1]
	External inputs d	
$C_{CO2,o}$	CO_2 concentration outdoor air	kg[CO_2] m^{-3}
$C_{H2O,o}$	H_2O concentration outdoor air	kg[H_2O] m^{-3}
I_o	outdoor shortwave solar radiation	W m^{-2}
T_o	temperature outdoor air	K
T_{sk}	temperature sky	K
v_o	outdoor wind speed	m s^{-1}

3. OPTIMAL CONTROL

Optimal control is used to exploit the solar radiation and the fluctuating weather as good as possible. This is done with a receding horizon controller, which acts as a closed loop solution.

3.1 The cost function

Optimal control uses a cost function to compute the optimal control input trajectories. The control solution consists of actuator trajectories (e.g., window apertures, valve positions) that result in state trajectories (e.g., temperature, humidity and CO_2 concentration) that optimize a cost function. Our aim is to minimize fossil energy consumption and to maximize crop yield. In the cost function, costs are defined

- to penalize fossil energy consumption,
- to reward biomass increase (maximize crop yield),

- to keep temperature, humidity, and temperature integral within bounds (for good crop development and quality and to decrease the risk for diseases and fungi),
- and to keep the aquifer energy content within bounds (demand by the government that the aquifer is approximately energy neutral year-round).

Using a state space greenhouse-with-crop model given by (1) describing the dynamic behaviour of the greenhouse and the crop x in time, together with weather predictions d, the influence of the control inputs u on greenhouse climate can be simulated.

The goal is to minimize the cost function J

$$J(u) = \Phi(x, t_f) + \int_{t_0}^{t_f} L(x, u, d, t)\, dt \qquad \text{(cost)} \quad (2)$$

where the terminal costs $\Phi : \mathbb{R}^{n_x+1} \to \mathbb{R}$ and the running costs $L : \mathbb{R}^{n_x+n_u+n_d+1} \to \mathbb{R}$ are differentiable a sufficient number of times with respect to their arguments. The final time t_f is set to the control horizon, which is equal to one day and therefore will not be subject to optimization.

The control inputs are constrained by

$$u_i^{\min} \leq u_i(\tau) \leq u_i^{\max} \qquad i = 1, \ldots, n_u;\ t_0 \leq \tau \leq t_f \quad (3)$$

A control input trajectory $u(\tau)$ that satisfies the constraints in (3) is called admissible. For the states there are trajectory constraints (bounds, see (8)). With these prerequisites the control problem is to find

$$u^*(\tau) = \arg\min_u J(u) \qquad t_0 \leq \tau \leq t_f \quad (4)$$

given the expected external inputs (weather prediction) $\widetilde{d}(\tau)$, subject to the differential equations (1) and the control input constraints (3). The optimal control and state trajectories will minimize the cost function J.

The values used for the weight factors c and the bounds in the cost function are given in table 2. The weight factors indicate how important specific greenhouse conditions are, although they do not represent money. They have to be balanced such that one penalty does not outweigh another penalty. The weight factors have been tuned based on open loop computations of single days throughout the year to make sure that they hold in different seasons.

Table 2. Cost function: weight factors and bounds

symbol	unit	$x^{\min}$	$x^{\max}$	$\frac{\text{cost}}{\text{day}\cdot\text{unit}}$	$J(u)$
T_a †	°C	10	34	$c_T = 5$	$\int P_{Ta}\, dt$
RH_a	%	–	85	$c_{RH} = 5$	$\int P_{RHa}\, dt$
ΔT_a^{TI} †	°C	-6	6	$c_{TI} = 25$	$\int P_{TI}\, dt$
E_{aq}	$\frac{\text{J}}{\text{m}^2}$	$E_{aq}^{\min}$	$E_{aq}^{\max}$	$c_{aq} = 10 \cdot 10^6$	$\int P_{aq}\, dt$
Q_{used}	$\frac{\text{W}}{\text{m}^2}$			$c_Q = 61.44$	$\int L_Q\, dt$
$C_{CO2,a}^{\text{ppm}}$	$\frac{\mu\text{mol[CO}_2]}{\text{mol[air]}}$	320	1000	$c_{CO2} = 0$	0
B	$\frac{\text{kg[f.w.]}}{\text{m}^2}$			$c_B = 76.8$	Φ_B
T_a^{ref} †	°C		19	$c_{TI} = 25$	Φ_{TI}

† T_a, ΔT_a^{TI} and T_a^{ref} in (K) in computations. These temperature bounds are taken from Körner (2003). As the temperature integral will keep the average temperature at its reference value T_a^{ref}, the temperature bounds can be quite wide.

