Open-Loop Optimal Temperature Control in Greenhouses

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Abstract

Earlier research has revealed that considerable energy savings can be achieved by maintaining an average temperature in the greenhouse in stead of maintaining rigid pre-defined temperature 'blue-prints'. A model based optimal control approach has proven to be a suitable framework to tackle these kind of control problems and it has been shown that these algorithms can be implemented on-line. But, when on-line optimal temperature control is considered, interesting questions arise, some of which are still unresolved. The issue tackled in this paper concerns the relation between the resolution of the control strategy (sample time) and energy savings of the control strategy. One would expect that an accurate and frequent anticipation to changing outdoor climate conditions might result in reduced energy consumption. It was indicated in the literature that a sample-time of 0.25 h or 1 hour should be sufficient, but these choices were hardly motivated. In this research, the relation between the control resolution and energy savings was quantitatively investigated using a dynamic greenhouse climate model and measurements of Dutch outdoor climate conditions containing high-frequency components. The results indicate that for an open-loop optimal control problem concerning the realization of an average temperature during a fixed period of one day using a minimum amount of energy with full a-priori knowledge of the outdoor weather, a resolution of the heating profile between half an hour and a hour suffices to produce accurate results in terms of energy conservation. These results were not much affected by parameter variations (heat capacity of the air, the solar heating efficiency) or opening and closing of thermal screens.

INTRODUCTION

Various researchers have shown that considerable energy savings can be achieved by maintaining an average temperature in the greenhouse in stead of maintaining rigid pre-defined temperature 'blue-prints'. The main feature of the former approach is that, heating is shifted from unfavourable periods with large energy losses to periods with smaller energy losses whilst requiring that during a predefined period of time an average temperature in the greenhouse is maintained. A model based optimal control approach has proven to be a suitable framework to tackle these kind of control problems (Bailey and Seginer, 1989; Gutman et al., 1993; Chalabi et al., 1996; Ioslovich et al., 1996).

Chalabi et al. (1996) have shown that this approach can be implemented on-line in a greenhouse with success. But, when on-line optimal temperature control is considered, interesting questions arise, some of which are still unresolved. The question tackled in this paper is: 'What is the relation between the resolution of the control strategy (sample time) and the energy savings?' Chalabi et al. (1996) calculated hourly optimum temperature setpoints but did not motivate this choice of the sample time. They used a dynamic greenhouse climate model but weather data consisted of predictions of one hour averages. Gutman et al. (1993) indicated that a sampling interval of 0.25 h was sufficiently short. Shorter sampling intervals gave essentially the same solution. However, they used a steady-state model of the greenhouse air temperature and data of external conditions like solar radiation, wind speed and temperature containing only very lowfrequency variations. In this research, for an open-loop optimal control problem concerning the minimum energy realization of pre-defined temperature integral, the relation between the sampling time and energy savings was quantitatively investigated using a dynamic greenhouse climate model and realistic Dutch outdoor climate conditions containing high-frequency components.

MATERIALS AND METHODS

Definition of the Optimal Control Problem

The dynamics of the greenhouse temperature X_T were described by:

$$\dot{X}_T = \frac{1}{c_{cap}}\left\{c_I V_I + U_Q - \left(sign(V_I)(5+0.5V_W) + (1-sign(V_I))(3+0.3V_W)\right)(X_T - V_T)\right\} \tag{1}$$

in which $c_{cap} = 5800$ J.m^{-3}.°C^{-1} is the heat capacity of the greenhouse air, V_I in W.m^{-2} is the solar radiation outside the greenhouse, $c_I = 0.25$ is the solar heating efficiency, U_Q in W.m^{-2} is the energy input by the heating system, V_W in m.s^{-1} is the wind speed and V_T in °C is the temperature outside the greenhouse. The function $sign(V_I)=0$ if $V_I = 0$ and $sign(V_I)=1$ if $V_I > 0$. Based on this notion, the term $(sign(V_I)(5+0.5V_W))$ + $(1-sign(V_I))(3+0.3V_W)$ represents the influence of thermal screens on thermal transmission losses at night time. In this model it was assumed that the heating system was able to produce heating energy instantaneously. This holds for direct fired air heating systems, but is a rather course approximation of generally used hot water heating systems commonly used in Dutch horticultural practice. This model of the air temperature is the dynamic equivalent of the quasi steady-state used by Gutman et al. (1993) and Ioslovich et al. (1996).

