Optimal control of greenhouse climate using minimal energy and grower defined bounds ☆

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Abstract

Energy saving in greenhouses is an important issue for growers. A method to minimize the total energy that is needed to heat and cool the greenhouse is presented. The grower defines bounds for temperature, humidity, CO_2 concentration, and the maximum amount of CO_2 available. Given these settings, optimal control techniques were used to minimize the energy input. To do this, an existing greenhouse climate model for temperature and humidity was expanded with a CO_2 balance. Heating, cooling, the amount of natural ventilation, and injection of industrial CO_2 were used as control variables.

Standard settings were defined to compare the strategy of the grower with the optimal solution. This resulted in a theoretical reduction of 47 % in heating, 15 % in cooling, and 10 % in CO_2 injection for the year 2012. The optimal control does not need to maintain a minimum pipe temperature, in contrast to current practice. When the minimum pipe temperature strategy of the grower was implemented, still a reduction of 28 % in heating and 10 % reduction in CO_2 injection was found.

The effect of different bounds on the optimal energy input was analyzed.

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The more freedom is allowed to the climate variables, the higher the potential of energy saving. However, in practice the grower is in charge of defining the bounds. The energy saving critically depend on the choice of the bounds. The effect was analyzed by varying the bounds. Not surprisingly, the more freedom is allowed to the climate variables, the higher the potential for energy saving. However, as the effect can be demonstrated to the grower, the outcome is valuable to the grower in taking his decisions.

Keywords: greenhouse climate, optimal control, energy, heating, cooling

Contents

1. Introduction

Temperature, humidity, CO_2 concentration, and light intensity at plant level are the main climate variables to control in a greenhouse. These are usually controlled by the greenhouse process control computer. Control rules in the process control computer are mostly heuristic rules based on experience of the growers and suppliers (Kamp and Timmerman, 1996; Berenguel *et al.*, 2003; Van Straten, 1999). To realize the desired greenhouse climate, a lot of settings have to be made by the grower. The grower defines and adapts these settings in the process control computer according to observations of the status of the crop, and based on his experience and skill (Van Straten *et al.*, 2000), but also on weather predictions, specific crop knowledge, production planning and product price prognosis.

Several approaches for more automation have been suggested. Seginer *et al.* (1996) proposed to mimic an expert greenhouse grower by monitoring the actions of the expert grower and, in this way to extract more objective knowledge from collected data using a neural-net. The latter requires a lot of data. Other authors proposed optimal control to maximize profit i.e. Van Henten *et al.* (1997); Seginer and Ioslovich (1998); Pohlheim and Heissner (1999); Van Straten *et al.* (2002); Van Ooteghem *et al.* (2004); Rodriguez *et al.* (2008); Ioslovich *et al.* (2009). Gutman *et al.* (1993) minimized heating costs by exploiting deviations allowed from the standard blueprints expressed in temperature sums, based on perfect weather predictions. Minimizing energy consumption instead of costs, with steady-state energy balance and daily weather forecasts was presented by Chalabi *et al.* (1996).

Incrocci *et al.* (2008) proposed optimal CO_2 concentration in the greenhouse based on economic evaluation. To maintain a given CO_2 concentration in the greenhouse the supply must balance the assimilated CO_2 flux and CO_2 flux to the outside air due to ventilation. Linker *et al.* (1998) optimized greenhouse operation, and in particular CO_2 control, with a neural network. In most of these approaches crop models and prices of the harvested product were used.

To our best knowledge, none of the optimal control approaches presented in the literature are currently applied in current process control computers. Various reasons why this may be so are listed below.

- Lack of reliable crop production models for the wide range of crops and species grown in horticultural practice.
- Limited trust of growers and doubts about the quality of (crop) models and lack of experimentally proven advantages (Van Straten, 1999).
- Need to leave part of the decision freedom to the responsibility of the growers (Van Straten *et al.*, 2000).
- The best approach to any model-based control strategy will need feedback of the crop state (Van Henten (1994); Day (1998); Van Henten and Bontsema (2009)). Proper on-line plant measurements are lacking.
- Proper predictions of market prices are not available.

To overcome the above listed obstructions to implement optimal control techniques in practice, here a method is proposed that avoids the need for crop models. The method focuses on minimizing energy input to the greenhouse, while obeying grower defined bounds for greenhouse air temperature, humidity, and CO_2 concentration. In this way the responsibility for the crop yield and hence income is left in the hands of the grower, while the cost side is tackled by minimizing the resource input. The formulation of the optimal control problem allows that settings that growers are familiar with, like minimum pipe temperature, can be taken into account in the optimization in a relatively easy way. Minimizing the energy input to the greenhouse with a dynamic energy balance was presented before in Van Beveren *et al.* (2013), and extended with a humidity balance in Van Beveren *et al.* (2015). The contribution of this work is the extension of the previous work with a dynamic CO_2 balance. This is important because of the trade-off between natural ventilation and injection of industrial CO_2 which is present in a greenhouse with active cooling. The optimization was done for one full year and compared with measurement data from a commercial greenhouse.

In the presented method, the grower defines the desired climate by defining the bounds on the climate variables. The main idea is to exploit the dynamics of the ambient conditions as much as possible under given constraints with minimal energy input to the greenhouse. The advantage of this method is that only a crop transpiration model for the humidity balance, and a relatively simple assimilation model for the CO_2 balance are needed. The grower weighs the expected yield and costs and makes the decisions about the bounds himself based on the minimal energy input. Moreover, by varying the bounds the grower can gain more insight into the effects of his choices on the expected total energy input and CO_2 injection.

2. Materials and Methods

2.1. The greenhouse

The data used in this research were collected in a $40\,709\,\mathrm{m}^2$ Venlo-type greenhouse in Bleiswijk, the Netherlands (52 °N, 4.5 °E). Eaves height was 6.4 m and ridge height was 7.2 m. The roof angle was 23°. The spans were equipped with 2020 ventilation windows of $1.35\,\mathrm{m} \times 1.67\,\mathrm{m}$. A movable shadow screen (XLS 13 F Ultra) with a light transmission of 70 % was installed. Also a black-out screen was present. Furthermore, the greenhouse was equipped with 4536 1000 W SON-T lamps ($110\,\mathrm{W\,m^{-2}}$) for artificial lighting. A pipe rail heating system was installed, consisting of $1.1\,\mathrm{m[pipe]\,m^{-2}}$. Per $80\,\mathrm{m}^2$ greenhouse one air-to-water heat exchanger (OPAC-106) was available that could be used to heat, cool, and dehumidify greenhouse air. The greenhouse was connected to the OCAP (organic CO_2 for assimilation by plants) network in the Netherlands which transports industrial CO_2 to growers. The maximum CO_2 injection capacity was $1200\,\mathrm{kg\,h^{-1}}$. Two different Avalanche+ rose cultivars were grown on substrate (rockwool) in separate sections of the greenhouse.

