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GREENHOUSE CLIMATE MODEL PREDICTIVE CONTROL FOR ENERGY COST SAVING

Dong Lin*, Lijun Zhang, Xiaohua Xia

Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria 0002, South Africa

ABSTRACT

In this paper, an optimal strategy for greenhouse climate control is proposed. The objective is to minimize the total energy cost for greenhouse heating and cooling while keeping the greenhouse climatic conditions (temperature, relative humidity, carbon dioxide concentration) within required ranges. A dynamic model with three inputs and three outputs is adopted. The time-of-use electricity tariff is considered to calculate the energy cost. The proposed strategy is compared with an optimal control strategy which aims at minimizing the total energy consumption. In order to reduce the impact of system disturbance, a model predictive control (MPC) method is presented. The performance index (relative deviation mean) of the proposed MPC and an open loop control are calculated under 2 % system disturbances. The results show that compared with the strategy of minimizing energy consumption, the proposed strategy has higher energy consumption but lower cost. Moreover, MPC has better tracking performance than open loop control.

Keywords: Greenhouse climate, Energy cost, Time-of-use, Model predictive control

NONMENCLATURE

Abbreviations	
MPC	Model Predictive Control
RDM	Relative Deviation Mean
TOU	Time-of-use

1. INTRODUCTION

Greenhouses provide suitable growth conditions for crops to increase crop yields and improve production quality [1]. Lots of energy is consumed to keep the climate factors in the greenhouse within the required range [2-3]. To reduce energy consumption, many different control strategies are proposed. For example, a strategy of decreasing the energy consumption of electric heaters in a greenhouse is studied in [4]. A control approach of greenhouse heating using computational fluid dynamics and energy prediction model for energy saving is proposed in [5]. These control methods can reduce energy consumption, but the energy costs may still be high. There are also some studies focusing on different methods to minimize the energy cost of greenhouse control. For instance, a hierarchical control approach to minimize the total energy cost and demand charges is proposed in [6]. In [7], the potential of a solar water system for reducing heating cost is studied.

In this paper, an optimal control strategy is proposed to minimize the total energy cost under the time-of-use (TOU) electricity tariff. The TOU tariff is a policy to encourage people to shift load from the peak period to the off-peak period [8]. The application of peak load shifting strategy for energy cost savings can be found in [9-11].

Moreover, in order to reduce the impact of system disturbances, a model predictive control (MPC) strategy is introduced and is compared with an open loop control strategy. MPC can effectively address system disturbances and has been applied to building energy efficient optimization [12], hybrid power system energy dispatching [13], heavy-haul trains operation optimization [14], energy-water management in urban households [15], and dynamic economic dispatch of power generation [16].

The rest of this paper is organized as follows. The greenhouse climate model is proposed in Section 2. The simulation results are shown in Section 3. Section 4 is the conclusion.

2. SYSTEM DESCRIPTION

The greenhouse climate control system studied includes three inputs (heating/cooling, ventilation, and CO_2 injection) and three outputs (temperature, relative humidity and CO_2 concentration). The system disturbances include the outdoor temperature, humidity, CO_2 concentration, and solar radiation, etc. Figure 1 is the schematic diagram of a greenhouse climate control system.

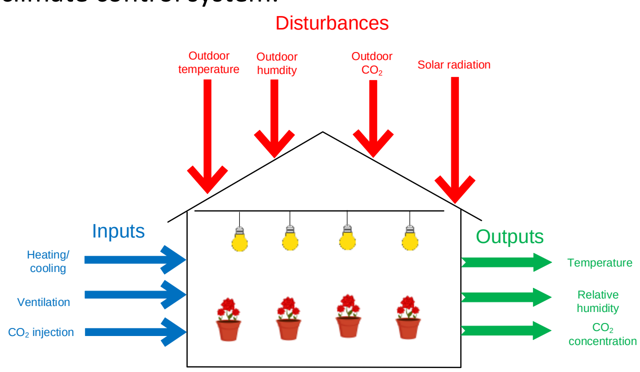

Fig. 1. Greenhouse climate control system.