The evolution of deviations from a desired mean temperature c_{Tref} was described by

$$\dot{X}_{TI} = \left(X_T - c_{Tref}\right) \tag{2}$$

Accumulated energy consumption was represented by the state X_{EC} of which the evolution was described by

$$\dot{X}_{EC} = U_Q \tag{3}$$

The objective was to generate an open-loop optimal control strategy $U_Q^*(t)$ on the fixed interval $t \in \left[t_b, t_f\right)$, given full a-priori information of the external inputs V_I, V_W and V_T, such that the performance measure J defined as

$$J = c_{XTI} X_{TI}\left(t_f\right)^2 + c_{EC} X_{EC}\left(t_f\right)^2 \tag{4}$$

was minimized. Given a suitable choice of the weighting parameters c_{XTI} and c_{EC}, this performance criterion assured that over the interval $\left[t_b, t_f\right)$ a control strategy was generated for U_Q such that using a minimum amount of energy $X_{TI}\left(t_f\right) \cong 0$, *i.e.* that over the time interval $\left[t_b, t_f\right)$ the average temperature equalled approximately c_{Tref}. In this research the optimization interval was set at one full day. In this optimization, the energy input by the heating system was required to satisfy the constraints

$$0 < U_Q < 150. \tag{5}$$

The current analysis was limited to cases in which only heating was needed. Cooling or ventilation based removal of humidity were not considered in this research.

Also, no limitations were imposed on the indoor temperature, *i.e.* this optimal control problem did not contain a constraint on X_T. The weighting parameters c_{XTI} and c_{EC}, were empirically chosen and then fixed during all optimization runs presented below.

Solution of the Optimal Control Problem

The methodology used in this research to solve the optimal control problem was based on the transformation of the infinite dimensional dynamic optimization problem of equations (1) to (5) into a finite dimensional Non-Linear Programming (NLP) problem by means of control parameterization. The continuous and infinite dimensional control trajectory $U_Q(t)$ were approximated by N piecewise constant control inputs as follows

$$U_Q(t)=U_Q(t_k),\, t\in[t_k,t_{k+1}),\; k=0,1,...,N-1, \tag{6}$$

where $t_0=t_b$ and $t_N=t_f$. Here t_k, $k=0,1,...,N$ are equidistant sampling instants, $t_{k+1}-t_k=\Delta t$ is a fixed sampling period and N is the number of time intervals. Then, with $\Upsilon_Q(k)=U_Q(t_k)$ for $k=0,1,...,N-1$, the control trajectory $U_Q(t)$, $t_b\le t\le t_f$ is fully determined by the so-called control parameter vector $\overline{\Upsilon}_Q\equiv[\Upsilon_Q(0),\Upsilon_Q(1),...,\Upsilon_Q(N-1)]\in\Re^{1\times N}$. Given $\overline{\Upsilon}_Q$ and the initial condition $X_T(t_b)$, numerical integration of equations (1) to (3) yielded a value for the performance measure J using equation (4). In this way the continuous time optimal control problem defined in equations (1) to (5) was transformed into the $1\times N$ - dimensional NLP problem of finding the control parameter vector $\overline{\Upsilon}_Q$ minimizing J.

In this research, the differential equations were solved using the variable time-step Runge-Kutta algorithm of Shampine (1978). The NLP problem was solved using the Sequential Quadratic Programming software FFSQP (Zhou et al., 1997).