2.2. Dynamic model of greenhouse climate

In this approach, greenhouse climate is defined in terms of temperature T_{air}, absolute humidity χ_{air}, and carbon dioxide concentration of greenhouse air $CO_{2,air}$. To minimize energy input to the greenhouse with optimal control techniques, a model of the greenhouse climate is needed. To this end, the dynamic model for temperature (Eq. (1)) and absolute humidity (Eq. (2)) of greenhouse air as presented in Van Beveren *et al.* (2013) was extended with a dynamic CO_2 mass balance (Eq. (3)). The latter is needed to study the utilization of the active cooling system in the greenhouse. The use of the cooling system leads to a lower ventilation requirement, and thus to a higher utilization of the injected CO_2 . This results in either higher possible CO_2 levels in the greenhouse or a lower CO_2 requirement. Control of light levels in the greenhouse was considered to be done by the grower.

Greenhouse air temperature is influenced by the following heat fluxes: incoming radiation Q_{sun}, heat losses through the cover Q_{cover}, transpiration by the crop Q_{trans}, artificial lighting Q_{lamps}, natural ventilation Q_{vent}, cooling $Q_{he,cool}$ and heating $Q_{he,heat}$ by the heat exchangers, and heating by the pipe rail system Q_{pipe} ($\mathrm{W\,m^{-2}}$). The absolute humidity of greenhouse air is influenced by the following vapour fluxes: crop transpiration ϕ_{trans}, condensation on the cover ϕ_{cov}, condensation in the heat exchangers due to cooling ϕ_{he}, and vapour exchange with outside air by natural ventilation ϕ_{vent} ($\mathrm{g\,m^{-2}\,s^{-1}}$). The calculation of fluxes in the energy and vapour balance, as in Van Beveren *et al.* (2015), were largely based on Van Henten (1994); De Zwart (1996); Van Ooteghem (2007); Van Henten and Bontsema (2009); Vanthoor (2011); Stanghellini and de Jong (1995). Energy and vapour exchange with outside air were calculated via the natural ventilation model of De Jong (1990). This yields the following equations for the air temperature and humidity:

$$\frac{dT_{air}}{dt} = \frac{1}{c_{cap}}(Q_{sun} - Q_{cov} - Q_{trans} + Q_{lamp} - Q_{vent} + Q_{he,heat} - Q_{he,cool} + Q_{pipe}) \quad (^{\circ}\mathrm{C\,s^{-1}}) \tag{1}$$

$$\frac{d\chi_{air}}{dt} = \frac{1}{h}\left(\phi_{trans} - \phi_{cov} - \phi_{he} - \phi_{vent}\right) \quad (\mathrm{g\,m^{-3}\,s^{-1}}) \tag{2}$$

The CO_2 model is based on the work of De Zwart (1996); Van Ooteghem (2007); Stanghellini *et al.* (2011). The CO_2 mass balance is described as:

$$\frac{dCO_{2,air}}{dt} = \frac{1}{h}\left(\phi_{c,inj} - \phi_{c,ass} - \phi_{c,vent}\right) \quad (\mathrm{g\,m^{-3}\,s^{-1}}) \tag{3}$$

where h is the average height of the greenhouse, $\phi_{c,inj}$ the injection of pure industrial CO_2 to the greenhouse, $\phi_{c,ass}$ the assimilation of CO_2 by the crop, and $\phi_{c,vent}$ the CO_2 exchange with outside air due to ventilation. Fluxes in the CO_2 balance are described in more detail in the following sections.

CO_2 coming from an external industrial source $\phi_{c,inj}$ was injected in the greenhouse. Injection data was available from the process control computer for validation of the model and for comparison with the grower's operation of the greenhouse.

The assimilation model of Nederhoff and Vegter (1994) was simplified by Stanghellini *et al.* (2011) to a two-variable model that reproduces the trend and the level of the complex model. Assimilation in this model (Eq. (4)) is a function of radiation at plant level $I_{rad,plant}$ ($\mathrm{W\,m^{-2}}$) and CO_2 concentration ($\mathrm{g\,m^{-3}}$). The model of Nederhoff and Vegter (1994) gives parameters for tomato, cucumber, and sweet pepper, but not for rose. In the simplified model, the maximum assimilation rate of a tomato crop is $2.2 \cdot 10^{-3}$ $\mathrm{g\,m^{-2}\,s^{-1}}$. A model of photosynthesis for rose (*Rosa hybrida L.*) was presented by Kim and Lieth (2001, 2003). This model has more parameters compared to the model of Stanghellini *et al.* (2011) and is based on measurements on a specific species of rose. Although there is no photorespiration in the model of Stanghellini *et al.* (2011), simulation with both models did not show much difference in model performance, and therefore, the simplified model of Stanghellini *et al.* (2011) was used without further calibration.

$$\phi_{c,ass} = 2.2 \cdot 10^{-3} \frac{1}{1 + \frac{0.42}{CO_{2,air}}} \left(1 - e^{-0.003 I_{rad,plant}}\right) \quad (\mathrm{g\,m^{-2}\,s^{-1}}) \tag{4}$$

Exchange of CO_2 with outside air due to natural ventilation was described as

$$\phi_{c,vent} = g_V \left(CO_{2,air} - CO_{2,out} \right) \quad (\mathrm{g\,m^{-2}\,s^{-1}}) \tag{5}$$

where g_V is the specific ventilation ($\mathrm{m^3\,m^{-2}\,s^{-1}}$), $CO_{2,air}$ the carbon dioxide concentration of indoor air ($\mathrm{g\,m^{-3}}$) and $CO_{2,out}$ the carbon dioxide concentration of outside air. Specific ventilation g_V is a function of window opening, indoor and outside temperature, and wind speed and was calculated according to the ventilation model of De Jong (1990).

2.3. Data collection

Data with a five minute sampling interval was collected from the HortiMaX® process control computer in the greenhouse from the whole year 2012. Temperature and humidity were measured with eight measurement boxes, two in each of the four compartments. CO_2 was measured at two locations in the greenhouse. To compare simulation results with measurements, the box values were averaged to represent the spatial mean. Differences between the separate temperature, humidity, and CO_2 measurements were analysed by comparing the mean absolute error (MAE, Eq. (A.1)) between the average and individual sensors and the correlation coefficient between the average and individual sensors in order to check the consistency of the measurements.

