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Model predictive control of a Venlo-type greenhouse system considering electrical energy, water and carbon dioxide consumption

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HIGHLIGHTS

- Four optimization strategies for the operation of greenhouse systems are studied.
- The proposed strategy improves water use efficiency and reduces water demand.
- A sensitivity analysis of prices and constraints is conducted.
- A model predictive controller is designed to address system disturbances.

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ABSTRACT

Greenhouse systems consume lots of energy, water and carbon dioxide (CO_2) to provide a suitable growth environment for crops. Due to the problems of operation mode, some greenhouse systems are inefficient and need to be optimized. In this paper, four optimization strategies for improving the operation efficiency of greenhouse systems are studied. Strategy 1 minimizes the energy consumed for greenhouse heating, cooling, ventilation and irrigation. Strategy 2 minimizes the water consumed for irrigation. Strategy 3 minimizes the CO_2 consumed for greenhouse CO_2 enrichment. Strategy 4 minimizes the total cost of energy, water and CO_2 consumed. These optimization strategies are based on a multi-input multi-output (MIMO) climate model and a modified evapotranspiration model. Moreover, a sensitivity analysis is conducted to study the influence of electricity price, water price, CO_2 price and the range of system constraints on the optimization results. Finally, a model predictive controller (MPC) is designed to reject system disturbances and address model plant mismatch. The MPC controller is compared with a commonly used open loop controller. A performance index relative average deviation (RAD) is introduced to evaluate the tracking performance of the proposed MPC and the compared open loop control. Simulation results show that Strategy 4 reduce the total cost by 66.60 %, 92.68 % and 68.83% compared with Strategy 1, Strategy 2 and Strategy 3 respectively. Changes in electricity price have a greater impact on optimization results than changes in water price and CO_2 price. Both temperature constraints and relative humidity constraints have a great influence on the optimization results. The controller designed is verified to be effective.

1. Introduction

In recent years, the problem of energy and water shortage has become more and more serious [1–3]. Research in [4] shows that about 1.2 billion people in the least developed countries have no access to electricity. Moreover, about 4 billion people in the world are facing serious water shortage [5]. The electrical energy shortage is particularly serious in South Africa [6]. In 2019, South Africa experienced its most serious energy crisis, and for the first time started load shedding stage 6 to protect the power system from total blackouts. The energy shortage problem has a profound negative impact on both people's daily life and the South African economy [7]. Moreover, South Africa is one of the 30 driest countries in the world [8]. Forty-nine percent of people in South Africa live in water-scarce areas. South Africa's average rainfall is about 40% less than the world's annual average rainfall. Research shows that the agricultural sector consumes the most water, followed by the

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municipal sector and the industrial sector [9].

The global population will reach 10.1 billion by 2050. Due to the limited arable land, the traditional cultivation mode is facing many challenges in meeting the increasing food demand [10]. For example, about 80% of the land in South Africa is used for agriculture, but only about 11% of the land is suitable for cultivation. Moreover, due to the construction of urbanization and the overuse of land, arable land is gradually decreasing. The food shortage in some countries and regions is getting worse [11].

Greenhouse cultivation can effectively solve the above problems. A greenhouse is a kind of agricultural building that can provide a suitable growth environment for crops [12]. Greenhouses are widely used all over the world. Research in [13] shows that there are approximately 3.64 million hectares of greenhouses worldwide. Greenhouse cultivation mode can obtain higher yield than outdoor cultivation mode [14]. Therefore, it is an effective way to alleviate food shortage. To maintain the environment required for the growth of crops, a lot of energy and water are consumed [15]. Research in [16] shows that the greenhouse energy consumption is the largest part of total agricultural energy consumption. In addition, carbon dioxide (CO_2) needs to be supplied to the greenhouse to increase crop yields. However, some traditional greenhouse operation modes are inefficient and cause a lot of waste. Therefore, it is necessary to optimize the operation of the greenhouse to improve the efficiency of energy, water and CO_2 utilization.

Some optimization methods are proposed to reduce greenhouse energy consumption. In [17], an optimal control algorithm for greenhouse tomato production is proposed and compared with a conventional proportional-integral (PI) control. The results show that compared with the PI control, the energy efficiency of the proposed optimal control is increased by 8.5%. In [18], the control of the LED array fill light for greenhouse cultivation based on parallel particle swarm optimization is studied. The results show that compared with fluorescent lamps, the energy saving is about 82.6%, and compared with incandescent lamps, the energy saving is about 54.2%. A model optimization forecasting method to predict the greenhouse energy demand for better accuracy and cost time performance is proposed in [19]. A hierarchical control strategy to optimize greenhouse operation is proposed in [20]. In [21], a model predictive control strategy is proposed to optimize the efficiency of greenhouse heating system.

Some research studied different methods to reduce greenhouse water and CO_2 consumption. In [22], a greenhouse multi-objective optimization strategy is studied to maximize profit, fruit quality and water use efficiency. In [23], a model-based predictive control strategy is proposed to reduce energy consumption and water consumption. However, this study only considered the water consumed for greenhouse fogging, not the water consumed for irrigation. In [24], the optimization of the irrigation amount for muskmelon in a plastic greenhouse is studied. The results show that different irrigation amounts have significant effects on plant growth, fruit yield and quality. In [25], the effects of four different levels of drip irrigation on crop growth are studied. The results show that the optimal water requirement is about 75% of crop evapotranspiration for the Troy 489 variety of tomato. Two optimal control strategies of CO_2 enrichment in greenhouse tomato crops are studied in [26]. In [27], the leakage rate, CO_2 supply amount, and CO_2 concentration are estimated and used to study the CO_2 enrichment efficiency in a greenhouse without ventilation.

Due to the complexity of the greenhouse environment, greenhouse modeling is challenging. Some research studied different modelling methods for greenhouse systems. For example, a nonlinear robust identification method of greenhouse model based on a multi-objective evolutionary algorithm is studied in [28]. Modelling and control of greenhouse temperature and humidity are studied in [29]. In [30], the applicability of extended Kalman filter in automatic, on-line and adaptive parameter estimation in a physical based greenhouse model is investigated. However, most studies only consider the control of greenhouse temperature, relative humidity and CO_2 concentration by heating and cooling, ventilation and CO_2 supply. Relatively few studies considered the influence of supplemental light on the greenhouse climate [31]. In [32], an irrigation modelling method for greenhouse hot pepper grown based on soil water balance is studied. A modified crop evapotranspiration model is used to calculate irrigation water requirement in the greenhouse and good predictive performance is obtained.