2.1 Greenhouse model

In this paper, the models presented in [17] and [18] are adopted and given by:

$$\frac{dT_{air}}{dt} = \frac{1}{C_{cap}}\left(Q_{sun} + Q_{lamp} - Q_{cov} - Q_{trans} - Q_{vent} + Q_c\right) \quad (1)$$

where T_{air} is the temperature in the greenhouse, C_{cap} is the heat capacity of air, Q_{sun} is the incoming radiation power, Q_{lamp} is the lamp heating power, Q_{cov} is the heat transfer through the cover, Q_{trans} is the energy extraction due to crop transpiration, Q_{vent} is the energy lose through ventilation, Q_c is the controlled heating or cooling power.

$$\frac{dH_{air}}{dt} = \frac{1}{h}\left(H_{trans} - H_{cov} - H_{vent}\right) \quad (2)$$

where H_{air} is the humidity in the greenhouse, h is the average height of the greenhouse, H_{trans} is the vapour evaporated by the crop, H_{cov} is the vapour condensation to the cover, H_{vent} is the humidity change due to ventilation.

$$\frac{dC_{air}}{dt} = \frac{1}{h}\left(C_{inj} - C_{ass} - C_{vent}\right) \quad (3)$$

where C_{air} is the CO_2 concentration in the greenhouse, C_{inj} is the CO_2 injection rate, C_{ass} is the CO_2 assimilation speed, C_{vent} is the CO_2 concentration change caused by ventilation. Q_{vent}, H_{vent} and C_{vent} are related to the ventilation rate g_v.

2.2 System constraints

The system constraints include inputs constraints and outputs constraints. The inputs constraints are given by:

$$Q_{c,\min} \le Q_c \le Q_{c,\max} \quad (4)$$

$$g_{v,\min} \le g_v \le g_{v,\max} \quad (5)$$

$$C_{inj,\min} \le C_{inj} \le C_{inj,\max} \quad (6)$$

where $Q_{c,\min}$ and $Q_{c,\max}$ are the lower and upper bounds of heating or cooling power. $g_{v,\min}$ and $g_{v,\max}$ are the lower and upper bounds of ventilation rate. $C_{inj,\min}$ and $C_{inj,\max}$ are the lower and upper bounds of the CO_2 injection speed.

$$\left|\frac{dQ_c}{dt}\right| \le c_1 \quad (7)$$

$$\left|\frac{dg_v}{dt}\right| \le c_2 \quad (8)$$

$$\left|\frac{dC_{inj}}{dt}\right| \le c_3 \quad (9)$$

where c_1, c_2 and c_3 are the change rate limits of the input variables heating or cooling power, ventilation rate and CO_2 injection speed.

The outputs constraints are given by:

$$T_{air,\min} \le T_{air} \le T_{air,\max} \quad (10)$$

$$RH_{air,\min} \le RH_{air} \le RH_{air,\max} \quad (11)$$

$$CO_{2,air,\min} \le CO_{2,air} \le CO_{2,air,\max} \quad (12)$$

where $T_{air,\min}$, $RH_{air,\min}$ and $CO_{2,air,\min}$ are the lower bounds of temperature, relative humidity and CO_2 concentration, $T_{air,\max}$, $RH_{air,\max}$ and $CO_{2,air,\max}$ are the upper bounds of temperature, relative humidity and CO_2 concentration.

2.3 Objective function

The objective of the proposed control strategy is to minimize the total energy cost for heating and cooling. Therefore, the following objective function is adopted.

$$J = \int_{t_i}^{t_f} s\left|Q_c(t)\,p(t)\right|dt \quad (13)$$

where t_i and t_f are the initial and the final time of optimization respectively. s is the greenhouse area. $p(t)$is the electricity price at the time t. In this paper, the time-of-use tariff in South Africa is adopted and given by:

$$p(t)=\begin{cases} p_o & t\in[0,6]\cup[22,24] \\ p_s & t\in[9,17]\cup[19,22] \\ p_p & t\in[6,9]\cup[17,19] \end{cases} \quad (14)$$

where p_o, p_s and p_p are the off-peak, standard, peak TOU tariff in R/kWh. R is the South Africa Currency, Rand.

2.4 Open loop controller design

The discretized state-space model is as follows:

$$x(k+1)=f(x(k),u(k)) \quad (15)$$

where k is the current time kT_s, T_s is the sampling interval, x=(T_{air}, RH_{air}, C_{air}) is the state variable, u=(Q_c, g_v, C_{inj}) is the input variable. The objective function is given by:

$$J_1=\sum_{k=1}^{N} s\left|u_1(k)\,p(k)\right| \quad (16)$$

where $N=T/T_s$. T is the total simulation time. u_1 is the input variable Q_c. The open loop controller is to solve the problem that minimizing the objective function Equation (16) subjects to the constraints from (4) to (12).

2.5 MPC controller design

The objective of MPC is to track the reference trajectories obtained from the open loop optimization (Equation (16)) and reduce the change of input variables. Therefore, the following objective function is adopted.

$$J_2=\sum_{i=1}^{N_p}\left(\Delta x(k+i\mid k)\right)^T Q\left(\Delta x(k+i\mid k)\right) + \sum_{i=1}^{N_c}\left(\Delta u(k+i-1\mid k)\right)^T R\left(\Delta u(k+i-1\mid k)\right) \quad (17)$$

where N_p and N_c are the optimization horizon and the control horizon respectively. Q and R are weighting matrices. Δx and Δu are the tracking error and change of variables respectively and given by:

$$\Delta x(k+i\mid k)=x(k+i\mid k)-x_{ref}(k+i) \quad (18)$$

$$\Delta u(k)=u(k\mid k)-u_{ref}(k) \quad (19)$$

where x_{ref} and u_{ref} are the reference values of state variables and input variables. u_{ref} is the results of the open loop optimization. x_{ref} is the state variables corresponding to the open loop optimization results u_{ref}.