The mean absolute error (MAE) between the average and the individual temperature sensors was on average 0.31 °C with a standard deviation (SD) of 0.31 °C. The mean correlation coefficient between the individual sensors was 0.98 on average. For the relative humidity, MAE was 1.3 % (SD=0.4 %) on average. The mean correlation coefficient between the RH sensors was 0.94 for the whole year. MAE between the two CO_2 sensors was 88.4(80) ppm. The correlation coefficient (r) between the two CO_2 measurements was 0.86, which means that at some times differences between the sensors occured.

The following measured outside weather conditions were used: radiation, temperature, wind speed, relative humidity, and CO_2 concentration. Because there was no outside CO_2 sensor installed at this greenhouse, CO_2 measurements from the Wageningen UR Greenhouse Horticulture research station, located about four kilometer from the rose greenhouse, were used. All other outside weather conditions were measured with a HortiMaX® weather station.

The crop transpiration, a modification of the model of Stanghellini (2010), was validated with data from the HortiMaX® Prodrain® weighing gutter system in Van Beveren *et al.* (2015).

2.4. Optimal control problem formulation

Four control variables were defined to keep temperature, humidity, and CO_2 concentration between the grower defined bounds and at the same time minimize the total energy input to the greenhouse. In contrast to Van Beveren *et al.* (2015) the total energy input was split up in heating and cooling and a control variable for injection of CO_2 was added to the optimization.

The first control variable was the energy input to the greenhouse $Q_{E,heat}$. This can be heating with the pipe rail heating system or heating with the water-to-air heat exchangers. The second control variable was the energy extracted from the greenhouse by active cooling $Q_{E,cool}$. Active cooling can only be done with the heat exchangers. The reasoning to separate these two energy inputs is that heating and cooling can be applied at the same time. This is also done in practice to remove vapour, and at the same time heat to maintain a desired temperature. It also enables implementation of a minimum pipe temperature in the greenhouse. The third control variable was the specific ventilation g_V which is related to the opening of the ventilation windows. The amount of air exchange between in- and outside air influences the temperature, humidity, and CO_2 concentration of greenhouse air. The fourth control variable was the injection of industrial CO_2 $\phi_{c,inj}$ to the greenhouse.

The optimization problem was formulated as a dynamic optimal control problem. Given the model, initial conditions $T_{air}(0)$, $\chi_{air}(0)$, and $CO_{2,air}(0)$, external inputs, and constraints on the climate variables and control inputs, the optimal control trajectory that minimizes total energy input over time can be found by minimizing the following functional J:

$$\min_{Q_{E,heat},Q_{E,cool},g_V,\phi_{c,inj}} J(Q_{E,heat},Q_{E,cool},g_V,\phi_{c,inj}) = \int_{t_0}^{t_f} \left(Q^2_{E,heat} + Q^2_{E,cool}\right) dt \tag{6}$$

where t_0 is the initial time and t_f the final time.

The bounds on the climate variables were defined as

$$T^{min}_{air}(t) \leq T_{air}(t) \leq T^{max}_{air}(t), \tag{7}$$

$$RH_{air}(t) \leq RH^{max}_{air}(t), \tag{8}$$

$$CO^{min}_{2,air}(t) \leq CO_{2,air}(t) \leq CO^{max}_{2,air}(t) \tag{9}$$

where $T^{min}_{air}(t)$ and $T^{max}_{air}(t)$ were the temperature bounds, $RH^{max}_{air}(t)$ was the upper bound for relative humidity, and $CO^{min}_{2,air}$ and $CO^{max}_{2,air}$ the lower and upper bounds for CO_2 .

The control variables were constrained by the following control inequality constraints:

$$Q^{min}_{E,heat}(t) \leq Q_{E,heat}(t) \leq Q^{max}_{E,heat}(t) \tag{10}$$

$$-Q^{min}_{E,cool}(t) \leq Q_{E,cool}(t) \leq Q^{max}_{E,cool}(t) \tag{11}$$

$$g^{min}_V(t) \leq g_V(t) \leq g^{max}_V(t) \tag{12}$$

$$0 \leq \phi_{c,inj}(t) \leq \phi^{max}_{c,inj}(t) \tag{13}$$

$$\int_{t_0}^{t_f} \Phi_{c,inj} dt \ \leq \phi^{max,day}_{c,inj} \tag{14}$$

where $Q^{max}_{E,heat}$ was the maximum heating capacity and $Q^{min}_{E,cool}$ was the maximum cooling capacity. The minimum specific ventilation g^{min}_V was equal to the leakage ventilation, and g^{max}_V was equal to the specific ventilation at 100 % window opening of both wind and leeward side windows, and thus changed over time. Once the required g_V was obtained from the optimization, the ventilation model was used to obtain the required window opening at the prevailing wind speed. $\phi^{max}_{c,inj}$ was the maximum CO_2 injection rate, and $\Phi^{max,day}_{c,inj}$ was the maximum amount of CO_2 that could be injected per day.

Table 1: Standard settings of the bounds for optimization

Symbol	Description	Value	Unit
$T_{air}^{min}(t)$	Lower temperature bound	$\overline{T}'_{air,meas}(t) - 0.5°C$	°C
$T_{air}^{max}(t)$	Upper temperature bound	$\overline{T}'_{air,meas}(t) + 0.5°C$	°C
$RH_{air}^{max}(t)$	Upper RH bound	$\max RH_{air,meas}(t)$	%
$CO_{2,air}^{min}(t)$	Lower CO_2 bound	$0.97 \cdot \overline{CO}'_{2,air,meas}(t)$	$g\,m^{-3}$
$CO_{2,air}^{max}(t)$	Upper CO_2 bound	2000 ppm	$g\,m^{-3}$
$Q_{E,heat}^{max}(t)$	Maximal heating capacity	200	$W\,m^{-2}$
$Q_{E,cool}^{min}(t)$	Maximal cooling capacity	200	$W\,m^{-2}$
$\phi_{c,inj}^{max}(t)$	Maximal CO_2 injection capacity	1200	$kg\,h^{-1}$
$\Phi_{c,inj}^{max,day}$	Total amount of CO_2 available per day	$\int \phi_{c,inj,meas} dt$	$g\,m^{-3}\,d^{-1}$

To compare the optimization results with the grower's operation of the greenhouse, first a trajectory of the climate variables has been defined. Next, for the optimization, bounds were defined as in Table 1, where the choice was guided by what would be realistic in practice. Also realistic equipment capacities were defined.