In our previous work, we studied how to reduce the total cost of greenhouse energy consumption, ventilation and CO_2 supply [33]. However, the cost of greenhouse water consumption was not considered. Few studies have analyzed optimization strategies that consider energy, water and CO_2 consumption of greenhouse system operation. In addition, solar radiation control has been neglected in many studies on greenhouse control. Therefore, there is a research gap in the optimization of greenhouse system operation that considers energy consumption, water consumption and CO_2 consumption. These problems are solved in this study. In this paper, four optimization strategies for a greenhouse operation under South Africa climate are studied. Strategy 1 minimizes energy consumption, Strategy 2 minimizes water consumption, Strategy 3 minimizes CO_2 consumption, and Strategy 4 minimizes the total cost of energy consumption, water consumption and CO_2 consumption. Strategy 1, Strategy 2 and Strategy 3 are three commonly used greenhouse optimization strategies in previous studies and are compared with Strategy 4 in this study. The greenhouse climate model proposed in [34,35] and a modified evapotranspiration model presented in [32] are used. Moreover, a sensitivity analysis is conducted to study the impact of electricity price, water price, CO_2 price and the range of constraints on the optimization results. Finally, to address system disturbances and model mismatch, an MPC controller is designed and compared with an open loop controller.

The main contributions of this paper include: 1) For greenhouse operation optimization, most research focus on how to reduce energy consumption, few studies consider water consumption and CO_2 consumption. In this paper, the proposed optimization strategy takes into account energy consumption, water consumption and CO_2 consumption. 2) For the greenhouse control, most studies only consider the control of greenhouse heating, cooling, ventilation and CO_2 supply, but not the control of solar radiation which has a great impact on both greenhouse climate and irrigation water demand. In this paper, the control of greenhouse heating, cooling, ventilation, CO_2 supply and solar radiation are considered. 3) Most studies adopt the method of changing crop planting mode or irrigation mode to save water. These studies focus on how to improve water use efficiency rather than how to reduce water demand. In this paper, a model for balancing crop irrigation water needs based on soil moisture is established. The influence of greenhouse climate and solar radiation power on irrigation water demand is analyzed. The proposed strategy improves water use efficiency and reduces water demand. 4) The influence of the changes of electricity price, water price, CO_2 price, temperature constraint and relative humidity constraint on the optimization results is studied through sensitivity analysis. The sensitivity analysis performed can provide a deeper insight into the greenhouse optimization problem. 5) To improve the control accuracy of the greenhouse system, an MPC controller is designed and a better reference trajectory tracking performance is obtained than the commonly used open loop controller.

The remainder of this paper is organized as follows: In Section 2, the system model is presented. In Section 3, the optimization problem is formulated. In Section 4, the controller design is conducted. Simulation results are shown in Section 5. Section 6 concludes this paper.

2. System model

Greenhouse systems generally include a heating and cooling system, a ventilation system, a CO_2 supply system and a lighting system, etc. People adjust the greenhouse temperature, relative humidity and CO_2 concentration by controlling greenhouse systems to provide a suitable environment for crop growth. Fig. 1 is the schematic diagram of a

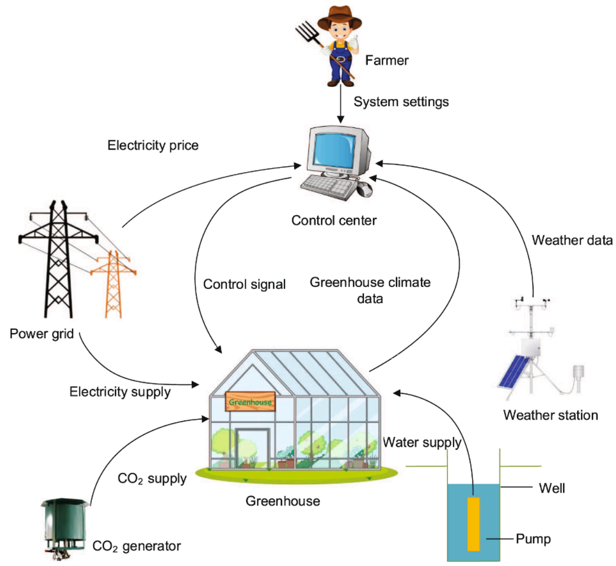

Fig. 1. Schematic diagram of a greenhouse control system.

greenhouse system.

In this paper, we studied greenhouse climate control and irrigation control. The corresponding greenhouse climate model and water demand model used are based on energy and mass balance. Fig. 2 shows the energy, water and CO_2 flow of a greenhouse control system.

2.1. Greenhouse climate model

In this paper, the greenhouse model presented in [34,35] is used and given below.

2.1.1. Temperature

Greenhouse temperature is an important factor affecting crop growth. It is determined by greenhouse heating, cooling, ventilation, lighting, solar radiation, etc. The temperature is governed by:

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

where T_{air} is the greenhouse temperature, C_{cap} is the greenhouse heat capacity, Q_{sun} is the incoming radiation from the sun, Q_{lamp} is the lamp heating power. Q_{cov} is the heat transfer through the cover, Q_{trans} is the energy absorption of crop transpiration. Q_{vent} is the energy change caused by ventilation. Q_c is the heating or cooling power.

Q_{sun} can be calculated by:

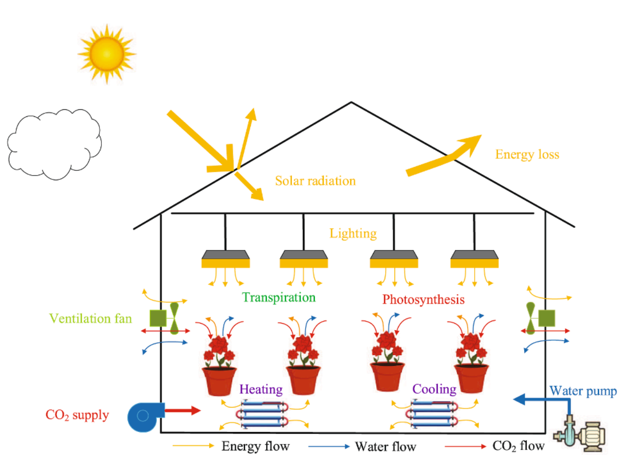

Fig. 2. Greenhouse energy, water and CO_2 flow.

$$Q_{sun} = \alpha_1(1 - s_r)I_{rad}, \tag{2}$$

where α_1 is the transmission coefficient of the cover material, s_r is the shading rate and is adjusted by the greenhouse shading system, I_{rad} is the solar radiation power.

According to [36], Q_{cov} can be described by:

$$Q_{cov} = \alpha_2(T_{air} - T_{out}), \tag{3}$$

where α_2 is the heat transfer coefficient of the cover, T_{out} is the outside temperature.

Q_{trans} can be obtained by:

$$Q_{trans} = g_e L(H_{crop} - H_{air}), \tag{4}$$

where g_e is the transpiration conductance, L is the energy needed to evaporate water from a leaf. H_{crop} is the absolute water vapour concentration at crop level. H_{air} is the absolute water vapour concentration of the greenhouse air.

g_e is obtained using:

$$g_e = \frac{2LAI}{(1+\epsilon)r_b + r_s}, \tag{5}$$

where LAI is the leaf area index, ϵ is the ratio of latent to sensible heat content of saturated air. r_b is the boundary layer resistance, r_s is the stomatal resistance.

