Hierarchical model predictive control of Venlo-type greenhouse climate for improving energy efficiency and reducing operating cost

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***Abstract*—In this paper, a hierarchical control strategy is proposed for improving the climate control of Venlo-type greenhouses in South Africa, aiming to enhance energy efficiency and reduce operational costs. The strategy features a two-layer control architecture. The upper layer is responsible for generating set points by solving various optimization problems, which involve three different approaches with distinct objectives. The first approach focuses on minimizing energy consumption, the second aims to minimize energy costs under a time-of-use (TOU) tariff, and the third seeks to minimize the total costs related to energy consumption, ventilation, and carbon dioxide (CO2) supply, using meteorological data from a typical winter day for analysis. The lower layer employs a closed-loop model predictive control (MPC) strategy to track the set points and manage model plant mismatches and system disturbances. Additionally, the MPC approach demonstrates superior tracking performance compared to the open-loop control. This study suggests that the proposed hierarchical MPC strategy is a viable method for enhancing greenhouse energy efficiency and supporting sustainable production practices.**

I. Previous works

The literature review highlights various strategies for greenhouse climate control. It discusses control methods to minimize production costs, such as fuzzy control, robust control, PID controllers, and adaptive fuzzy control strategies. While these methods maintain climate conditions within required ranges, they often lack energy optimization. Some approaches focus on reducing energy consumption, but typically ignore costs related to ventilation and CO2 supply, and do not consider time-of-use tariffs. Greenhouse modeling methods range from black box models requiring extensive data to first-principle models considering physical and biological laws. However, traditional control strategies face challenges due to external climate disturbances and model uncertainties.

II. Introduction

The increasing population and decreasing cultivable lands have led to more serious food shortages in some countries, while the demand for freshwater in arid regions is becoming harder to meet. Greenhouse cultivation offers an effective solution, yielding higher crop production with less water consumption compared to outdoor farming. Venlo-type greenhouses, common in agricultural production, allow farmers to control climate variables like temperature, humidity, CO2 concentration, and light intensity. However, greenhouse climate control requires significant energy to maintain optimal conditions, relying on sources such as electricity, fuel oil, natural gas, and renewable energies like wind and solar. High energy consumption not only raises production costs but also increases greenhouse gas emissions. Various control strategies have been proposed to minimize these costs yet energy efficiency remains suboptimal due to a lack of energy optimization processes. Some control strategies have incorporated energy optimization. However, these studies often overlook ventilation and CO2 supply costs and do not consider time-of-use tariffs. Additionally, greenhouse modeling is challenging due to the complexity of the environment and the interdependence of controlled variables like temperature and humidity, which are sensitive to external weather conditions and crop growth. To improve control accuracy, robust and adaptive fuzzy control strategies, as well as model predictive control (MPC), have been proposed. MPC can predict future responses and solve optimization problems online, effectively handling system disturbances and improving control in various applications. In this paper, a hierarchical control strategy is proposed, featuring an upper layer with three optimization objectives (minimizing energy consumption, minimizing energy cost under TOU tariffs, and minimizing total cost including ventilation and CO2 supply) and a lower layer using MPC to track optimal operation trajectories. This hierarchical approach reduces computational complexity and improves control accuracy, significantly cutting greenhouse operating costs compared to traditional methods.

III. System Description

A greenhouse is a structure with transparent walls and roofs made of materials like glass or plastic, designed to prevent energy loss and maintain a higher indoor temperature compared to the outside. Ventilation in the greenhouse helps reduce humidity and provides CO2 for the crops, while sunlight offers the necessary light. However, maintaining the greenhouse climate within required ranges can be challenging. For example, additional heating may be necessary when outdoor temperatures are too low. To achieve higher yields and better quality, supplemental CO2 and lighting might also be required. A greenhouse climate control calculates the optimal control variables by considering electricity prices, indoor climate data, and outdoor weather conditions. Finally, actuators adjust the greenhouse climate based on the controller's signals.