The terminal cost Φ is determined by the biomass yield B (kg[f.w.] m^{-2}) and the average temperature deviation ΔT_a^{TI} (K) at the end of the control horizon t_f

$$\Phi(x, t_f) = \underbrace{-c_B \cdot (B(t_f) - B(t_0))}_{\Phi_B(x, t_f)} + \underbrace{c_{TI} \cdot |\Delta T_a^{TI}(t_f)|}_{\Phi_{TI}(x, t_f)} \qquad \text{(cost)} \quad (5)$$

in which terminal cost Φ_B should preferably be large and negative and Φ_{TI} should be zero. These are used as soft terminal constraints.

The running cost L is the sum of the penalties P for the loss of crop yield due to exceeding bounds for temperature T_a (P_{Ta}), relative humidity RH_a (P_{RHa}), temperature integral ΔT_a^{TI} (P_{TI}), year-round aquifer energy content E_{aq} (P_{aq}), and the running cost L for the energy consumption Q_{used} (L_Q).

$$L(x, u, t) = P_{Ta}(x, u, t) + P_{RHa}(x, u, t) + P_{TI}(x, u, t) + P_{aq}(x, u, t) + L_Q(x, u, t) \qquad (\text{cost}\,\text{s}^{-1}) \quad (6)$$

The cost for energy consumption L_Q is given by

$$L_Q(x, u, t) = c_Q \cdot Q_{used} \qquad (\text{cost}\,\text{s}^{-1}) \quad (7)$$

where $Q_{used} = (Q_{boil} + Q_{hp})/A_s$ (W m^{-2}) is the total amount of energy used per square meter greenhouse, where Q_{boil} and Q_{hp} (W) are the energy use by the boiler and the heat pump and A_s (m^2) is the soil surface area. The total energy use Q_{used} is a measure for the total gas use F_{gas} (m^3 m^{-2}).

The penalties P_{Ta}, P_{RHa}, P_{TI}, and P_{aq} are given by

$$P_x(x, u, t) = \frac{c_x}{2} \cdot \Big(\sqrt{\big(x^{\min} - x(t)\big)^2 + \beta} + \sqrt{\big(x^{\max} - x(t)\big)^2 + \beta} - (x^{\max} - x^{\min}) \Big) \qquad (\text{cost}\,\text{s}^{-1}) \quad (8)$$

in which c_x is the weight factor associated with exceeding the bounds $x^{\min}$ and $x^{\max}$ and $\beta = 1 \cdot 10^{-3}$. This penalty function increases linearly with the deviation from the bounds. In between the bounds the value is zero and the function is smooth around $x^{\min}$ and $x^{\max}$. These penalties are used as soft constraints.

The temperature integral is used as a descriptive method for long-term temperature effects on crop development, for lack of a reliable long term crop model. It safeguards the system from moving into physiologically unattractive or unacceptable temperature regions over a longer time period. The aims are to keep the average temperature deviation ΔT_a^{TI} within its bounds (penalty $\int P_{TI}$) and to obtain a deviation of zero at the end of the control horizon t_f of one day ($\Delta T_a^{TI}(t_f) = 0$) (terminal cost Φ_{TI}). The predicted average temperature deviation at time t

$$\Delta T_a^{TI}(t, \tau) = \frac{S_T(t, \tau)}{\frac{t_p + \tau}{n_{secs}}} \qquad \forall\ 0 \leq \tau \leq t_f \qquad \text{(K)} \quad (9)$$

gives the average deviation between the reference T_a^{ref} and the past and predicted temperatures T_a and $\hat{T}_a$. The temperature integral $S_T(t, \tau)$ has a time horizon of 6 days, of which 5 days are in the past and 1 day in the future (prediction).

The government requires the aquifer to be approximately energy neutral year-round. Since we are only looking one day ahead with our RHOC control this poses a bit of a problem. To solve this an average annual energy content curve is determined based on the greenhouse-with-crop model. Then bounds are set on this curve ($E_{aq}^{\min}$, $E_{aq}^{\max}$), which are used in the cost function to make the year-round energy content approximately zero.