Interesting feature of this approach is that it allows to vary the number of control parameters N and to evaluate the effect on the calculated optimal performance J^*. Goh and Teo (1988) have shown that for $N\to\infty$, $J^*(\overline{\Upsilon}_Q)$ converges to $J^*(U_Q)$. Usually, the computational load increases with increasing N. Based on the results of Goh and Teo (1988), a practical approach to calculating an accurate approximation of U_Q is to start with a small number of control parameters and to use the computed result as an initial guess for a calculation with a larger number of control parameters and to increase N until $J^*(\overline{\Upsilon}_Q)$ does not significantly change anymore. In this research, this approach was used to investigate the relation between the resolution of the control strategy and the resulting energy consumption, to assess the smallest value of N producing satisfactory returns in terms of additional energy conservation.

Optimizations

Optimal heating profiles were calculated for 20 individual days ranging from day 71 to day 90 in 2004. One minute measurements of the solar radiation, the wind speed and the outdoor temperature were used as external inputs. The average daily temperature was required to be 20°C. In the consecutive optimization runs the number of control parameters N was set at 1, 2, 4, 8, 32, 64, 128, 256, 512 and 1024. In all cases the optimization was started with a start value of the control parameter set $\Upsilon_Q(k)=0$, $k=0,1,...,N-1$. In total four different optimization runs were done.

1. Relation between the Resolution of the Heating Profile and the Energy Consumption. For 20 days in 2004, optimization of the heating profile with an increasing resolution of the control heating profile yielded a first insight into the relation between control resolution and energy consumption.

2. The Effect of the Heat Capacity on the Relation between Control Resolution and Energy Consumption. Since the heat capacity of the air both influences the energy consumption as well as the dynamic response of the system, the results were expected to be sensitive to the actual value of the heat capacity. Therefore, the sensitivity of the results to variations in the heat capacity of the air was evaluated by performing an optimization using a heat capacity 0.1 as well as 10 times the originally used value.
3. The Effect of the Solar Radiation on the Control Resolution and Energy Consumption. Since solar radiation is a major energy input into the greenhouse system the effect of variations in the solar radiation was evaluated by performing an optimization using a solar heating efficiency of 0.2 and 0.3, respectively.
4. The Effect of Thermal Screens on the Relation between Control Resolution and Energy Consumption. Thermal screens have a strong impact on the energy consumption of the greenhouse. Therefore, optimizations were done for twenty days for a greenhouse without thermal screens to assess their impact on the results obtained.

RESULTS AND DISCUSSION

Figure 1 shows an example of the outdoor conditions during one of the 20 days. Although slow trends are clearly present, some more high frequent variations are present as well. Figure 2 shows with an increasing resolution, for the similar day as in Figure 1, the heating profile and the temperature profile. This figure demonstrates two things. First of all, as expected, with an increasing resolution more and more variations become eminent in the heating profile although these variations are relatively small and slowly varying. Secondly, with an increasing resolution the heating profiles seem to converge as suggested and formally proven by Goh and Teo (1988). With increasing number of control parameters the modifications of the heating profile become smaller and smaller. The same holds for the temperature profile as can be seen in the same figure. In all cases the mean temperature of 20°C was realized with an accuracy better than ±0.1°C. At this point, it is interesting to get more insight into the relation between the resolution and the energy consumption. Figure 3 shows the relative energy consumption as a function of N for the 20 individual days. The energy consumption for $N = 1$ was used as reference value. This figure reveals essentially three things. First of all, with increasing N, energy consumption decreases, but the reduction of the energy consumption becomes smaller when N becomes larger. Secondly, there is a difference in energy savings between the individual days. Some days, energy conservation is large when the number of sample intervals is increased. On other days, the energy savings are smaller. Energy conservation ranges between 5 and 13% for the days considered in this research. Finally, it is intriguing to see that reductions in energy consumption are achieved for values of N up to 100. Beyond 100 sample intervals the additional energy conservation becomes very very small, i.e. less than 0.1%. Even between 32 and 100 improvements are relatively small. In most cases additional energy conservation reduces to less than 0.5% for $N > 32$. This suggests that for this particular optimization problem an update frequency of the heating profile of approximately every half an hour to an hour is sufficient.