The MPC control is to minimize the objective function Equation (17) and subjects to the constraints from (4) to (12). The optimal control is implemented in a receding horizon scheme that the first value of the solutions is adopted and the rest are discarded.

3. SIMULATION RESULTS

In this paper, a Venlo-type commercial greenhouse for rose cultivation presented in [17] and [18] is studied. The meteorological data is from a weather station at the University of Pretoria and shown in Figure 2 and Figure 3. The parameters of the greenhouse are shown in Table 1.

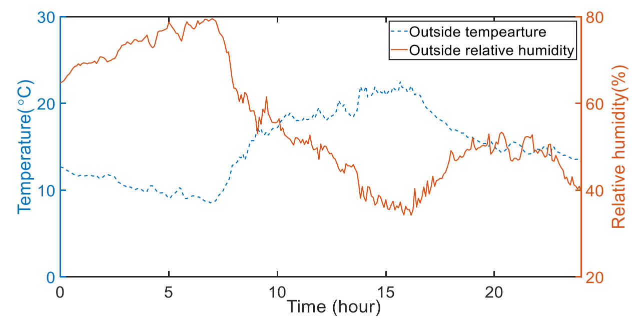

Fig.2 Temperature and relative humidity

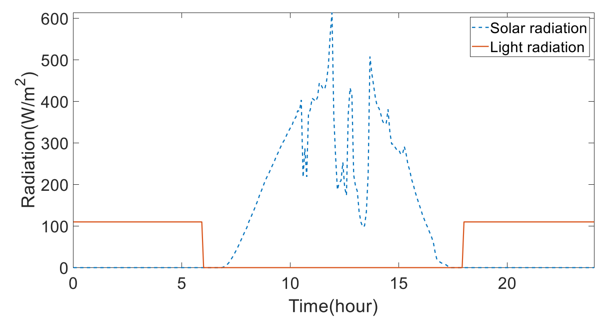

Fig.3 Solar radiation and light radiation

Table 1. Greenhouse parameters

Variable	Value	Unit
C_{cap}	30000	J/m² °C
h	7	m
s	40709	m^2
$Q_{c,min}$	-200	W/m^2
$Q_{c,max}$	200	W/m^2
$g_{v,min}$	0	m/s
$g_{v,max}$	0.02	m/s
$C_{inj,min}$	0	g/m^2s
$C_{inj,max}$	0.02	g/m^2s
c_1	0.51	W/m^2s
c_2	5.1×10^{-5}	m/s^2
c_3	5.1×10^{-5}	g/m^2s^2
$T_{air,min}$	14	°C
$T_{air,max}$	26	°C
$RH_{air,min}$	50	%
$RH_{air,max}$	90	%
$CO_{2,air,max}$	500	ppm
$CO_{2,air,min}$	2000	ppm