As temperature bounds a deviation of 0.5 °C around the smoothed realized temperature was chosen. The smoothing was done with a moving average filter with a span of 36 measurements, which corresponds to a time span of 3 hours. The upper bound for RH was defined as a constant value per day, according to the highest, measured RH on that day. The lower bound for CO_2 was defined as 97 % of the smoothed and measured CO_2 concentration in the greenhouse. The upper boundary was chosen as a constant value of 2000 ppm to prevent damage to the crop.

The maximum heating and cooling capacity were fixed at $200\,W\,m^{-2}$. For the standard situation, the minimum heating capacity $Q_{E,heat}^{min}$ and minimal cooling capacity $Q_{E,cool}^{max}$ were set to zero. The maximum injection capacity with standard settings was $1200\,kg\,h^{-1}$, which corresponds to $33\,g\,m^{-2}\,h^{-1}$.

For the total amount of CO_2 available per day, the total amount of CO_2 that was injected by the grower was used as the upper bound.

To implement minimum pipe temperature, as often used in practice, a lower bound for the minimum heating capacity $Q_{E,heat}^{min}$ was set to the pipe temperature that the grower used at that time in the greenhouse (measured time series). The lower bound for heating was calculated as

$$Q_{E,heat}^{min} = \alpha_{pipe} \left(T_{pipe,min} - T_{air} \right) \quad (\mathrm{W\,m^{-2}}). \tag{15}$$

Here, α_{pipe} is the heat transfer coefficient of the heating pipes ($\mathrm{W\,m^{-2}}$).

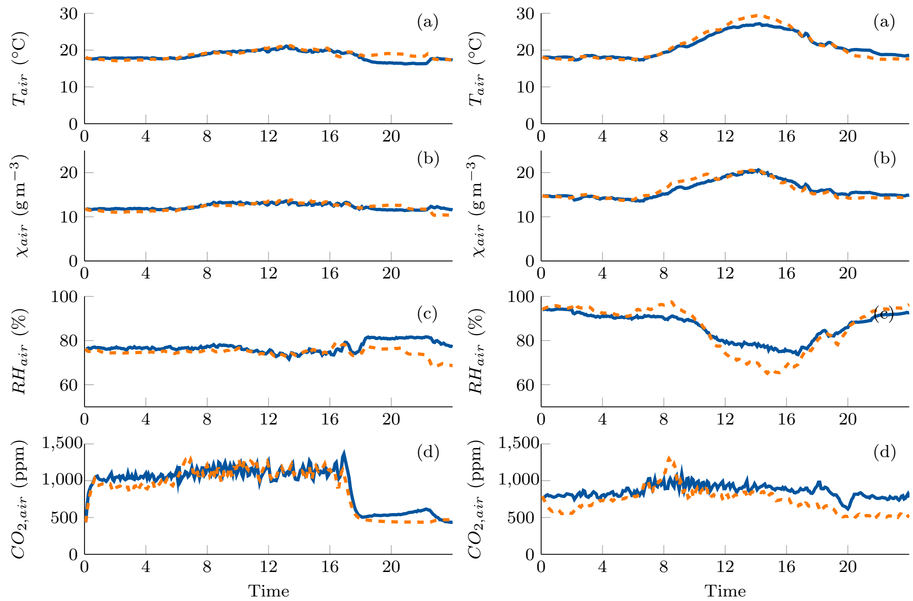
The optimal control problem was solved with PROPT - Matlab Optimal Control Software (Rutquist and Edvall, 2010). PROPT uses a collocation method for solving optimal control problems, which means that the solution takes the form of a polynomial which satisfies the differential algebraic equations and path constraints at the collocation points (Edvall and Goran, 2009). The input data were interpolated between the collocation points and an optimization horizon of one day was used. Data processing, model building, validation, and optimal control formulation with PROPT were done in Matlab (version 7, The MathWorks Inc., Natick, USA).

3. Results

3.1. Model Performance

Measured and simulated greenhouse air temperature T_{air}, absolute humidity χ_{air}, relative humidity RH_{air} and CO_2 concentration $CO_{2,air}$ for a cold (18 February, 2012) and a warm day (23 July, 2012) are shown in Figs. 1a and 1b. The day in February had a mean outside temperature of 7.1 °C and mean global radiation was $103\,\mathrm{W\,m^{-2}}$ during the light period, while the day in July was a warmer day than the day in February and had a mean outside temperature of 18.3 °C and mean global radiation was $437\,\mathrm{W\,m^{-2}}$.

The simulated values match the measured values very well on these two days. The largest differences occurred in the simulation of CO_2 concentration and the estimation of the relative humidity, which is a function of the temperature and absolute humidity. The former is because of the dependence of the CO_2

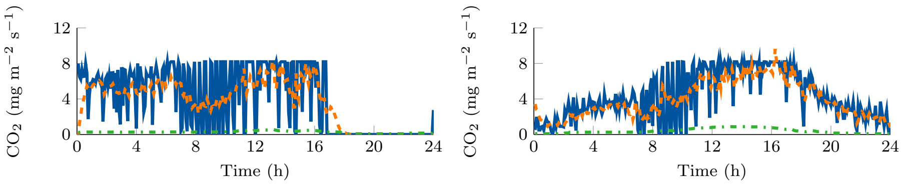


(a) 18 February, 2012 (b) 23 July, 2012

Figure 1: Measured (—) and simulated (- - -) T_{air} (a), χ_{air} (b), RH_{air} (c), CO_2 concentration (d) for 18 February (a) and 23 July (b), 2012.

balance on the ventilation model and the measurement of the CO_2 injection. The different fluxes in the CO_2 balance are shown in Figs. 2a and 2b for the two selected days in 2012. The main factors that influence the ambient CO_2 concentration are ventilation and CO_2 injection. From the figure it can be seen that the injection of CO_2 is for a great part necessary to compensate for the CO_2 losses due to ventilation. Assimilation of CO_2 has, compared to the other two fluxes, a relative small impact on the CO_2 balance. For 18 February, only 7 % of the total outgoing CO_2 (ventilation + assimilation) was assimilation. For the summer day, this was 9 %. Higher assimilation rates are expected during summer because of the higher light levels in the greenhouse.