There is no penalty on the CO_2 concentration ($c_{CO2} = 0$); the bounds are used for a proportional controller.

3.2 Receding Horizon Optimal Control

The receding horizon optimal control (RHOC) concept is used to compute the control inputs u (actuator trajectories). A conjugate gradient method is used in combination with a line search method to improve the search direction.

Unfortunately the solar greenhouse only exists on paper, so the results of this feasibility study are based on simulations in which we tried to mimic reality as closely as possible. Year-round simulations have been performed with RHOC, where the actual weather is different from the predicted weather used in the optimal control computations (as in reality). This long period will provide insight concerning the use of the boiler, heat pump, and heat exchanger in the different seasons of the year.

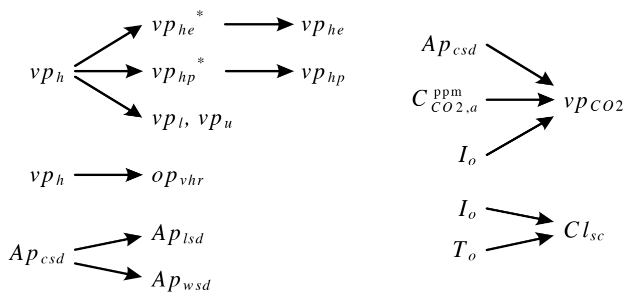
The system has various time-scales:

- minute scale: fast variation of weather (temperature),
- daily scale: daily variation of weather, also found in crop growth through the formation and conversion of assimilates to biomass,
- multiday scale: the crop through its development stages,
- seasonal scale: seasonal variation of weather, also found in the increase and decrease of the aquifer energy content.

The latter two slow timescales are taken into account through average aquifer energy content and the time integral. The biomass increase is assumed to be instantaneous. A small timescale is needed for the computations, since we want to make maximum use of momentary variations in the weather. The RHOC controller therefore uses a control horizon t_f of one day for the control input trajectories. These control input trajectories are piecewise constant over a time interval $t_{s,u}$ of 30 min, which is equal to the time shift t_s between the RHOC computations. This means that $\frac{t_f}{t_{s,u}} = 48$ values are determined for each control input at each receding horizon time step. The fourth order Runge-Kutta integration uses a time interval of 1 min to ensure that the fast dynamics are correctly incorporated.

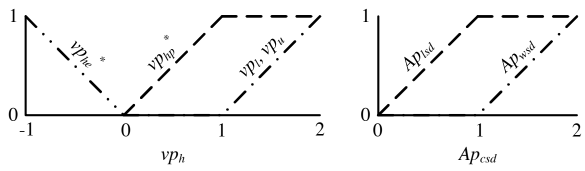
3.3 Control inputs

In the first tests all control inputs were optimized. This led to unexpected results, where e.g. both heating and cooling were used at the same time: the RHOC got stuck in a local minimum. Therefore some control inputs have been coupled into combined control inputs, which are optimized by the optimal control (see Fig. 2a). Other control inputs are determined directly from other control inputs, external inputs or states (see Fig. 2b).



a: set by optimal control b: directly derived

Fig. 2. Relations control inputs



a: vp_h, with $vp_{he}{}^*$ $(-\cdot\cdot-)$, $vp_{hp}{}^*$ $(--)$ and vp_l and vp_u $(-\cdot-)$ b: Ap_{csd}, with Ap_{lsd} $(--)$ and Ap_{wsd} $(-\cdot-)$

Fig. 3. Combined heating valve position vp_h and combined window aperture Ap_{csd}

For heating/cooling the *combined heating valve position* vp_h $[-1,2]$ is used (see Fig. 3a). Heating (vp_{hp}, vp_l, vp_u) and cooling (vp_{he}) at the same time should be ruled out. When heating is needed, it should preferably be done at the lowest cost, so first with the heat pump (vp_{hp}) and then with the boiler (vp_l, vp_u) if the heat pump cannot supply enough heat.

For ventilation the *combined window aperture* Ap_{csd} [0,2] is used (see Fig. 3b). To prevent the wind from blowing through the greenhouse, the lee-side windows Ap_{lsd} are opened before the windward-side windows Ap_{wsd}.