Figure 2 shows a phenomenon more often encountered when solving fixed period optimal control problems. In all cases, towards the end of the optimization period the heating profile and consequently the greenhouse temperature shows a rapid decline. Apparently, towards the end of the optimization period there is no reward for a continuing or additional investment of energy. Though theoretically sound, this is not a practical approach from a horticultural point of view.

Variations in the heat capacity did affect energy consumption. As expected, a higher heat capacity resulted in higher energy consumption and vice-versa. But variations in the heat capacity did not strongly affect the relation between the number of control samples N and additional energy conservation. The same holds for variations in the solar heating efficiency parameter. As expected, a higher solar heating efficiency resulted in reduced energy costs and vice versa. Since solar heating and gas fired heating have similar effects on the system, rapid anticipation of the heating strategy to variations in the solar radiation was expected to be advantageous. And consequently, varying the solar heating efficiency parameter should have a clear effect. An effect, however, was not clearly visible. Due to limited space, simulation results are not shown.

Finally, Figure 4 shows the relation between the relative energy consumption and the control resolution in case thermal screens were not closed at night. These results are rather interesting. Two things can be observed. First, the effect of the resolution of the control strategy on the relative energy consumption is much smaller than with a greenhouse in which screens are closed at night. Apparently, accurate anticipation with the heating strategy to the transients in the air temperature and changes in energy loss due to opening and closing of the thermal screens, pays off. Secondly, as observed in the other optimizations, increasing N beyond 100 hardly has a return in terms of additional energy conservation.

CONCLUDING REMARKS

The results indicate that for an open-loop optimal control problem concerning the realization of an average temperature during a fixed period of one day using a minimum amount of energy, a resolution of the heating profile between half an hour and a hour is sufficient to produce results with sufficient accuracy in terms of energy conservation. These results were not much affected by variations in the heat capacity of the air, the solar heating efficiency or opening and closing of thermal screens.

Future research will focus on the effect of ventilation needed to cool or de-humidify the greenhouse, limitations on the indoor temperature and the assumption on a-priori knowledge of the outdoor climate, on the relation between the control resolution and energy savings will be explored.