The model was validated for the whole year 2012. To identify potential differences in performance in time, the model performance was assessed per month. The monthly correlation coefficient r and Root Mean Square Error ($RMSE$, Eq. (A.2)) for the three climate variables are presented in Table 2.



(a) 18 February, 2012

(b) 23 July, 2012

Figure 2: CO_2 injection (—), ventilation (- - -), and assimilation flux (· - · -) for 18 February (a) and 23 July, 2012 (b).

Table 2: Correlation coefficient r and Root Mean Square Error $RMSE$ of measured and simulated greenhouse air temperature, relative humidity, and CO_2 concentration per month and for the whole year 2012. Values were calculated with the equations in Appendix A.

r	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Tot	Unit
T_{air}	0.65	0.72	0.85	0.84	0.92	0.92	0.94	0.96	0.92	0.79	0.71	0.69	0.89	–
RH_{air}	0.32	-0.33	0.58	0.79	0.71	0.59	0.66	0.73	0.75	0.76	0.77	0.57	0.54	–
$CO_{2,air}$	0.49	0.62	0.78	0.73	0.82	0.84	0.75	0.80	0.68	0.75	0.79	0.58	0.75	–
$RMSE$	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Tot	Unit
T_{air}	1.20	1.64	1.38	1.32	1.26	1.26	1.19	1.11	1.06	1.14	1.16	1.34	1.26	°C
RH_{air}	6.2	14.8	4.3	3.4	6.3	7.4	8.6	6.7	9.0	5.1	6.5	8.4	7.7	%
$CO_{2,air}$	219	288	159	167	153	153	178	170	213	158	190	237	194	ppm

Correlation between measured and simulated values is highest for temperature. A negative correlation only exist for RH in February. At the beginning of this month, there was a period with outside temperatures below zero, whereas in all other months the differences between inside and outside temperature were not as big as in that part of February. The correlation for the three climate variables is better in the summer period than in the winter period.

The $RMSE$ for temperature is around 1.2 °C for the whole year, with a higher error in February. This outlier is also there for relative humidity and CO_2 . $RMSE$ for RH_{air} is not lowest in summer, but in March and April. For CO_2 the differences between measured and simulated values are relatively high. From visual inspection of the simulation results of the whole year, it was observed that there are days with an almost perfect fit between measured and simulated values, and days with very large deviations between measured and simulated values. These days are spread over the whole year, and usually in periods of a few days. No clear explanation for these differences can be indicated.

3.2. Optimization results

The optimization result with the standard settings as defined in Table 1 for June 16, 2012 is shown in Fig. 3. This date was chosen because it is a typical example of a situation where CO_2 is limiting and active cooling was used both by the grower as well as in the optimal situation. CO_2 was a limiting factor because all available CO_2 was used in the optimal case. The temperature

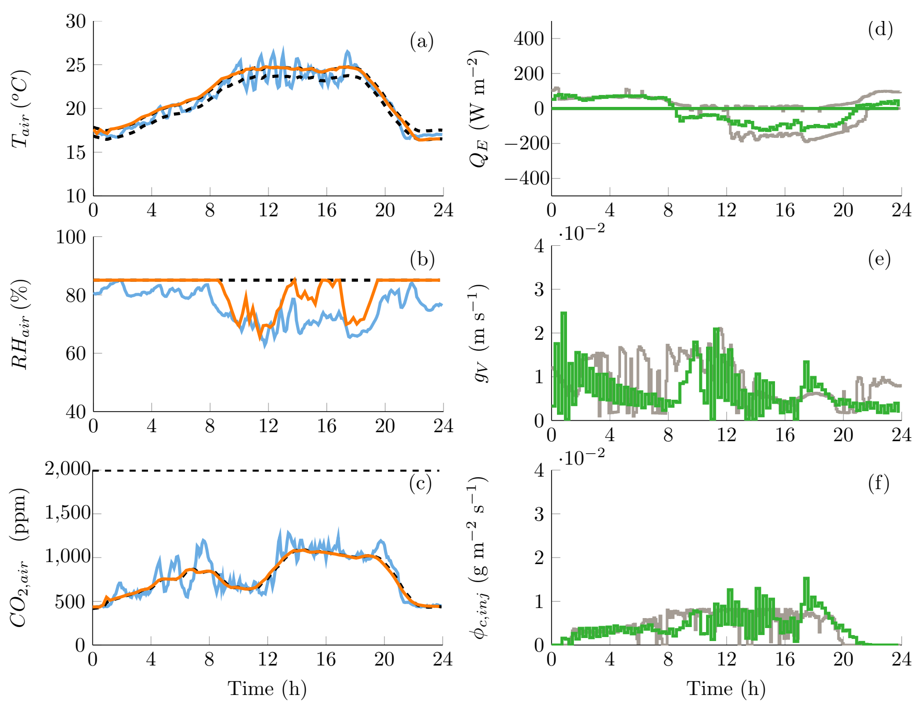


Figure 3: Optimal states (———) and optimal control trajectories (———) for June 16, 2012 with standard settings. The dashed black lines are the bounds. The realized climate variables (———) and the control trajectories resulting from grower's operation (———) are also shown.

sum for the realized situation by the grower at 16 June, 2012 was 504 °C h and

511 °C h for the optimal situation. The temperature sum will, with the chosen standard settings, always be comparable with the realized temperature sum of the grower, which ensures comparable plant growth and development. The maximum allowed relative humidity in the greenhouse was 85 %. The relative humidity is kept at the upper bound during night, and is lower during day time. The amount of CO_2 injected by the grower and in the optimal situation were both 355 $\mathrm{g\,m^{-2}\,d^{-1}}$, which means that all available CO_2 was used. In the optimal situation, CO_2 is on the lower boundary all the time. Higher CO_2 concentrations are allowed, but not favorable because there is only a limited amount of CO_2 available, and the amount of heating and active cooling are minimized at the same time. Higher CO_2 levels can be achieved in the greenhouse, but more active cooling is needed to do so with the given constraints.