H_{crop} can be calculated by:

$$H_{crop} = H_{air,sat} + \epsilon \frac{r_b}{2LAI}\frac{R_n}{L}, \tag{6}$$

where $H_{air,sat}$ is the saturated vapour concentration. According to [37], $H_{air,sat}$ can be approximated by:

$$H_{air,sat} = 5.5638e^{0.0572T_{air}}. \tag{7}$$

ϵ and r_s can be obtained by:

$$\epsilon = 0.7584e^{0.0518T_{air}}, \tag{8}$$

$$r_s = (82 + 570e^{-\gamma\frac{R_n}{LAI}})(1 + 0.023(T_{air} - 20)^2), \tag{9}$$

where γ is a crop parameter, R_n is the net radiation at crop level.

$$R_n = 0.86(1 - e^{-0.7LAI})(Q_{sun} + P_E), \tag{10}$$

where P_E is the power of lighting.

$$Q_{lamp} = \eta P_E, \tag{11}$$

where η is the conversion coefficient of lamp power into heating power.

$$Q_{vent} = g_v \rho_{air} C_{p,air}(T_{air} - T_{out}), \tag{12}$$

where g_v denotes the specific ventilation rate, ρ_{air} is the density of the air, $C_{p,air}$ is the heat capacity of the air.

Please note that this paper gives a brief introduction to the model used. For further details, such as the model parameters and the physical meaning of the variables, please refer to [38,39].

2.1.2. Relative humidity

The relative humidity of the greenhouse has a great influence on the growth of crops. The relative humidity is affected by crop transpiration, water vapor condensation and ventilation. The relative humidity RH_{air} can be obtained using:

$$RH_{air} = H_{air}/H_{air,sat}, \tag{13}$$

where H_{air} is the vapour concentration of the greenhouse air. H_{air} can be calculated by:

$$\frac{dH_{air}}{dt} = \frac{1}{h}(H_{trans} - H_{cov} - H_{vent}), \tag{14}$$

where H_{trans} is the vapour produced by plant transpiration, H_{cov} is the vapour condensation to the cover, H_{vent} is the vapour flux caused by ventilation. h is the average height of the greenhouse.

H_{trans} is influenced by H_{crop} and H_{air}, and it can be described by:

$$H_{trans} = g_e(H_{crop} - H_{air}). \tag{15}$$

H_{cov} can be obtained by:

$$H_{cov} = g_c\left[0.2522e^{0.0485T_{air}}(T_{air} - T_{out}) - (H_{air,sat} - H_{air})\right], \tag{16}$$

where g_c is the condensation. g_c can be obtained by:

$$g_c = \begin{cases} 0 & \text{if} \quad T_{air} \leqslant T_{out} \\ p_{gc}(T_{air} - T_{cov})^{1/3} & \text{if} \quad T_{air} > T_{out}, \end{cases} \tag{17}$$

where p_{gc} is related to the properties of the condensation surface.

H_{vent} is influenced by the ventilation and the humidity both inside and outside the greenhouse. The value of H_{vent} can be obtained by:

$$H_{vent} = g_v(H_{air} - H_{out}), \tag{18}$$

where g_v is the ventilation rate. In this paper, g_v is controlled by changing the power of the ventilation fan.

2.1.3. CO_2 concentration

CO_2 concentration is also an important climatic factor affecting greenhouse crop growth. CO_2 concentration can affect crop photosynthesis [40]. People can use CO_2 enrichment to improve crop yield. The CO_2 concentration model is as follows.

$$\frac{dC_{air}}{dt} = \frac{1}{h}(C_{inj} - C_{ass} - C_{vent}), \tag{19}$$

where C_{air} is the CO_2 concentration inside the greenhouse, C_{inj} is the CO_2 injection rate, C_{ass} is the CO_2 assimilation, C_{vent} is the changes in CO_2 concentration due to ventilation.

C_{ass} and C_{vent} can be obtained by:

$$C_{ass} = 2.2 \times 10^{-3}\frac{1}{1 + \frac{0.42}{C_{air}}}(1 - e^{-0.003(Q_{sun} + P_E)}), \tag{20}$$

$$C_{vent} = g_v(C_{air} - C_{out}). \tag{21}$$

2.2. Irrigation water demand model

The irrigation water demand model used in this paper is based on the soil water balance. The schematic diagram of soil water balance is shown in Fig. 3. Crop water demand is affected by precipitation, irrigation, evapotranspiration, surface runoff, etc.

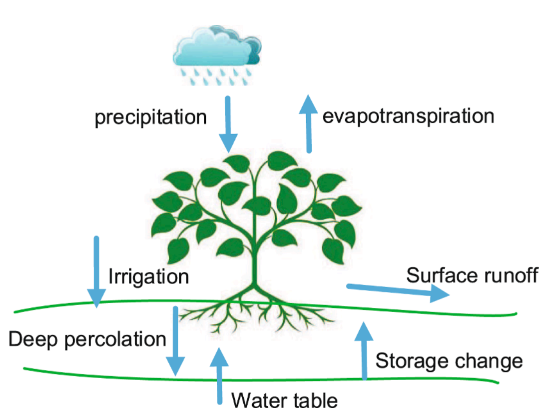

Fig. 3. Schematic diagram of soil water balance.

The water balance can be given as:

$$P + I + W = ET + R + D + \Delta S, \tag{22}$$

where P is the precipitation, I is the irrigation, W is the water from the water table, ET is the crop evapotranspiration, R is the surface runoff, D is the deep percolation, ΔS is the soil water content change. Due to the greenhouse is a closed environment, there is no precipitation, $P = 0$. W can be ignored because the water table is more than 25 meters deep. R is negligible because the greenhouse is flat and there is no loss of irrigation water. D can be ignored according to the research in [41]. Therefore, the soil water balance can be changed to:

$$I = ET + \Delta S. \tag{23}$$

The dynamic model of soil water content can be expressed as:

$$\frac{dS}{dt} = I - ET. \tag{24}$$

In this paper, the real-time irrigation mode is used. However, it is difficult to measure soil water content quickly and accurately without causing damage to crops. Therefore, the control of irrigation in many studies is to keep the soil water content constant. The greenhouse irrigation water demand is equal to the greenhouse water consumption. The soil water content measurement is not needed. Related research can be found in [42,43]. The water demand for irrigation can be obtained by:

$$I = ET. \tag{25}$$

ET can be calculated by:

$$ET = ET_o \times K_c, \tag{26}$$

where ET_o is the reference evapotranspiration, K_c is the crop coefficient and depends on the crop type and growth stage.

According to [44], the Penman–Monteith equation can be used to calculate ET_o.

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T_{air}+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}, \tag{27}$$

where Δ is the slope of the vapor pressure curve, G is the soil heat density, γ is the psychometric constant, e_s is the saturation vapour pressure, e_a is the average daily actual vapour pressure, u_2 is the wind speed at 2 meter height.

$$e_s = 0.6108 \times \exp\left(\frac{17.27 \times T_{air}}{T_{air} + 237.3}\right), \tag{28}$$

$$e_a = e_s \times RH_{air}, \tag{29}$$

$$\Delta = \frac{4098 \times e_s}{(T_{air} + 237.3)^2}. \tag{30}$$

Please note that the Penman–Monteith equation in (27) is for the calculation of outdoor evapotranspiration. Related research can be found in [45,46]. However, it is not suitable for the greenhouse evapotranspiration calculation. The reason is that the wind speed in the greenhouse is very low. If (27) is used to calculate the evapotranspiration in the greenhouse, there will be a large error [47].