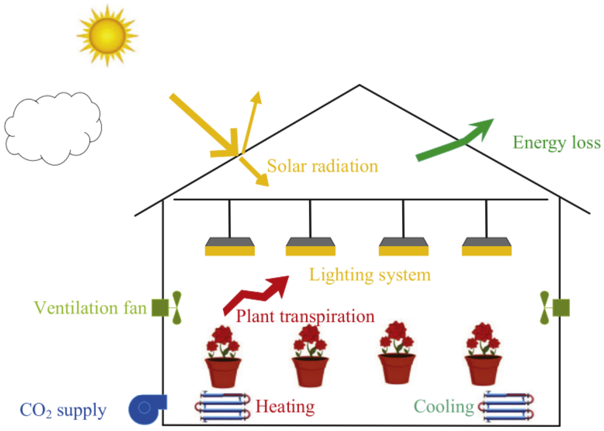

Fig. 1. Greenhouse climate control system structure [1]

A. Temperature Model

Greenhouse temperature modeling is based on the energy balance of the greenhouse. The temperature is governed by:

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

Where Tair is the temperature inside the greenhouse, Ccap is the heat capacity of the greenhouse, Qsun is the incoming radiation from the sun, Qlamp is the lamp heating power. Qcov is the heat transfer through the cover, Qtrans is the energy absorption of crop transpiration. Qvent is the energy exchange through ventilation. Qc is the heating or cooling power.

B. Relative Humidity Model

The factors affecting the change of greenhouse relative humidity include crop transpiration, vapour condensation, and ventilation. The relative humidity RHair can be obtained using: $RH_{air} = \frac{H_{air}}{H_{air,sat}}$ Where Hair is the vapour concentration of the greenhouse air. Hair can be calculated by:

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

Where Htrans is the vapour produced by plant transpiration, Hcov is the vapour condensation to the cover, Hvent is the vapour flux due to ventilation. h is the average height of greenhouse.

C. CO2 Concentration Model

The CO2 concentration model based on mass balance is as follows:

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

Where Cair is the CO2 concentration inside the greenhouse, Cinj is the CO2 injection rate, Cass is the CO2 assimilation, Cvent is the changes in CO2 concentration due to ventilation.

D. State constraints

Too high or too low temperature, relative humidity and CO2 concentration will have a negative impact on both crops yields and quality. For instance, too high relative humidity in the greenhouse will accelerate the spread of pests and diseases, too high or too low temperature will result in crop wilting and even death.Therefore, the state variables should be kept within appropriate ranges to provide suitable growing conditions for crops. The state constraints are represented by the following:

$$T_{air,\min} \le T_{air} \le T_{air,\max} \tag{4}$$

$$RH_{air,\min} \le RH_{air} \le RH_{air,\max} \tag{5}$$

$$C_{air,\min} \le C_{air} \le C_{air,\max} \tag{6}$$

where Tair,min and Tair,max are the lower and upper bounds of temperature, RHair,min and RHair,max are the lower and upper bounds of relative humidity, and Cair,min and Cair,max are the lower and upper bounds of CO2 concentration.

E. Input constraints

There are also some input constraints, due to operational constraints and physical limits.

$$Q_{c,\min} \le Q_c \le Q_{c,\max} \tag{7}$$

$$g_{v,\min} \le g_v \le g_{v,\max} \tag{8}$$

$$C_{inj,\min} \le C_{inj} \le C_{inj,\max} \tag{9}$$

where Qc,min and Qc,max are the lower and upper bounds of heating or cooling power. gv,min and gv,max are the lower and upper bounds of ventilation rate. Cinj,min and Cinj,max are the lower and upper bounds of CO2 injection rate. To reduce the wear of actuators, extreme changes should be prevented. Therefore, the following input rate of change constraints are adopted:

$$\left|\frac{dQ_c}{dt}\right| \le k_1 \tag{10}$$

$$\left|\frac{dg_v}{dt}\right| \le k_2 \tag{11}$$

$$\left|\frac{dC_{inj}}{dt}\right| \le k_3 \tag{12}$$

where k1, k2 and k3 are the change rate limits of input variables Qc,gv and Cinj respectively.

F. Sample Time: Linearized Model

To evaluate the right sampling time, the system was linearized. The Jacobian has been calculated and evaluated at equilibrium points ($x_{eq} = [22, 60, 600 * 10^-6 * 1977]; u_{eq} = [0, 0.003, 415, 20, 13, 500 * 10^-6 * 1977]$). Nyquist sampling theorem states that the sampling time should be at least twice the system time constant. In practice, it's often chosen a time that is one tenth of the time constant. The time constant of the linearized system is about 2.6656e+03s. A sampling time of 5 minutes is therefore used as in the case study [1].