The minimal energy input (heating and cooling) at June 16, 2012 is 5.71 $\mathrm{MJ\,m^{-2}\,d^{-1}}$, of which 3.54 $\mathrm{MJ\,m^{-2}\,d^{-1}}$ cooling, and 2.15 $\mathrm{MJ\,m^{-2}\,d^{-1}}$ heating. Heating and active cooling resulting from grower's operation was 8.25 $\mathrm{MJ\,m^{-2}\,d^{-1}}$ where 4.97 $\mathrm{MJ\,m^{-2}\,d^{-1}}$ was cooling, and 3.28 $\mathrm{MJ\,m^{-2}\,d^{-1}}$ was heating. The net energy (heating - cooling) that was extracted from the greenhouse was 1.39 $\mathrm{MJ\,m^{-2}\,d^{-1}}$ for the optimal situation and 1.69 $\mathrm{MJ\,m^{-2}\,d^{-1}}$ for the grower's situation. The energy fluxes due to artificial lighting, radiation, and heat loss through the cover for the optimal situation were similar to the fluxes realized when following the strategy of the grower. The energy flux due to transpiration was little lower in the optimal case, which is caused by different temperature and humidity levels. Natural ventilation was higher in the optimal situation. However, active cooling was applied in the optimal situation to keep CO_2 in the greenhouse and maintain the desired CO_2 levels. Therefore, also less heating was applied in the greenhouse in the optimal situation. This difference was mainly due to the lower heating starting at 21 hour. Heating from 0 hour till 8 hour was almost the same in both situations. Active cooling started more early in the optimal situation, and less natural ventilation was applied between 8 and 12 hour than in the grower situation. The amount of active cooling was just enough to keep temperature on the upper bound. Because of the active cooling, also less CO_2

was injected between 8 and 12 hour.

Based on the realized greenhouse air temperature (Fig 3.a blue line) we can conclude that the chosen bandwidth of the smoothed temperature $\pm 0.5\,^{\circ}\mathrm{C}$ during night is also realised by the grower, while the grower allows higher fluctuations in the indoor temperature during day time. A larger bandwidth would allow the temperature to be higher, and thus less cooling would be needed. This could save energy too.

The daily optimization results with standard settings for the whole year 2012 are shown in Fig. 4. Not on all days optimal conditions were satisfied with the standard optimization settings. On 78 days (21 %), mainly during summer time, optimality conditions could not be satisfied. For these days, the calculated energy fluxes from the grower where used as optimal result. A correlation was observed between days with poor simulation performance and days with no optimal solution, especially for the simulation of the relative humidity. The average root mean square error between simulation and measurements of relative humidity was 6 % for days with an optimal solution, while this was 8 % for days with no optimal solution.

For most days in 2012, the optimal heat and cold input was lower than as the heat and cold input resulting from grower's operation. Energy input on days with outside temperatures below zero were comparable with the energy input obtained by the grower. In the optimal case, active cooling was applied on the same days as when the grower used active cooling. However, the grower applied active cooling ($Q_{he,cool} < 0.5\,\mathrm{MJ\,m^{-2}\,d^{-1}}$) on 127 days, where in the optimal result, active cooling ($Q_{E,cool} < 0.5\,\mathrm{MJ\,m^{-2}\,d^{-1}}$) was applied on only 105 days. Also the amount of cooling was lower in the optimal case. The total amount of heating, cooling, and CO_2 injection for the optimal situation and based on grower's operation are shown in Table 3. In the optimal case, 47 % less heating, 15 % less cooling, and 10 % less CO_2 were supplied to the greenhouse in the optimized situation.

Less CO_2 was supplied to the greenhouse in the optimal situation to fulfill the

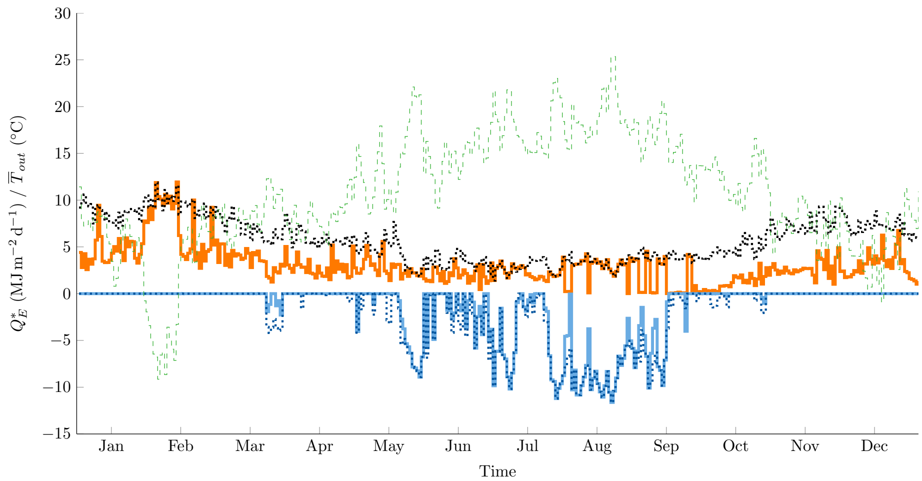


Figure 4: Results of daily optimization with standard settings for the year 2012. Optimal heating (—), optimal cooling (—), heating grower (⋯), cooling grower (⋯), and mean outside temperature(- - -).

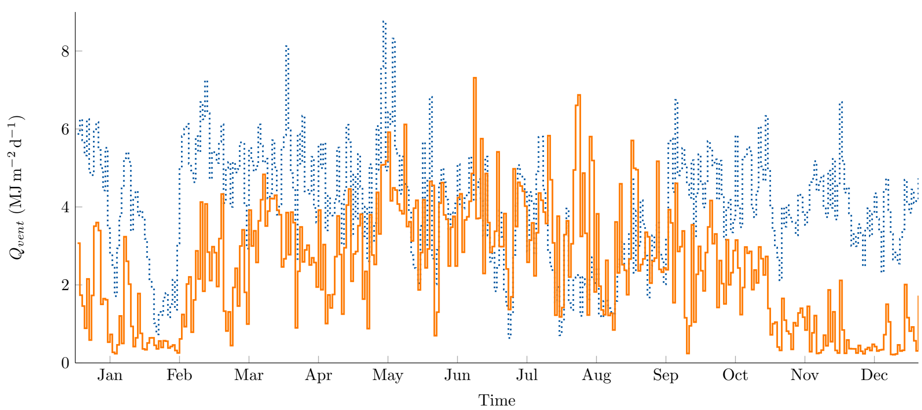


Figure 5: Daily optimal ventilation (—) and ventilation of the grower (⋯) Q_{vent} (MJ m^{-2} d^{-1}) for 2012.

CO_2 constraints (Table 3). This is mainly because of the lower daily ventilation flux in the optimal situation compared to the situation calculated based on grower's operation of the greenhouse (Fig. 5). In the optimal situation, daily ventilation was higher during some days in summer time. On these days, less heating and cooling were applied in the optimal situation, and temperature and

Table 3: Total heating, cooling, and CO_2 injection of the grower, the optimal situation with standard settings, and the optimal situation with minimum pipe temperature as used by the grower for 2012.