According to [32], a modified Penman–Monteith equation for greenhouse evapotranspiration calculation is introduced and given below.

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{1713}{T_{air}+273}(e_s - e_a)}{\Delta + 1.64\gamma}. \tag{31}$$

Compared with R_n, the soil heat density G is relatively small. According to [48], G can be approximately zero when the ground is covered with vegetation.

2.3. Model analysis

The proposed greenhouse climate model had been validated in [34,35]. The proposed greenhouse crop reference evapotranspiration model had been validated in [32]. It should be pointed out that in most cases, the developed model can accurately predict the actual value, but when the temperature outside the greenhouse is low (below 0 °C), the prediction error is large. Similar results can be found in [49]. However, the average temperature in South Africa is high. For example, in Pretoria, the administrative capital of South Africa, the average temperature of the winter is above 10 °C. Therefore, the proposed model is suitable for greenhouse climate prediction in this study.

According to (31), ET_o is related to the temperature, relative humidity and radiation power. As shown in Fig. 4, ET_o increases with the increase of temperature and radiation power but decreases with the increase of relative humidity. Therefore, the following methods can be used to reduce greenhouse water demand: reducing the temperature of the greenhouse, reducing the radiation power, and increasing the relative humidity in the greenhouse.

3. Optimization

This paper aims to study different optimization strategies for greenhouse operation to reduce energy, water and CO_2 consumption while keeping greenhouse climate within the required range to provide a suitable environment for crop growth. The corresponding optimization problems are formulated in the following sections.

3.1. Decision variables

In this paper, the system studied is a multiple-input multiple-output (MIMO) system. There are four inputs and three outputs. The inputs (decision variables) include the controlled heating or cooling power Q_c, the ventilation rate g_v, the CO_2 injection rate C_{inj} and the controlled shading rate s_r. The outputs are greenhouse temperature T_{air}, relative humidity RH_{air}, CO_2 concentration C_{air}. People use the greenhouse heating and cooling system, ventilation system and CO_2 supply system to control the temperature, relative humidity and CO_2 concentration.

3.2. Objective functions

3.2.1. Strategy 1

Greenhouse operation consumes lots of energy, especially in winter when the temperature is low. The objective of Strategy 1 is to minimize greenhouse energy consumption. Most of the previous studies on energy optimization only considered the energy consumption of greenhouse heating and cooling. In this paper, the energy consumed for heating, cooling, ventilation and irrigation is considered. The objective function of Strategy 1 is given by:

$$J_1 = E_1 + E_2 + E_3, \tag{32}$$

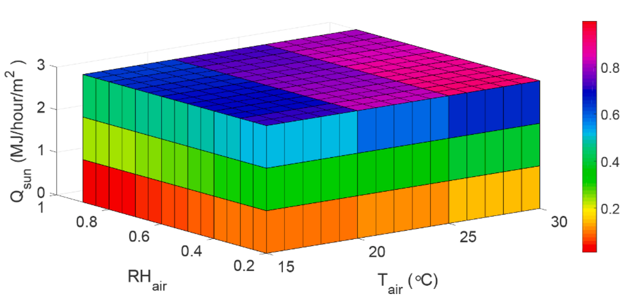

Fig. 4. Crop reference evapotranspiration (mm/hour).

where E_1 is the energy consumed for heating and cooling, E_2 is the energy consumed for ventilation, E_3 is the energy consumed for irrigation water pumping.

$$E_1 = \int_{t_i}^{t_f} |Q_c(t)|dt, \tag{33}$$

$$E_2 = \int_{t_i}^{t_f} Q_v dt, \tag{34}$$

$$Q_v = \lambda g_v, \tag{35}$$

where t_i is the initial time, t_f is the final time for optimization. λ is the conversion coefficient from g_v to the ventilation power Q_v and is determined by the type of ventilation fan.

$$E_3 = \int_{t_i}^{t_f} Q_w dt, \tag{36}$$

$$Q_w = \frac{1}{\eta}\rho_w V_w g h_w, \tag{37}$$

where Q_w is the pumping power, η is the energy efficiency of the water pump system, ρ_w is the water density, V_w is the volume of pumped water, g is the acceleration of gravity, h_w is the height of water pumping.

3.2.2. Strategy 2

The objective of Strategy 2 is to minimize greenhouse water consumption. In this paper, the water consumed for greenhouse irrigation is considered. The objective function is as follows:

$$J_2 = \int_{t_i}^{t_f} I(t)dt. \tag{38}$$

3.2.3. Strategy 3

The CO_2 used for CO_2 enrichment is very expensive and should be used effectively. The objective of Strategy 3 is to minimize greenhouse CO_2 consumption. Therefore, the objective function can be obtained by:

$$J_3 = \int_{t_i}^{t_f} C_{inj}(t)dt. \tag{39}$$

3.2.4. Strategy 4

The objective of Strategy 4 is to reduce the cost of greenhouse energy consumption, water consumption and CO_2 consumption. Therefore, the objective function can be given by:

$$J_4 = \omega_1 J_1 + \omega_2 J_2 + \omega_3 J_3, \tag{40}$$

where ω_1, ω_2 and ω_3 are prices of energy, water and CO_2 respectively. The time-of-use (TOU) electricity tariff in South Africa is used for energy cost calculation and given by:

$$\omega_1(t) = \begin{cases} \omega_o & t \in [0,6] \cup [22,24] \\ \omega_s & t \in [9,17] \cup [19,22], \\ \omega_p & t \in [6,9] \cup [17,19] \end{cases} \tag{41}$$

where $\omega_o, \omega_s, \omega_p$ are the off-peak, standard, peak tariff in R/kWh. R is the South Africa Currency, Rand. In this study, the groundwater is used for greenhouse irrigation. Due to the groundwater is free, $\omega_2 = 0$. $\omega_3 =$ R1000/ton.

3.3. System constraints

3.3.1. Input constraints

In this study, inputs include the heating/cooling power Q_c, ventilation rate g_v, CO_2 injection rate C_{inj} and shading rate s_r. The corresponding constraints are as follows:

$$Q_c^{min} \leqslant Q_c \leqslant Q_c^{max}, \tag{42}$$

$$g_v^{min} \leqslant g_v \leqslant g_v^{max}, \tag{43}$$

$$C_{inj}^{min} \leqslant C_{inj} \leqslant C_{inj}^{max}, \tag{44}$$

where Q_c^{min} and Q_c^{max} are the lower and upper limit of the heating or cooling power. g_v^{min} and g_v^{max} are the lower and upper limit of ventilation rate. C_{inj}^{min} and C_{inj}^{max} are the lower and upper limit of CO_2 injection rate. The range of input constraints is determined by the characteristics of the greenhouse system studied.

$$\begin{cases} 0 \leqslant s_r \leqslant 1, & if\ I_{rad} \geqslant I_{rad}^{min} \\ s_r = 0, & if\ I_{rad} < I_{rad}^{min} \end{cases} \tag{45}$$

where I_{rad}^{min} is the lower limit of solar radiation power for shading control. To provide sufficient light for crop growth, the shading control should be implemented only when the radiation power is greater than I_{rad}^{min}. Moreover, the controlled shading rate s_r varies between 0 and 1.