At times of heat demand ($vp_h > 0$) *ventilation with heat recovery* op_{vhr} (0=false, 1=true) is used instead of ventilation with windows, recovering 90% of the sensible heat.

During daytime ($I_o > 0$) the *CO_2 supply valve* vp_{CO2} is controlled by a proportional controller with a set point $C_{CO2,a}^{\mathrm{ppm},sp}$ between 660 and 1000 µmol[CO_2] mol^{-1}[air], depending on the window opening Ap_{csd}.

The 'rules' for the *thermal screen closure* Cl_{sc} are similar to those used in greenhouse horticulture. Its value is either 0 (open) or 0.97 (closed, with a 3% crack opening to carry off moisture). It can be interpreted as an external input d, since it only depends on the external inputs I_o and T_o.

Initial guess control inputs Optimal control input trajectories u^* that minimize the cost function value J have to be found. With two optimal control inputs, vp_h and Ap_{csd}, which both consist of 48 values (section 3.2), 96 values have to be computed at each receding horizon time step. The optimization algorithm is repeated with a time interval t_s. The optimization starts with an initial guess u_0 for the control input trajectories and changes these values until the minimum cost function value J is found. At the next time interval t_s the optimization is started with the values found in the previous optimization, shifted in time.

The initial guess u_0 of the optimal control input $u(t)$ is very important. A poor guess leads to more iterations (thus more computation time) to find a solution, and it may end up in a local minimum. A grid search method (van Ooteghem et al. 2003) is used to find good control input trajectories, partly based on a priori knowledge of the system, and partly on common sense.

A grid is made by discretizing the control space: the possible values of the control inputs are restricted to vp_h={-1 -0.5 0 0.5 1 1.5 2} and Ap_{csd}={0 0.5 1 1.5 2}. First the control inputs vp_h and Ap_{csd} are kept constant: during the whole horizon t_f of one day the same value is used. A constant value may however not be desirable for a whole day. Therefore so called state dependent control input bounds are introduced, to rule out control values that make no sense based on knowledge of the system. The bounds are based on the initial values of temperature T_a, relative humidity RH_a, and thermal screen closure Cl_{sc} for the time interval $t_{s,u}$

$$\begin{array}{ll} vp_h^{\min}(t) = 0 & T_a < T_a^{\min} \\ vp_h^{\max}(t) = 1 & T_a^{ref} < T_a \leq T_a^{\max} \\ vp_h^{\max}(t) = 0 & T_a^{\max} < T_a \end{array} \quad (10)$$

$$\begin{array}{ll} Ap_{csd}^{\max}(t) = 1 & T_a < T_a^{ref} \bigvee RH_a < 0.9\, RH_a^{\max} \\ Ap_{csd}^{\max}(t) = 0.1 & Cl_{sc} = 0.97 \end{array} \quad (11)$$

The minimum and maximum values for T_a and RH_a are the bounds given in table 2.

The cost function value J is computed for each control input combination in the grid, with the state dependent control input bounds. The control input combination u_0 with the lowest cost function value $J_{\min}$ is chosen. This is a good first guess for the control inputs.

3.4 External inputs: the weather predictions

For both the current weather conditions and the weather prediction the *SELyear* weather data is used (Breuer and van de Braak 1989), which is fairly representative for the Dutch climate. The *SELyear* weather data contains hourly values for I_o, v_o, T_o, RH_o and T_{sk}. A CO_2 concentration $C_{CO2,o}^{\text{ppm}} = 320$ µmol[CO_2] mol^{-1}[air] is assumed. The weather conditions are linearly interpolated to match $t_s = 30$ min of the RHOC.

For the weather prediction a 'lazy man' weather prediction is used, which assumes that the weather conditions $\widetilde{d}(t,\tau)$ for the next time period are equal to the previous time period $d(t, t - t_f + \tau)$ (Tap et al. 1996). We need a weather prediction for 1 day (instead of 1 hour as Tap et al. used), which would make this assumption to crude. Therefore an adjustment is made to match the current weather conditions $d(t, t_0)$

$$\widetilde{d}(t,\tau) = d(t, t - t_f + \tau) + \big(d(t, t_0) - d(t, t - t_f + t_0)\big) \quad \forall\, \tau \in [t_0, t_f] \quad (12)$$

This adjustment is made at every time interval t_s. The wind speed v_o is set to zero if it becomes negative. The solar radiation I_o is used without correction. Unless otherwise stated, the current weather d is not equal to the weather prediction $\widetilde{d}$ in the year-round computations.