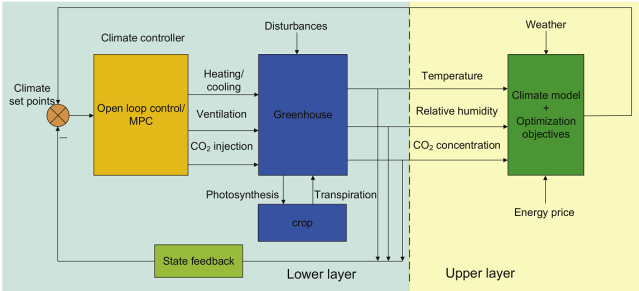

Fig. 2. Greenhouse climate hierarchical control architecture [1]

IV. Hierarchical Control Strategy

The hierarchical control can effectively reduce the computational complexity of complex problems by decomposing them into different subproblems. The hierarchical control architecture of greenhouse climate is shown in Fig.2.

On the upper layer, an optimization problem that takes into account weather data and energy price is solved to obtain the set points. On the lower layer, a climate controller is designed to track the reference trajectories obtained from the upper layer.

A. *Upper Layer Design (optimization layer)*

The upper layer is to find the set points for greenhouse climate controllers. In this paper, three different strategies with different optimization objectives are studied. For these optimization problems, the control variables are the heating or cooling power Qc, ventilation rate gv and CO2 injection rate Cinj. The controlled variables are the temperature Tair, relative humidity RHair and CO2 concentration Cair. The objective of Strategy 1 is to minimize the energy consumption for greenhouse heating and cooling. Therefore, the optimization objective of Strategy1 can be given by:

$$J1 = \int_{ti}^{tf} |Q_c(t)|dt \tag{13}$$

Where ti is the initial time, tf is the final time of optimization. The objective of Strategy 2 is to minimize the energy cost under the TOU tariff. The objective function of Strategy 2 is as follows.

$$J2 = \int_{ti}^{tf} |Q_c(t) * w(t)|dt \tag{14}$$

Where w(t) is the electricity price at the time t. The objective of Strategy 3 is to minimize the total operating cost which includes the energy cost, ventilation cost and CO2 supply cost. The objective function of Strategy 3 can be obtained by:

$$J3 = \int_{ti}^{tf} (Q_c(t)w(t) + g_v(t)w(t) + C_{inj}p_c)dt \tag{15}$$

where pc is the price of organic CO2, pc=R1000/ton, λ is the conversion coefficient from the ventilation rate (gv) to the ventilation fan power (Qv). λ=0.06 W/m3. All the optimization problems are subject to the constraints already defined. Moreover, the discrete state-space model is as follows: $x(k+1) = f(x(k), u(k))$ where k is the current time kTs and Ts is the sampling interval. This equation represents an other constraint. Finally, the objective function is adopted and given by:

$$J_0 = sum_{k=1}^{N} |Pu(k)| \tag{16}$$

Where N=T/Ts.T is the total simulation time. For Strategy 1, P = [1,0,0]. For Strategy 2, P = [w,0,0]. For Strategy 3, P = [w,λw,pc].

The open loop controller solves the optimization problem:

$$\dot{u_{ref}} =^{\arg\min}_{u} J_0 \tag{17}$$

subject to the state, input and system dynamics constraints.

B. *Lower Layer Design (control layer)*

In this paper, the focus is on the lower layer responsible for tracking reference trajectories provided by the upper layer. A closed-loop model predictive controller is designed, and its performance is compared with that of an open-loop controller. For the closed-loop model predictive control (MPC), the input variables derived from the upper layer are used as the input reference trajectories uref. Correspondingly, the state variables are used as the state reference trajectories xref. The objective function is the following:

$$J_m = sum_{k=1}^{Np}(\Delta x(k+1|k))^T Q((\Delta x(k+1|k)) + sum_{k=1}^{Nc}((\Delta u(k+1-i|k) \tag{18}$$

where Np and Nc are optimization horizon and control horizon respectively. Q and R are the weighting matrices. Δx(k+1—k) is the changes of state variables because of Δu. Δu is the change of input variables, and it is used to compensate model plant mismatch and system disturbances. These are given by Δ u(k) = u(k—k) - $u_{ref}(k)$. The MPC controller solves the nonlinear optimization problem: ΔU*(k) =Δu$^{\arg\min}$$J_m(k)$ subject to the state, input and system dynamics constraints. The optimal control is implemented in a receding horizon scheme that the first value of ΔU*(k) is adopted and the rest are discarded. Repeat the above steps until k reaches the predefined value. The final optimal inputs obtained by the MPC controller is given by: $u(k) = u_{ref}(k)$+Δ u(k).