3.3.2. State constraints

Greenhouse climate factors such as temperature, relative humidity, CO_2 concentration and light intensity affect crop growth and yield. Therefore, the greenhouse climate factors should be in a suitable range to provide the necessary environment for crop growth. The too high or low temperature will cause crops to wither or even die [50]. Too high relative humidity will cause the outbreak of some diseases in crops [51]. Too low or too high CO_2 concentration will affect crop photosynthesis and thus affect crop yield [52]. Too low lighting power will reduce crop yield [53]. Please note that different types of crops have different state constraints at different growth stages. The range of state constraints is set by farmers based on their experiences (weigh the expected yield and costs) or obtained from the optimization of crop growth. The state constraints are as follows:

$$T_{air}^{min} \leqslant T_{air} \leqslant T_{air}^{max}, \tag{46}$$

$$RH_{air}^{min} \leqslant RH_{air} \leqslant RH_{air}^{max}, \tag{47}$$

$$C_{air}^{min} \leqslant C_{air} \leqslant C_{air}^{max}, \tag{48}$$

where T_{air}^{min} and T_{air}^{max} are the lower and upper limit of greenhouse temperature. RH_{air}^{min} and RH_{air}^{max} are the lower and upper limit of greenhouse relative humidity. C_{air}^{min} and C_{air}^{max} are the lower and upper limit of greenhouse CO_2 concentration.

$$I_{rad}^{min} \leqslant Q_{sun}, \tag{49}$$

The radiation power after shading control (Q_{sun}) should be greater than the limit value I_{rad}^{min} to provide sufficient light for crop growth.

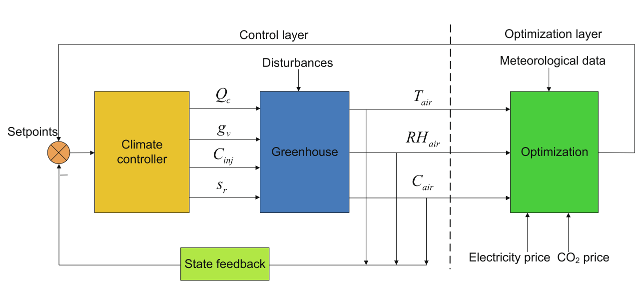

Fig. 5. Greenhouse hierarchical control structure.

4. Controller design

Fig. 5 shows the hierarchical structure of greenhouse control. Hierarchical control can decompose complex problems into different sub-problems, thus effectively reducing the computational complexity of complex problems [54,55]. It can be seen that the greenhouse control includes two layers. On the optimization layer, reference points are generated by greenhouse optimization. On the control layer, a climate controller is designed to track the reference trajectories obtained from the optimization layer.

4.1. Open loop controller design

The discrete state-space model is as follows:

$$x(k+1) = f(x(k), u(k)), \tag{50}$$

where $x(k), u(k)$ are the state vector, input vector at time kT_o. $x(k) = [T_{air}(k), RH_{air}(k), C_{air}(k)]^T, u(k) = [Q_c(k), g_v(k), C_{inj}(k), s_r(k)]^T$. $k = 0, 1, 2, \cdots, N_o - 1$. $N_o = T_t/T_o$. T_t is the total simulation time. T_o is the sampling period.

The open loop controller solves the optimization problem:

$$u^* = \underset{u}{\text{argmin}}\ J, \tag{51}$$

subject to the constraints (42)–(50). $J \in [J_1, J_2, J_3, J_4]$.

4.2. MPC controller design

The MPC sampling interval T_m is smaller than the open loop control sampling interval T_o. $T_m = T_o/N_m$, where N_m is a positive integer. For the time $t_m \in [k_1 T_o + k_2 T_m, k_1 T_o + (k_2 + 1)T_m], k_1 = 0, 1, 2, \cdots, N_o - 1$, $k_2 = 0, 1, 2, \cdots, N_m - 1$, the MPC take the value $u(k_1 + 1)$ that obtained from the open loop optimization (51) as the inputs reference $u_{ref}(k_1 + 1)$ to track the corresponding state variables reference trajectories $x_{ref}(k_1 + 1)$.

In the sequel, a commensurate quantification assumption is made: all variables are quantized in the two sampling schemes, they are represented by starting values and remained in the same sampling interval. This assumption ensures that the MPC can reach the steady state obtained from the open loop optimization.

The MPC objective function can be given by:

$$J_m = \sum_{i=1}^{N_p} (\Delta x(k+i|k))^T Q \left(\Delta x \left(k + i|k \right) \right) + \sum_{i=0}^{N_c - 1} (\Delta u(k+i|k))^T R \left(\Delta u \left(k + i|k \right) \right), \tag{52}$$

where N_p and N_c are optimization horizon and control horizon respectively. $|k$ means that the predicted value is based on the information up to time k. Δx is the tracking error. Δu is the control effort. Q and R are the weighting matrices that penalize the future tracking and control efforts respectively. The control effort in the objective function is to avoid abrupt changes in the control action [56]. $\Delta x(k+i|k)$ and $\Delta u(k+i|k)$ are given by:

$$\Delta x(k+i|k) = x(k+i|k) - x_{ref}(k+i). \tag{53}$$

$$\Delta u\left(k+i|k\right) = \begin{cases} u(k+i|k) - u(k-1), i = 0 \\ u(k+i|k) - u(k+i-1|k), i = 1, 2, \cdots, N_c - 1 \end{cases} \tag{54}$$

Denote $U = [u(k|k), u(k+1|k), u(k+2|k), \cdots, u(k+N_c-1)|k]^T$. The MPC controller solves the nonlinear optimization problem:

$$U^*(k) = \underset{U}{\text{argmin}}\ J_m(k), \tag{55}$$

subject to the constraints (42)–(50).

The MPC algorithm is as follows.

Algorithm 1. The proposed MPC algorithm

Initialization: Given initial state value $x(0)$, $u(0)$ and set $k=0$;

while $k \le N_m - N_p$ **do**

  Compute the solution U of the optimal problem formulated in (55);

  Apply the first value of the solution U and discard the rest of the solution;

  Calculate the state of next interval $x(k+1)$ by $x(k+1)=f(x(k),u(k))$;

  $k=k+1$;

end

$N_p = N_p - 1$;

while $k < N_m$ **do**

  Compute the solution U of the optimal problem formulated in (55);

  Apply the first value of the solution U and discard the rest of the solution;

  Calculate the state of next interval $x(k+1)$ by $x(k+1)=f(x(k),u(k))$;

  $k=k+1$; $N_p = N_p - 1$;

end

Table 1
Greenhouse model parameters.