3.5 Optimization method: gradient search

The gradient search method uses the conjugate gradient algorithm (Pagurek and Woodside 1968). With our non-linear model, this method cannot guarantee that the global minimum is found. A good initial guess u_0 for the control inputs increases this probability. The grid search is therefore repeated at every full hour. The gradient search is reinitialized if the grid search gives lower costs J.

The year-round RHOC computation was first performed with the grid search method (van Ooteghem et al. 2005) to get an idea of the year-round values with a fast computation (about 8 hours). The results were also used to determine the aquifer energy content curve (section 3.1). The gradient search method (section 3.6; van Ooteghem 2007) was more time consuming (about 8 days).

3.6 Results RHOC

Table 3. RHOC results, averages and ranges

a: averages of control input values

	Ap_{lsd}	Ap_{wsd}	op_{vhr} †	Cl_{sc}	vp_{CO2}	vp_l, vp_u	vp_{hp}	vp_{he}
spring	0.74	0.27	69%	0.25	0.11	0.09	0.62	0.15
summer	0.87	0.50	61%	0.05	0.12	0.07	0.54	0.28
fall	0.62	0.23	92%	0.51	0.09	0.29	0.88	0.01
winter	0.56	0.20	92%	0.72	0.09	0.35	0.89	0.02
year-round	0.70	0.30	78%	0.37	0.10	0.20	0.73	0.12

† op_{vhr} is given as the percentage of the cases where ventilation with heat recovery is used when there is ventilation ($Ap_{csd} \neq 0$)

b: ranges and results of output values

	T_a			RH_a		Q_{used}	F_{gas}	ΔB
	min	max	avg	min	max	max	$\frac{\text{m}^3}{\text{m}^2}$	$\frac{\text{kg}}{\text{m}^2}$
spring	10.2	38.4	19.10	37.4	94.4	150.4	3.4= 2.9+0.5	28.8
summer	11.4	30.3	19.29	49.1	96.7	148.6	2.6= 2.1+0.5	27.5
fall	4.9	32.6	19.22	39.4	93.3	158.4	9.8= 9.0+0.8	5.6
winter	5.7	35.9	19.11	36.3	96.6	165.9	12.1=11.3+0.8	3.2
year-round							27.9=25.3+2.6	65.1

F_{gas} is given as: total gas use = gas use by boiler + gas use by heat pump

c: costs, a priori and a posteriori

	$\int P_{RHa}$		$\int L_Q$		Φ_B		Φ_{TI}		J	
spring	2.04	*3.45*	1.79	*2.21*	−24.26	*−23.60*	2.71	*7.28*	−17.72	*−10.65*
summer	2.64	*5.73*	1.32	*1.69*	−22.65	*−22.23*	7.69	*10.44*	−10.99	*−4.37*
fall	2.84	*3.21*	4.58	*6.76*	−5.49	*−4.81*	0.83	*7.44*	2.76	*12.65*
winter	3.20	*2.72*	5.90	*8.36*	−3.25	*−2.52*	0.83	*7.65*	6.69	*16.23*
year-round	2.67	*3.80*	3.35	*4.69*	−14.14	*−13.52*	3.08	*8.22*	−5.04	*3.21*

normal = a priori values; *italic* = a posteriori values

$\int P_{TI} = 0$, $\int P_{Ta}$ and $\int P_{aq}$ are very small

In table 3a we see that the heat pump (vp_{hp}) is used year-round, either to increase temperature or to decrease humidity. In fall and winter the boiler (vp_l, vp_u) is used to supply additional heat to the greenhouse, since the capacity of the heat pump is limited, while in spring and summer it is used less often. In fall and winter the thermal screen (Cl_{sc}) is closed almost every night. In the second half of spring and in summer, the thermal screen rarely closes. The heat exchanger (vp_{he}) is frequently used to decrease the temperature in spring and summer but seldom in fall and winter. The windows (Ap_{lsd}, Ap_{wsd}) are mainly opened to decrease humidity, since the temperature can be decreased with the heat exchanger. When ventilation is used in fall and winter, it is mainly ventilation with heat recovery (op_{vhr}). CO_2 supply (vp_{CO2}) is used whenever there is radiation.