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Figures

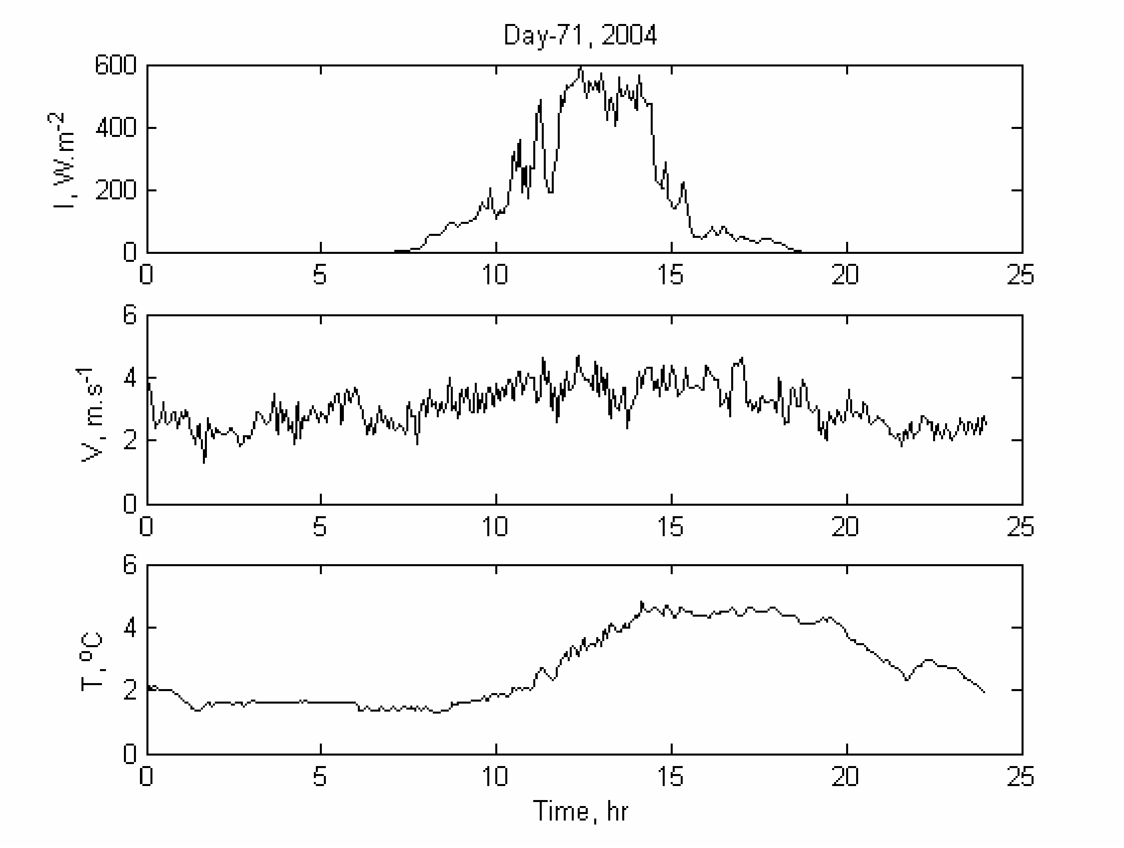

Fig. 1. Outdoor climate conditions on day 71 in 2004; solar radiation (top), windspeed (middle) and temperature (bottom).

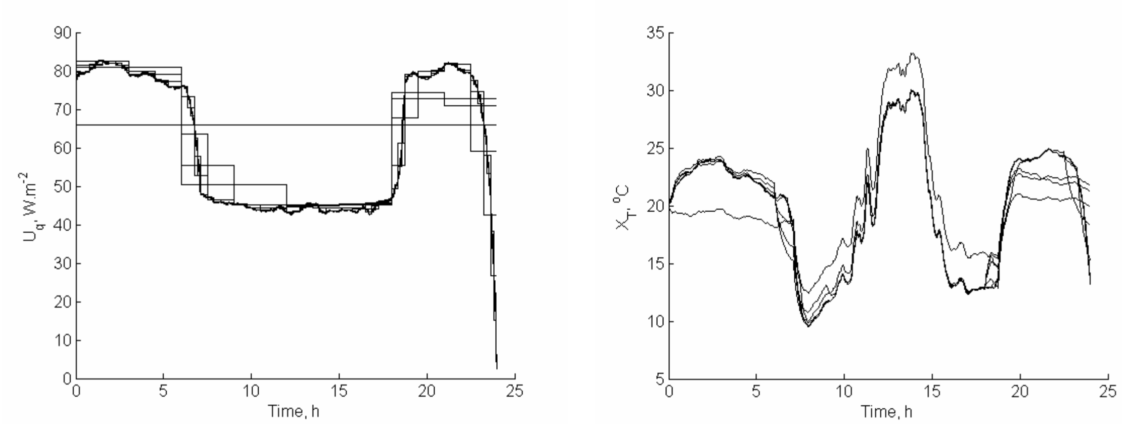

Fig. 2. Heating profiles (left) and the resulting greenhouse air temperature (right) using a control profile resolution of 1, 2, 4, 8, 16, 32, 64, 128, 256, 512 and 1024 control samples, calculated for day 71 in 2004.