	Heating $GJ\,m^{-2}\,y^{-1}$	Cooling $GJ\,m^{-2}\,y^{-1}$	CO_2 injection $kg\,m^{-2}\,y^{-1}$
Grower	2.08	0.71	95.4
Opt standard settings	1.10	0.60	85.7
Opt minimum pipe	1.49	0.71	85.9

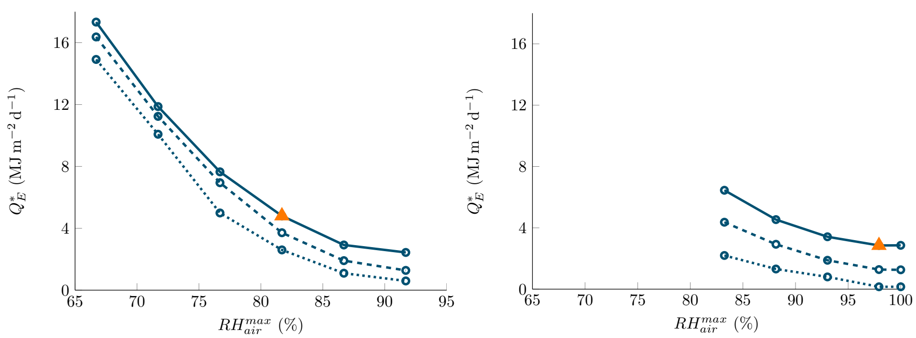
humidity constraints were fulfilled by a combination of some active cooling and natural ventilation. The energy input during the cold period in February was comparable with the strategy of the grower. The difference with strategy of the grower is that there is less ventilation in the optimal situation, and thus also less CO_2 injected to the greenhouse.

Optimal heating and cooling were also studied for the case with minimum pipe temperature. The minimum pipe temperature was the same as used by the grower. Reasons to use this in practice include creating air movement in the greenhouse and prevention of condensation on leaves and fruits. There were 59 days (16 %) where no optimal solution was found with the used optimization settings. Here, again the data from the grower was used. These days were all in periods with warmer outside conditions. Optimal heating was still 28 % lower and optimal cooling was 1 % higher compared to the grower (Table 3). Due to the minimum pipe, more heat was brought in the greenhouse, and greenhouse air temperature stays more close to or on the upper bound, compared to optimization with the standard settings. Therefore, more ventilation and active cooling was applied in case of optimization with minimum pipe temperature. Active cooling was used on 136 days. The CO_2 needed on a yearly basis was comparable to the situation with standard settings.

3.3. Analysis of optimization settings

3.3.1. Effect of temperature and humidity bounds

The effect of the lower and upper temperature bounds and the upper bound for the relative humidity RH_{air} on the optimal energy input was analyzed. The following temperature deviations ΔT were used: 0.5 °C (standard case), 2.0 °C, and 3.5 °C. A deviation of $\Delta T = 0.5$ °C means that the temperature is allowed to be 0.5 °C above or below the smoothed measured indoor temperature. The range for RH_{air}^{max} was −15 % to 10 % in steps of 5 % according to the highest measured RH_{air}. The analysis was done again for February 18, 2012 and for June 16, 2012.



(a) 18 February, 2012

(b) 16 June, 2012

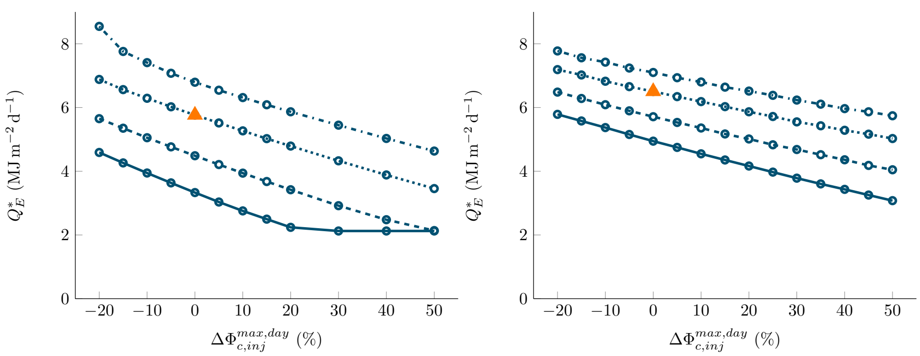
Figure 6: Optimal energy input Q_E^* for different temperature and humidity bounds for 18 February, 2012 (a) and 16 June, 2012 (b). Values for ΔT_{air} were 0.5 °C (), 2.0 °C (), and 3.5 °C (). All other settings were standard settings. ▲ is optimization with standard settings.

The required energy input to fulfill the constraints with standard settings for 18 February, 2012 was 4.8 MJ m^{-2} d^{-1}. It follows from the analysis that expanding the allowed temperature region leads to a lower energy input. Maintaining a lower relative humidity in the greenhouse leads to an increased energy input, because of the extra heating and ventilation needed to keep temperature between the bounds, on the one hand, and, on the other hand, to remove vapour from the air by natural ventilation. For June 16, 2012 the same effect was observed

(Fig. 6b).

3.3.2. Effect of CO_2 bounds

The effect of the lower bound for $CO_{2,air}$ and the total amount of CO_2 available per day $\Phi_{c,inj}^{max,day}$ on the optimal energy input were analyzed. This was done for June 16, 2012 and September 4, 2012. The former was a more cloudy day with high radiation levels (average radiation was $431\,\mathrm{W\,m^{-2}}$) and a mean outdoor temperature during the light period of 17.4 °C. The latter was a bright day with a mean outdoor temperature during the light period of 21.0 °C and average radiation of $437\,\mathrm{W\,m^{-2}}$. Active cooling was used by the grower on both days. Results of optimizing with four different levels of the lower bound $CO_{2,air}^{min}$ are shown in Fig. 7. February 18 was not selected to perform the analysis because no active cooling was applied on this day and CO_2 was not limiting the energy input. Therefore, there was no effect of small changes of the CO_2 bounds on the energy input. For the whole year, all available CO_2 was used on 282 days (77 %). The days where CO_2 was not limiting were days in spring and winter time.