From table 3b we find that the temperature T_a seldom exceeds its bounds. At times of high radiation, temperature is allowed to rise, since this yields a higher biomass increase. The average temperature deviation ΔT_a^{TI} over six days is small: the maximum deviation is 2℃, so it never reaches its bounds of ± 6℃. The reference temperature T_a^{ref} of 19℃ is well met in all seasons. The relative humidity RH_a exceeds its bound quite frequently, although the optimal control is doing everything it can (heating, ventilating) to decrease it. The main gas use F_{gas} is found in fall and winter due to the low outdoor radiation and temperature. The main biomass increase ΔB is found in spring and summer due to higher radiation in these seasons.

A priori versus a posteriori results In the year-round simulations with the RHOC controller, the actual weather d is different from the predicted weather $\widetilde{d}$. The control input trajectories are determined a priori at every time interval t_s based on the initial states x_0 and the weather prediction $\widetilde{d}$. When the next initial states x_0 are determined with the model a posteriori, the actual weather $d \neq \widetilde{d}$ is used, which causes the states x to deviate from the expected states.

Deviations between a priori and a posteriori results are partly due to the fact that the a priori results are open loop results whereas the a posteriori results are closed loop (feedback) results, and partly due to the difference between the actual weather d and the weather predictions $\widetilde{d}$. It is important to know how much the realized costs deviate from the costs expected during the optimization if i.e. the expected results are going to be used in a presentation tool for the grower.

The running costs, penalties, terminal costs and cost function values of the year-round computation with RHOC are presented in table 3c. These are the averages over the whole season of the costs evaluated at each half hour (t_s) integrated over one day (t_f).

The main deviations are found in the running cost $\int L_Q$ and the terminal cost Φ_{TI}. The actual energy use Q_{used} in fall and winter is much higher than initially expected. It is found that the greenhouse is heated to decrease humidity. Furthermore the realized average temperature ΔT_a^{TI} over a period of 6 days is different from what was initially expected. This was likely to happen, since any deviation of the average temperature from the target value $T_a^{ref} = 19$℃ at time t_f is penalized. When the horizon is shifted, this terminal constraint is no longer imposed in the cost function, so it is unlikely that it will be maintained in the receding horizon approach. To maintain $\Phi_{TI} = 0$ at all times would mean either to keep the temperature constant, or to have a fixed periodic symmetrical pattern.

A year-round computation is performed with $\widetilde{d} = d$ to remove the influence of the weather prediction. It is found that all results are better. Note that a real weather forecast will probably lead to larger deviations in the biomass increase ΔB than the weather prediction used here.

Influence of the separate solar greenhouse elements The solar greenhouse with all solar greenhouse elements (heat pump, heat exchanger, ventilation with heat recovery and CO_2 separate from boiler operation) is compared with a greenhouse without all these features. This non-solar greenhouse does have a double layer zigzag roof cover and a thermal screen. Both the solar and the non-solar greenhouse are controlled by optimal control to obtain a fair comparison.

We found that the gas use F_{gas} is decreased by 52%, the biomass increase ΔB is higher (139%), the CO_2 use $\Phi_{CO2}^{\max}$ is much higher (352%) and more ventilation F_{as_o} is used (118%) with much less energy loss Q_{as_o} (32%). This shows that it is possible to obtain a higher biomass increase with a much lower gas use. The solar greenhouse uses (all values per m^2[gh] per year) 27.9 m^3 gas, 160.2 kg CO_2, and it produces 65.1 kg biomass. The non-solar greenhouse uses 57.9 m^3 gas, 45.5 kg CO_2, and it produces 46.7 kg biomass.

Additional computations were done to distinguish the influence of the separate solar greenhouse elements (van Ooteghem 2007). It was found that

- The use of the heat pump, heat exchanger and aquifer decreases the gas use by 23%. This is due to the use of the heat pump which uses less gas ($COP \approx 5$).
- Ventilation with heat recovery decreases the gas use by 26%. This is due to the decrease of the energy loss through ventilation by 59%.
- The use of CO_2 supply independent of boiler operation leads to a much higher CO_2 use $\Phi_{CO2}^{\max}$ (289%), which gives a higher biomass increase ΔB (137%).

From this we can conclude that the main gas use reduction is due to the ventilation with heat recovery.

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