V. Simulation

The simulation parameters are listed in Table 1. The meteorological data such as solar irradiation, outdoor temperature and outdoor relative humidity are from weather station at the University of Pretoria. The data for a typical winter day is used and shown in Fig 4 and Fig 5.

A. *Optimization results*

1) Strategy 1: The optimization result of Strategy 1 is shown in Fig. 6. The control input trend Qc turns out to be the smoothest of the three because in strategy 1 the objective is to minimize only the energy used for heating and cooling.

Variable	Value	Unit
α_1	0.7	–
α_2	10	–
γ	0.008	–
LAI	2.6	–
C_{cap}	30000	$\mathrm{J/m^2\ ^\circ C}$
h	7	m
s	40709	$\mathrm{m^2}$
L	2450	J/g
r_b	150	s/m
ρ_{air}	1.225	$\mathrm{kg/m^3}$
$C_{p,air}$	1003	$\mathrm{J/kg^\circ C}$
p_{gc}	1.8×10^{-3}	$\mathrm{m^\circ C^{-1/3} s^{-1}}$
$T_{air,min}$	14	$^\circ$C
$T_{air,max}$	26	$^\circ$C
$RH_{air,min}$	0	%
$RH_{air,max}$	90	%
$C_{air,min}$	400	ppm
$C_{air,max}$	2000	ppm
$Q_{c,min}$	-200	$\mathrm{W/m^2}$
$Q_{c,max}$	200	$\mathrm{W/m^2}$
$g_{v,min}$	0	m/s
$g_{v,max}$	0.05	m/s
$C_{inj,min}$	0	$\mathrm{g/m^2s}$
$C_{inj,max}$	0.05	$\mathrm{g/m^2s}$
k_1	0.51	$\mathrm{W/m^2s}$
k_2	5.1×10^{-5}	$\mathrm{m/s^2}$
k_3	5.1×10^{-5}	$\mathrm{g/m^2s^2}$

Fig. 3. Table1 [1]

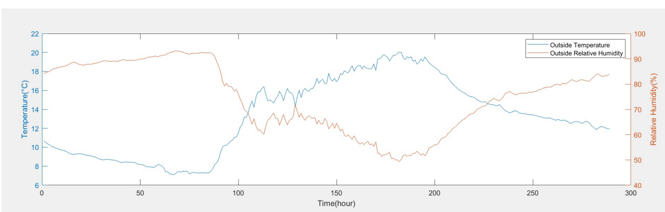

Fig. 4. Outdoor temperature and relative humidity in a typical winter day

2) Strategy 2: The comparison of optimization results between Strategy 1 and Strategy 2 under the TOU tariff is shown in Fig. 7. Strategy 2 does not minimize energy use, but minimizes energy cost, which is part of the objective function. The energy consumed with Strategy 2 is greater than the energy consumed with Strategy 1 but the cost is optimized. Peak utilization occurs in the time slot that corresponds to lower cost.

3) Strategy 3: The optimization result of strategy 3 is shown in Fig. 8. Strategy 3 considers not only costs due to heating and cooling, but also costs due to Co2 injection and