(a) 16 June, 2012

(b) 4 September, 2012

Figure 7: Optimal energy input Q_E^* for different lower CO_2 bounds ($CO_{2,air}^{min}$) and available CO_2 ($\Phi_{c,inj}^{max,day}$) for 16 June, 2012 (a) and 4 September, 2012 (b). Values for $CO_{2,air}^{min}$ were the standard settings −20 % ( ), −13 % ( ), −3 % ( ), and 7 % ( ). All other settings were standard optimization settings. ▲ is optimization with standard settings.

On both 16 June (Fig. 7a) and 4 September (Fig. 7b) the total amount of available CO_2 has a strong effect on the minimal energy input. If CO_2 $\Phi_{c,inj}^{max,day}$ is reduced, then the energy input Q_E^* is higher. Less CO_2 is available and to still maintain the desired CO_2 concentration the windows have to be closed more to prevent CO_2 loss to the environment. If $\Phi_{c,inj}^{max,day}$ is higher, then the energy input is lower. This is not the case for situations where CO_2 is not a limiting factor and energy input is needed to fulfill temperature and humidity constraints. This is the case at 16 June when more than 20 % extra CO_2 is available per day. Changing the lower CO_2 bound $CO_{2,air}^{min}$ from the standard settings to lower values, i.e. when the CO_2 concentration is allowed to be lower, this leads to a lower energy input and vice versa. In this situation the ventilation windows can be opened more and less active cooling (which costs energy) can be applied to fulfill all constaints.

4. Discussion

The optimization method as presented in this paper has the advantage that no crop production models and price forecasts are needed. As a consequence, one of the most important factors that determines the real energy input in this method is the grower who defines the bounds. Defining the bounds based on the status and needs of the crop remains a task of the grower, while these do not necessarily have to be the most economic or energy efficient. Nevertheless, the formulation of the optimal control problem as proposed here has the potential for implementation in practice because it saves energy while ensuring the yield as envisaged by the grower. Settings where growers feel comfortable with like minimum pipe temperature and minimum ventilation can be easily implemented. Optimization with minimum pipe temperature can be done by changing the lower bound of Eq. (10) and optimization with minimum ventilation can be done by changing the lower bound of Eq. (12). After the optimization, the effect of these bounds on the energy input becomes clear and can be presented to the grower so that he can decide and learn on the basis of various scenarios.

The accuracy of the model and the measurements influences the result of the optimization. Therefore, a good model performance is important for the use of optimal control in practice.Another uncertain factor for the model performance is the accuracy and consistency of the measurement data. The CO_2 concentration was only measured at two locations in the greenhouse, while temperature and humidity were measured at eight different locations. Differences between the separate sensors occurred. The differences between the sensors (Section 3.1) were in the same range as the differences found by Bontsema *et al.* (2011), who studied the effect of inaccurate measurements on the energy consumption in a greenhouse. Other causes of these differences are spatial (horizontal and vertical) differences in the greenhouse climate. Opdam *et al.* (2005) explained the largest temperature deviations by the position of the sun. Also the measurements of the outdoor weather and control inputs have influence on the energy input and could be inaccurate. The sensitivity of the model and optimization procedure for these errors are part of further research.

In the optimization procedure, active cooling with the heat exchangers is used when there is a cooling demand and the total amount of available CO_2 is limited. When more CO_2 would be available, also less active cooling will be used in order to save energy. However, CO_2 also has costs and benefits. Higher CO_2 levels in the greenhouse influence the production. More available CO_2 also means that less active cooling can be used as long as all constraints are satisfied. To prevent excessive temperatures, as a consequence also more natural ventilation will be applied. This means that more CO_2 is then emitted to the environment, which could also be a goal to be minimized.

Compared to minimizing energy input as described in Van Beveren *et al.* (2015) the energy savings are lower in the current work. In the current work, a whole year was analyzed with constraints on temperature, humidity, and CO_2 concentration, while in the previous work 16 days spread over the year where analyzed with constraints on temperature and humidity only. The addition of the CO_2 balance and the maximum amount of CO_2 available per day are extra constraints which force the system to use active cooling more often. On many days when the grower used active cooling, this was also done in the optimal situation. This leads to a higher energy input compared to the previous work. However, still a distinct reduction in energy and CO_2 input was demonstrated with standard settings. How do these figures compare to other research reported on energy saving climate control? Other researchers applied optimal control techniques to greenhouse climate management and found energy savings in the range of 8 % (Tap, 2000) to 52 % (Van Ooteghem, 2007). The results reported in the current paper are in line with previous research. Also recent practical experiments reported high potential energy savings. De Zwart (2014) showed that energy savings of 24 % for a tomato crop are possible without effect on crop growth. Kempkes *et al.* (2014) reported savings up to 60 % of energy without affecting the production level by the use of a double glass cover, new growing strategies and a dehumidification system.

To realize the potential energy savings, practical implementation is needed. In current greenhouse climate control systems growers can specify a lot of settings in the process control computer, whereas the resulting greenhouse climate and consequences on the energy use of all these settings are not always clear to the grower. The optimization procedure as proposed in this paper would help growers to give them more insight in their decision making process regarding energy management. This can be done a posteriori, and the grower can learn from alternative strategies that could be followed instead of his own strategy based on historical data. This would be the first step towards a fully automated system where the grower has only a supervisory role, and defines the long term goals. This first step is an important step for successful implementation to let the grower build trust in the outcome of the system (Van Straten *et al.*, 2000). An intermediate step would be prediction of the optimal trajectories one day ahead. To do this, a weather forecast for the next day is needed, and it would require an additional tool to determine the greenhouse climate based on the actual settings of the grower.

5. Conclusion

An optimization framework to minimize energy input to greenhouses, which takes into account temperature, humidity, and CO_2 concentration was presented. A model for temperature, humidity, and CO_2 concentration was validated for one year of data from a 4 ha commercial greenhouse. A potential reduction of 47 % for heating and 15 % for cooling were found for the year 2012 with standard settings. When the minimum pipe temperature of the grower was implemented, still, a reduction of 28 % for heating was found. Cooling in this case was comparable to the grower. Total CO_2 injection was in both cases 10 % lower. Furthermore, it was shown that active cooling was used on days were CO_2 was a limiting factor. Also the potential effect of changing the bounds on energy and CO_2 input can be demonstrated to the grower.

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Appendix A. Model performance measures

The Mean Absolute Error (MAE) and Root Mean Square Error ($RMSE$) were calculated as

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid \tag{A.1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}. \tag{A.2}$$

where $\hat{y}_i$ is the simulated value at time i, y_i is the measured value at time i, and n the number of measurements Wallach *et al.* (2014).

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