Parameter	Value	Unit	Parameter	Value	Unit
α_1	0.7	–	p_{gc}	1.8×10^{-3}	$m°C^{-1/3}s^{-1}$
α_2	10	$Wm^{-2}°C^{-1}$	ω_o	0.5157	R/kWh
γ	0.008	–	ω_s	0.9446	R/kWh
LAI	2.6	–	ω_p	3.1047	R/kWh
C_{cap}	30000	$J/m^2°C$	λ	0.06	W/m^3
h	7	m	η	0.75	–
s	40709	m^2	g	9.8	m/s^2
L	2450	J/g	h_w	7	m
r_b	150	s/m	ω_3	1000	R/ton
ρ_{air}	1.225	kg/m^3	K_c	0.7	–
$C_{p,air}$	1003	J/kg°C			

Table 2
Greenhouse system constraints.

Variable	Value	Unit
T_{air}^{min}	14	°C
T_{air}^{max}	26	°C
RH_{air}^{min}	0	%
RH_{air}^{max}	90	%
C_{air}^{min}	400	ppm
C_{air}^{max}	2000	ppm
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

5. Simulation

5.1. Simulation data

In this research, we studied four optimization strategies for the operation of a Venlo-type greenhouse under South Africa climate. The meteorological data of a winter day (July 1, 2016, 0:00 to 23:59) is used. The data come from a weather station at the University of Pretoria (25°75′S, 28°23′E) and is shown in Fig. 6. The greenhouse model parameters are from [34,35] and are shown in Table 1. The system constraints are shown in Table 2.

Lamps are installed to provide artificial lighting. Air–water heat exchangers are installed for heating and cooling. For CO_2 enrichment, the OCAP (organic CO_2 for assimilation by plants) network supplies the organic CO_2 crops needed. For greenhouse supplemental lighting, the artificial lighting power is set to zero for day time(07:00 to 18:00) and $110 W/m^2$ for night time (19:00 to 06:00).

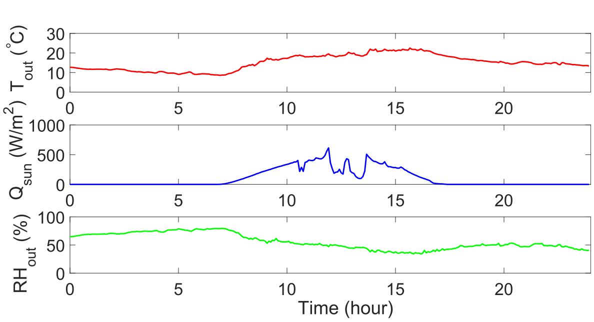

Fig. 6. Meteorological data for July 1, 2016.

5.2. Optimization results

The optimization problem is solved by the ’fmincon’ code of the MATLAB Optimization Toolbox. The interior point algorithm is selected as the optimization algorithm. The optimization results of proposed four strategies are shown in the following sections.

5.2.1. Strategy 1

The optimization result of Strategy 1 is shown in Fig. 7. We can find that the energy consumed is mainly used for heating in the morning. The reason is that the temperature in the greenhouse has gradually dropped to the set lower temperature limit after a cold night. There is very little energy from solar radiation available in the early morning. Therefore, the greenhouse heating system should work to maintain the greenhouse temperature.

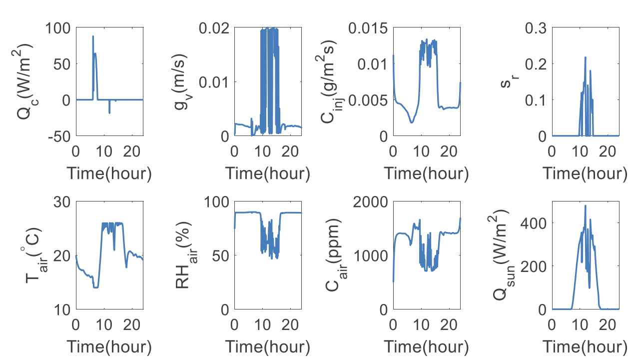

Fig. 7. Optimization results of Strategy 1.

In addition, we can find that greenhouse ventilation is mainly at noontime. That is because the outdoor temperature is high and ventilation will not lose a lot of energy during this period.

5.2.2. Strategy 2

The optimization result of Strategy 2 is shown in Fig. 8. The energy consumption of Strategy 1 is mainly used for greenhouse heating, while the energy consumption of Strategy 2 is used for both greenhouse heating and greenhouse cooling. Moreover, we can find that the greenhouse temperature is low but the relative humidity is high. Moreover, the shading rate of Strategy 2 is greater than that of Strategy 1, and the radiation power of Strategy 2 is smaller than that of Strategy 1. That is because low temperature, high relative humidity and low radiation power help reduce crop evapotranspiration and thus reduce water consumption. It should be pointed out that the energy consumption of Strategy 2 is much higher than that of Strategy 1.

5.2.3. Strategy 3

The optimization results of Strategy 3 is shown in Fig. 9. It can be seen that the CO_2 injection rate is small. The CO_2 concentration is low. Strategy 3 consumes less CO_2 than other strategies. Moreover, we can find that the ventilation rate is high. The reason is that ventilation can send the outdoor CO_2 into the greenhouse to keep the greenhouse CO_2 concentration within the required range. It should be noted that ventilation will cause energy loss in the greenhouse and increase the energy consumption of the greenhouse.

5.2.4. Strategy 4

The optimization result of Strategy 4 is shown in Fig. 10. We can find that the energy consumption and CO_2 consumption of Strategy 4 are very small. That is because energy cost and CO_2 cost are the main part of the greenhouse total cost. Reducing energy consumption and CO_2 consumption will effectively reduce the total cost.

Table 3 shows the energy consumption, water consumption, CO_2 consumption and total cost of the proposed four strategies. We can find that Strategy 1 has the least energy consumption, Strategy 2 has the least water consumption, Strategy 3 has the least CO_2 consumption, and Strategy 4 has the lowest total cost. Fig. 11 shows the comparison between Strategy 1 and Strategy 4 under the TOU tariff. It can be seen that the energy consumption of Strategy 4 is higher than that of Strategy 1, but the energy cost of Strategy 4 is lower than that of Strategy 1. The reason is that Strategy 4 consumes less energy than Strategy 1 in the peak time with a high price.

The control variable shading rate s_r is shown in Fig. 12. It can be seen that the shading rate of Strategy 2 is bigger than that of other strategies. The reason is that the increase of shading rate can reduce the solar radiation, and thus reduce the evapotranspiration and water consumption. Although reducing solar radiation power can reduce water consumption, the energy consumed to maintain the greenhouse temperature within the required range increases accordingly. Therefore, the control of solar radiation power should be in a reasonable range.