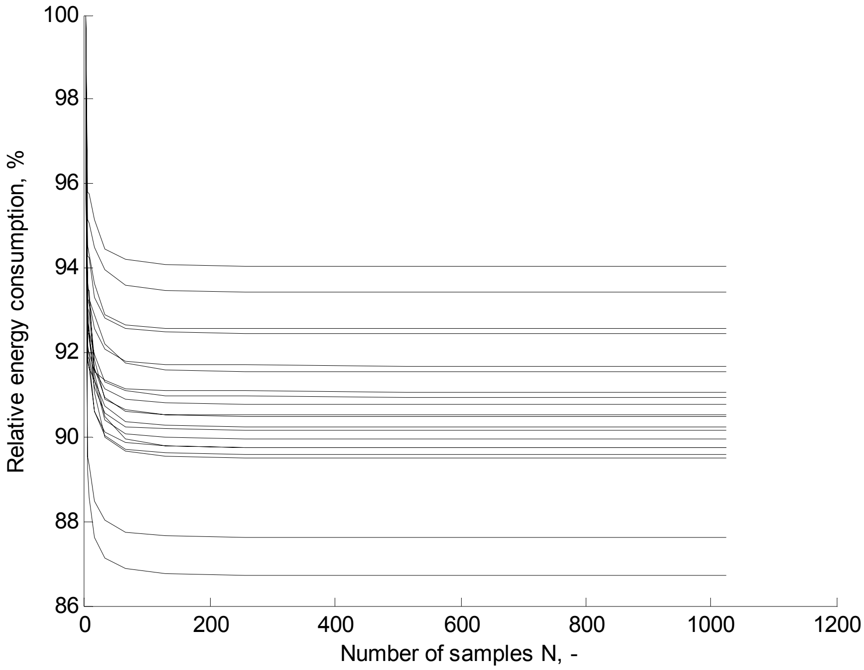

Fig. 3. The relation between the resolution of the heating profile calculated for day 71 to day 90 in 2004 using a control resolution of 1, 2, 4, 8, 16, 32, 64, 128, 256, 512 and 1024; each line represents one of the twenty individual days.

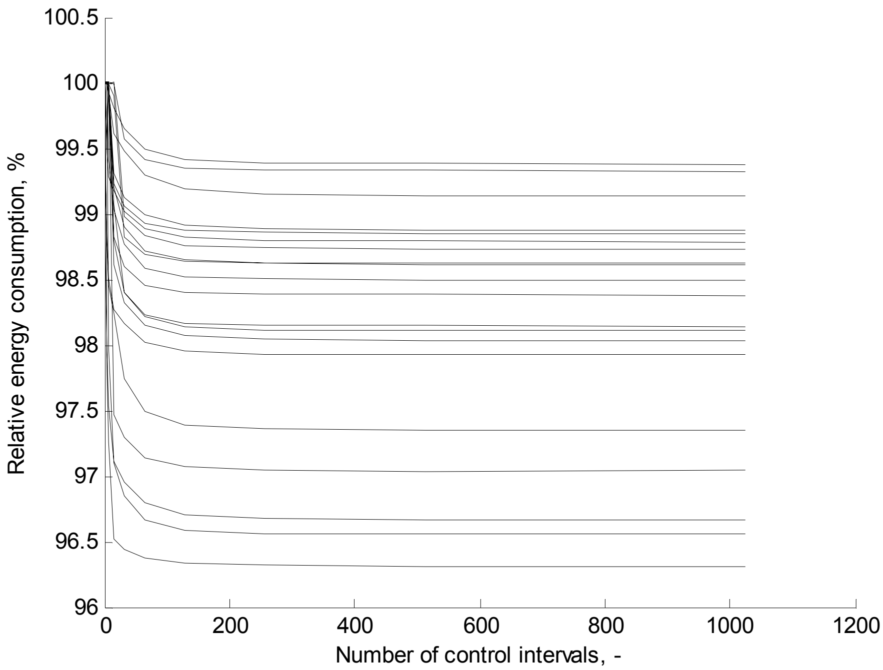

Fig. 4. The relation between the resolution of the heating profile calculated for day 71 to day 90 in 2004 using a control resolution of 1, 2, 4, 8, 16, 32, 64, 128, 256, 512 and 1024 for a greenhouse without thermal screens; each line represents one day.