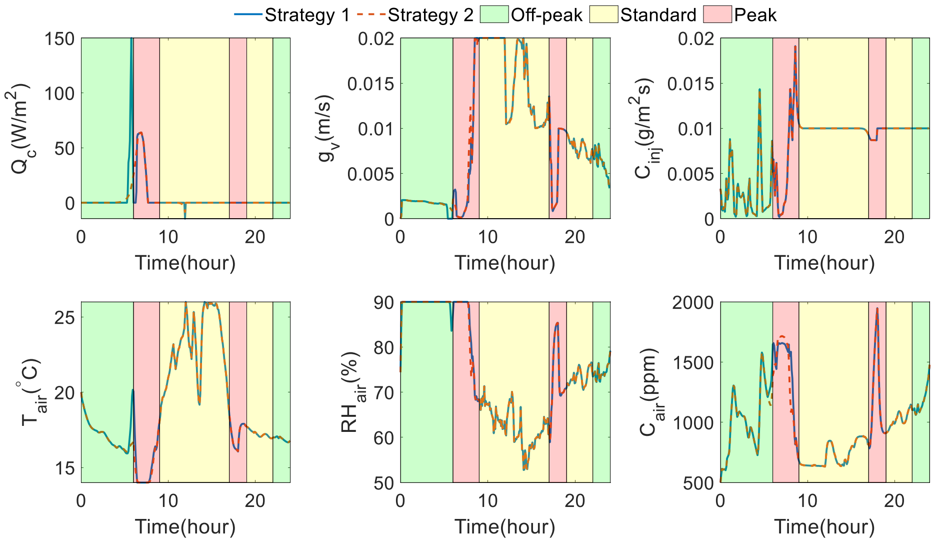

Fig. 4. Comparison of different optimization strategies

The proposed strategy (Strategy 1) is compared with a strategy which aims to minimize the total energy consumption (Strategy 2). For Strategy 2, $p(t)$=1. The simulation results are shown in figure 4. The energy consumption and energy cost are calculated and shown in Table 2. The total energy consumption of Strategy 1 (4502.37 kWh) is more than the total energy consumption of Strategy 2 (3587.39 kWh). However, the total energy cost of Strategy 1 (R 9052.08) is less than the total energy cost of Strategy 2 (R 9941.20). That is because Strategy 1 consumes less energy (2591.36 kWh) than Strategy 2 (3111.91 kWh) during peak periods when the electricity price is much higher than the standard period and off-peak period.

Table 2. Comparison between MPC and open loop control.

	Energy consumption (kWh)		Energy cost (Rand)	
	Strategy 1	Strategy 2	Strategy 1	Strategy 2
Off-peak	1861.67	395.15	960.07	203.78
Standard	49.34	80.33	46.61	75.88
Peak	2591.36	3111.91	8045.40	9661.54
Total	4502.37	3587.39	9052.08	9941.20

An MPC method is proposed to compare with the open loop control used in Strategy 1. The MPC parameters are as follows: the predictive horizon N_p=600 s, the control horizon $N_p=N_c$, the weighting matrix Q=diag(100,100,100), R=diag(1,1,1). The results of minimizing the total energy cost (Strategy 1) are taken as the reference trajectories. The comparison between the MPC and the open loop control under 2% system disturbances is shown in Figure 5. The performance index relative deviation mean (RDM) is calculated to compare the tracking performance of the open loop and MPC. Denote the value of measurement as x_{meas}, the reference value as x_{ref}, then the RDM can be obtained by:

$$\mathrm{RDM} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_{meas}(i) - x_{ref}(i)}{x_{ref}(i)}\right| \tag{20}$$

The RDM of open loop control and MPC are shown in Figure 6. Compared with open loop control, MPC reduces 48.40% temperature RDM (from 2.81 to 1.45), 66.77% relative humidity RDM (from 3.31 to 1.10), 78.83% CO_2 concentration RDM (from 4.77 to 1.01). The results show that MPC has better tracking performance than open loop control.

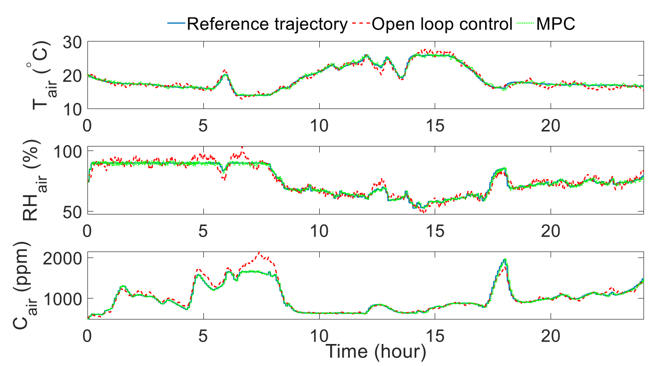

Fig. 5. Comparison of MPC and open loop control under 2% system disturbances.

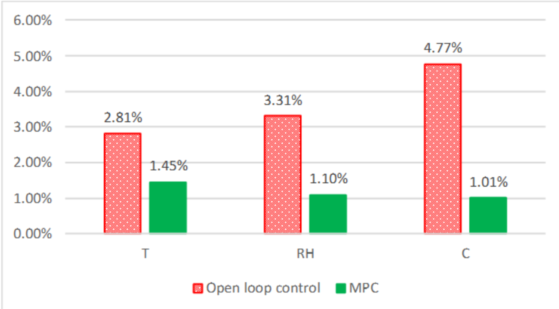

Fig. 6. Comparison of RDM of open loop control and MPC.

4. CONCLUSION

An optimal control strategy is proposed to minimize the total energy cost for greenhouse heating and cooling while keeping greenhouse temperature, relative humidity and CO_2 concentration within required ranges. The time-of-use electricity tariff is considered to calculate the energy cost. The proposed strategy is compared with another optimization strategy which aims at minimizing energy consumption. A model predictive control (MPC) strategy is proposed to address system disturbance. The performance index relative deviation mean (RDM) of MPC and open loop control under 2% system disturbance are calculated. The results show that the proposed strategy increases energy consumption but reduces energy cost. The proposed MPC has better tracking performance than open loop control.

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