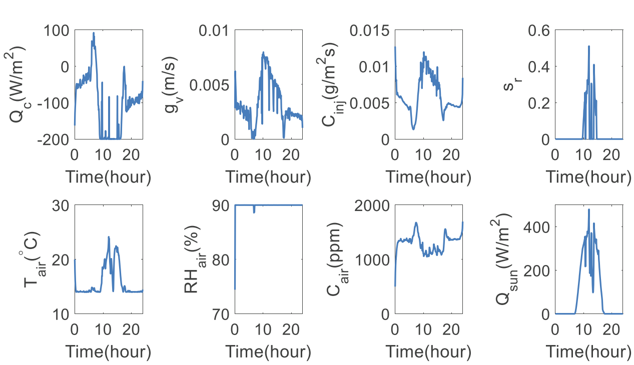

Fig. 8. Optimization results of Strategy 2.

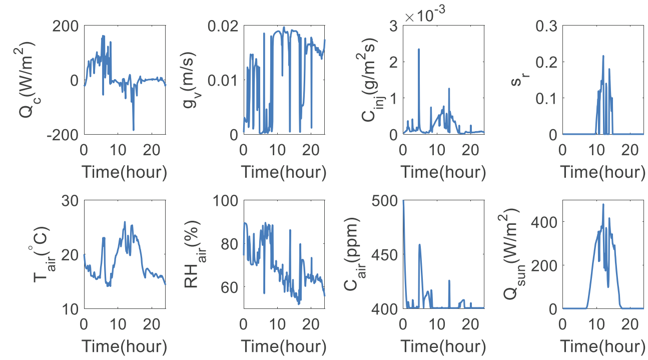

Fig. 9. Optimization results of Strategy 3.

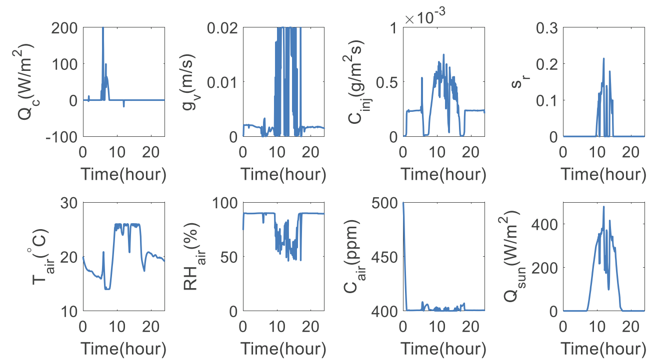

Fig. 10. Optimization results of Strategy 4.

Table 3
Comparison of four strategies.

	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Energy consumption (kWh)	4243.20	106656.73	31299.40	5539.21
Water consumption (ton)	86.61	68.16	94.50	86.92
CO_2 consumption (ton)	21.18	21.08	0.65	0.95
Cost (Rand)	32307	147410	34624	10791

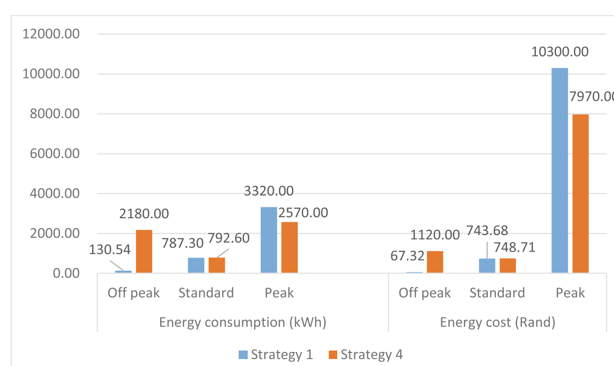

Fig. 11. Comparison of Strategy 1 and Strategy 4 under TOU tariff.

Fig. 13 shows the energy consumption composition of four strategies. It can be seen that most energy consumed for heating and cooling, followed by ventilation and the least for irrigation. Among the four strategies, Strategy 1 has the least total energy consumption and Strategy 2 has the most energy consumption. The cost composition of four strategies is shown in Fig. 14. We can find that Strategy 2 has the highest total cost and Strategy 4 has the lowest cost. The reason is that Strategy 2

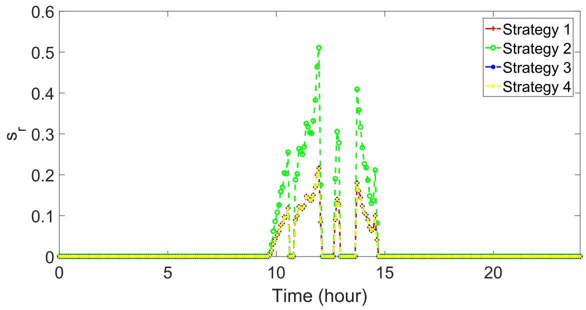

Fig. 12. Greenhouse shading rate s_r.

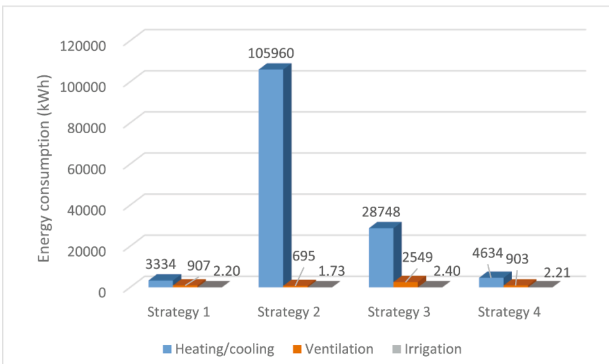

Fig. 13. Energy consumption composition of four strategies.

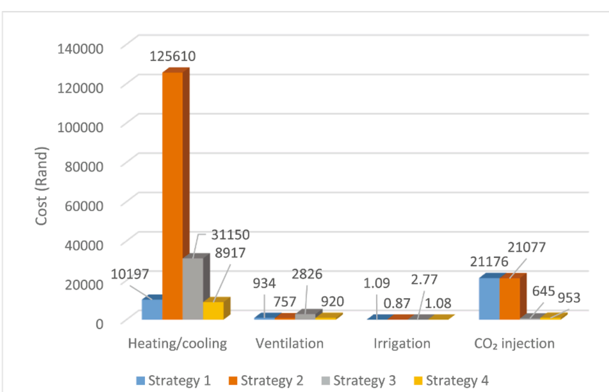

Fig. 14. Cost composition of four strategies.

consumes much more energy for heating and cooling than the other three strategies.

5.3. Sensitivity analysis

Sensitivity analysis can provide insights into the influence of model parameter uncertainties on the performance of the optimal controller [36]. In this paper, the initial electricity price is R 0.5157/kWh for the off peak period, R 0.9446/kWh for the standard period, and R 3.1047/kWh for the peak period. The initial water price is zero. The initial CO_2 price is R 1000/ton. The initial upper limit of temperature is 26 °C, the lower limit of temperature is 14 °C, and the upper limit of relative humidity is 90%. However, the electricity price and CO_2 price may change over time. The water price should not be set to zero if the impact of water consumption on the sustainable development of society is considered. The state constraints of different types of crops at different growth stages should be different values. Therefore, it is necessary to analyze how the changes of these parameters and constraints affect the optimization results.

In this paper, we take Strategy 4 as an example to analyze the influence of the changes of electricity price, water price, CO_2 price, temperature constraint and relative humidity constraint on the optimization results. The change is in increments of 5%. The maximum change of electricity price, CO_2 price and constraints range is 15% of the initial value. The maximum change of water price is 15% of South Africa's water tariff (R 14.27 per kiloliter).