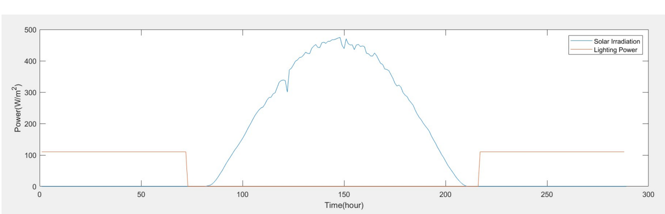

Fig. 5. Solar Irradiation and Lighting power during a typical winter day

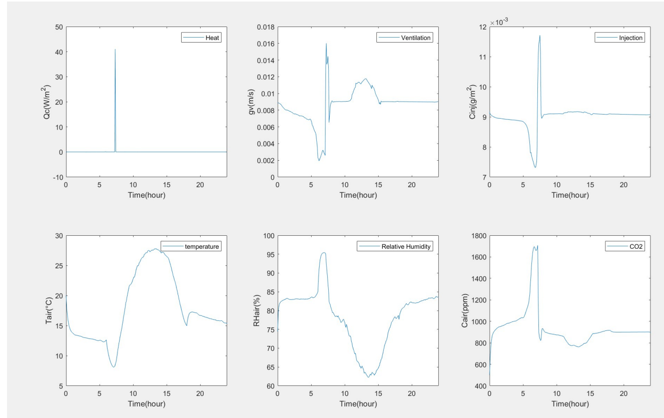

Fig. 6. Strategy 1

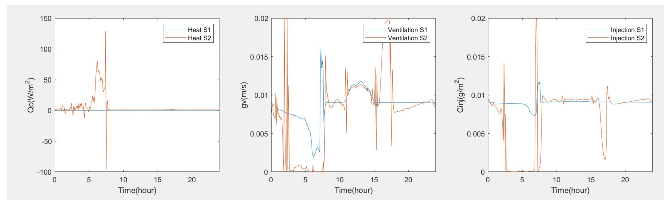

Fig. 7. Strategy 1 vs. Strategy 2

ventilation. in this case minimization also affects the other two inputs, particularly the third one.

B. Model Predictive Control

In this paper, we examine and compare a closed-loop model predictive control (MPC) strategy with an open-loop control strategy. The optimization results of Strategy 3 are used as reference trajectories because Strategy 3 outperforms both Strategy 2 and Strategy 1 in enhancing greenhouse energy efficiency and reducing production costs. The MPC parameters are set as follows: the predictive horizon $N_p = 10$, the control horizon $N_c = N_p$, the sampling interval $T_s = 60$ seconds, the total simulation time $T = 24$ hours, and the weighting matrices $Q = \mathrm{diag}(100, 100, 100)$ and $R = \mathrm{diag}(1, 1, 1)$. The

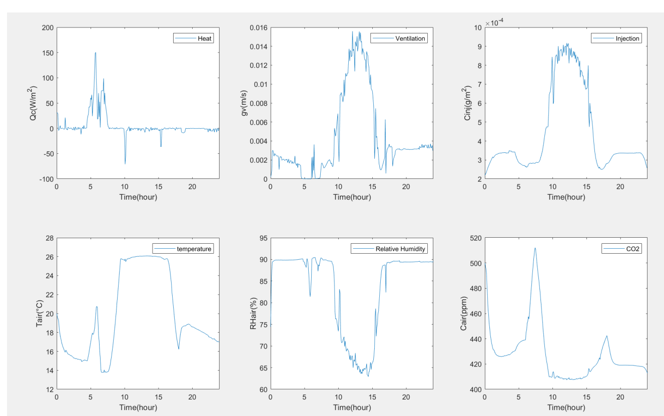

Fig. 8. Strategy 3

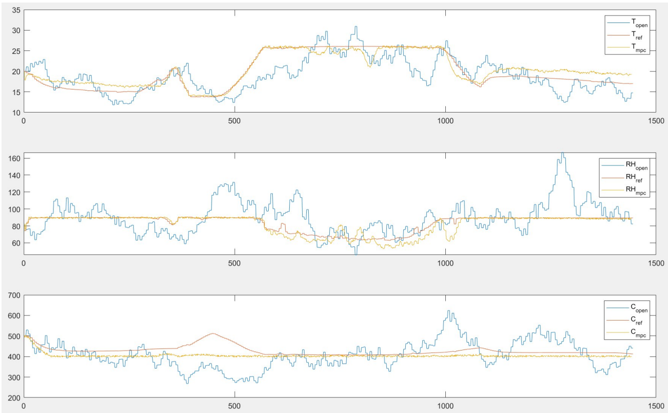

Fig. 9. Mpc vs Open Loop

comparison results between open loop control and MPC under 2% system disturbances are shown in Fig. 9. It is evident that the three yellow curves (MPC results) fluctuate within a very narrow range close to the corresponding reference trajectories. In contrast, the three blue curves (open-loop control results) exhibit fluctuations within a relatively wider range near their corresponding reference trajectories. This comparison demonstrates that MPC has superior tracking performance compared to open-loop control.

VI. Further Results

Up to this moment, the cost of the three inputs is minimized, without considering the particular scenario of the greenhouse. For example, if the plants in the greenhouse are particularly sensitive to CO2 concentrations, it may be appropriate to minimize CO2 use to avoid negative effects on their growth or health. By assigning a greater weight to CO2 injection in the objective function, it is ensured that this parameter is kept under strict control, even if this leads to an increase in costs associated with heating or ventilation. Furthermore, in a context where the energy comes from renewable sources or from a highly efficient heating system, it may be willing to incur higher costs for heating than for CO2 injection or ventilation. By assigning a lower weight to heating in the objective function, costs related to CO2 injection and ventilation are minimized, making maximum use of the efficiency of the heating system.

$$J4 = \int_{ti}^{tf} (K_1 Q_c(t) w(t) + K_2 g_v(t) \lambda w(t) + K_3 C_{inj} p_c) dt \tag{19}$$

A. A new strategy: Strategy 4

Fig. 10 shows the comparison between two different scenarios: in the first, a greater weight is assigned to the energy for the injection of CO2; in the second, a greater weight is assigned to the energy for heating and cooling. Note that the first strategy minimizes the third control input more, at the expense of the first and second inputs, which take on higher values instead. The same is true for the second compared to the first input.

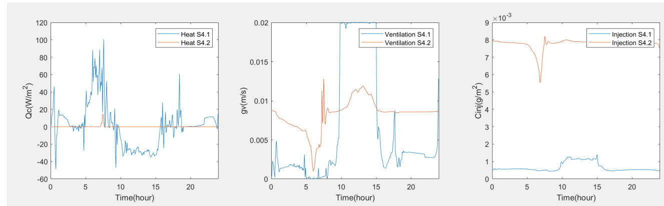

Fig. 10. Strategy 4

1) Application: Strategy 4 can be applied in the case of using renewable resources as a source of energy. These represent an alternative to the classical energy drawn from the electricity grid. In particular, it's assumed that photovoltaic panels have been installed. The photovoltaic panels will be a source of energy in the 9:00-17:00 time slot in which solar irradiation is sufficient to ensure the proper energy supply needed by the greenhouse. The objective function is suitably modified by introducing a null-weight coefficient that neglects the cost of electricity in the time slot when energy is supplied by the solar panels. It is further assumed that the only control input that takes advantage of this alternative energy is gv. The

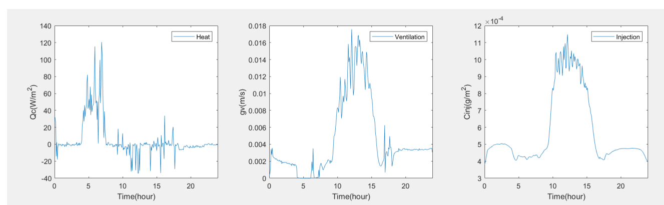

Fig. 11. Strategy 4 with panels

results of this case study are shown in figure 11. It can be appreciated that compared with strategy 3, in this case the second input gv reaches higher peaks in the 9:00-17:00 time slot. This happens because the cost due to ventilation was not weighted in this precise time slot, since the energy source is from the PV panels.

VII. Conclusion

A hierarchical control strategy of a Venlo-type greenhouse system is proposed to reduce greenhouse cost while keeping greenhouse climatic conditions such as the temperature, humidity and CO2 concentration within required ranges. The hierarchical control architecture consists of two layers. The upper layer investigates three distinct strategies with different optimization objectives. Strategy 1 aims to minimize energy consumption. Strategy 2 focuses on minimizing energy costs under the time-of-use (TOU) tariff. Strategy 3 seeks to minimize the total operating cost. Next, a fourth strategy was introduced that considers the particular greenhouse scenario. The optimization results are taken as the trajectories for the lower layer. On the lower layer, an MPC controller is designed to track the reference trajectories obtained from the upper layer. MPC can track the reference trajectories better than the open loop control under system disturbances.

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