5.3.1. Influence of prices change

The sensitivity analysis of electricity price, water price and CO_2 price is shown in Fig. 15. It can be seen that the cost increases with the increase of electricity price, water price and CO_2 price. Moreover, compared with the change of water price and CO_2 price, the change of electricity price has a greater impact on the cost. When the price of electricity increased by 15%, the cost increased by 13.68%. However, when the price of water and CO_2 increased by 15%, the cost only increased by 1.9% and 1.33% respectively.

5.3.2. Influence of constraints change

The optimization results of strategy 4 under the constraints of different percentage changes are shown in Fig. 16. We can find that both increasing the upper limit of temperature (T_{max}) and reducing the lower limit of temperature (T_{min}) will reduce the cost of greenhouse operation. The difference is that reducing the lower limit of temperature can significantly reduce the cost while increasing the upper limit of temperature cannot. When the lower limit of the temperature constraint is reduced by 15% (from 100% to 85%), the cost is reduced by 43.31% (from R 10791 to R 6123). However, when the upper bound is increased by 15% (from 100% to 115%), the cost is only reduced by 2.90% (from R 10791 to R 10490). Moreover, when the upper limit of temperature reaches 110%, increasing the upper limit will no longer affect the optimization results.

In addition, the cost decreases with the increase of the upper limit of relative humidity (RH_{max}). Therefore, the greenhouse operating cost can be effectively reduced by setting appropriate temperature and relative humidity constraints. It can be concluded that cost is sensitive to changes in greenhouse temperature and relative humidity. Therefore, it is important to carefully set the temperature and relative humidity constraints for the optimization.

5.4. MPC

The optimization results shown in Fig. 10 are taken as the reference trajectories. The MPC parameter settings are as follows: the predictive horizon $N_p = 10$, the control horizon $N_c = N_p$, the sampling interval $T_{sm} = 60$ s, the total simulation time $T_m = 24$ h. In this paper, $Q = \mathrm{diag}(100, 100, 100)$, $R = \mathrm{diag}(1, 1, 1)$.

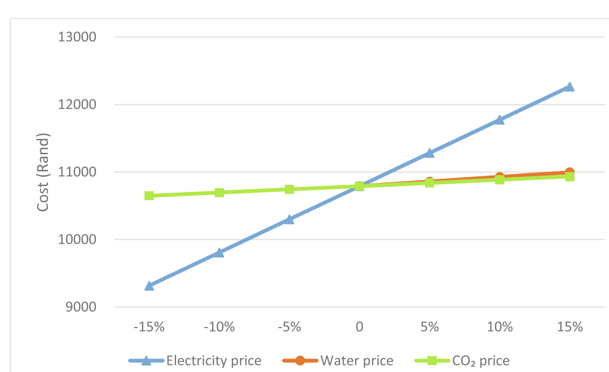

Fig. 15. Sensitivity analysis of electricity price, water price and CO_2 price.

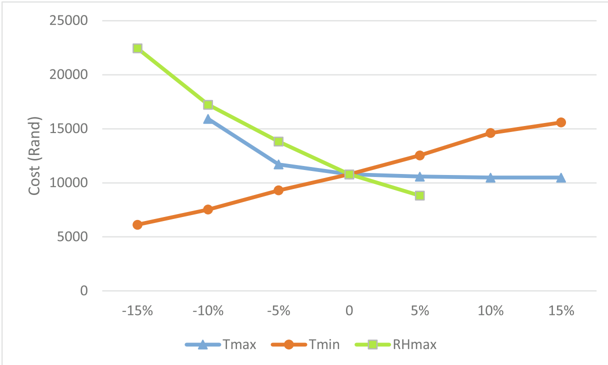

Fig. 16. Greenhouse operation cost under the constraints of different percentage changes.

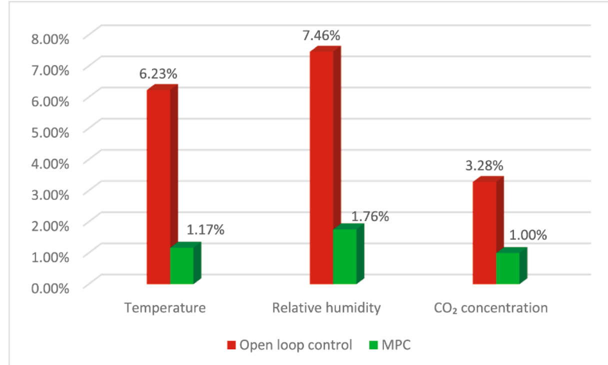

Fig. 18. Comparison of RAD between open loop control and MPC.

The comparison results between the open loop control (51) and the proposed MPC (55) under 2% system disturbances are shown in Fig. 17. To compare the tracking performance of open loop control and MPC, the tracking performance index relative average deviation (RAD) is introduced.

Denote the value of actual measurement as x_{meas}, the relative deviation (RD) of x is defined by:

$$\mathrm{RD}(i) = \left|\frac{x_{meas}(i) - x_{ref}(i)}{x_{ref}(i)}\right|. \tag{56}$$

The RAD can be obtained by:

$$\mathrm{RAD} = \frac{1}{N}\sum_{i=1}^{N}\mathrm{RD}(i). \tag{57}$$

where N is the total sampling times. For the open loop control, $N = 288$. For the MPC, $N = 1440$.

The comparison of RAD between open loop control and MPC is shown in Fig. 18. It can be seen that, compared with the open loop control, the MPC can reduce 81.22% temperature RAD (from 6.23% to 1.17%), 76.41% relative humidity RAD (from 7.46% to 1.76%), and 69.51% CO_2 concentration RAD (from 3.28% to 1%). Compared with the open loop control, the proposed MPC can effectively reduce the tracking error.

6. Conclusion

Four optimization strategies to improve the operating efficiency of a Venlo-type greenhouse are studied. These strategies are to minimize greenhouse energy consumption (Strategy 1), irrigation water consumption (Strategy 2), CO_2 consumption (Strategy 3) and operation cost (Strategy 4) while keeping greenhouse climatic factors include the temperature, relative humidity, and CO_2 concentration within the required range. A multi-input multi-output greenhouse (MIMO) climate model and a modified evapotranspiration model are adopted. Moreover, a sensitivity analysis is conducted to study the influence of electricity price, water price, CO_2 price and system constraints on optimization results. Finally, a model predictive controller (MPC) is designed to address system disturbances. A performance index relative average deviation (RAD) is introduced to evaluate the tracking performance.

Simulation results show that the cost of Strategy 4 (R 10791) is reduced by 66.60%, 92.68% and 68.83% compared with Strategy 1 (R 32308), Strategy 2 (R 147440) and Strategy 3 (R 34624) respectively. Changes in electricity price have a greater impact on optimization results than changes in water price and CO_2 price. Both temperature constraints and relative humidity constraints have a great influence on the optimization results. The MPC controller designed is verified to be effective.

In future research, we will focus on the following aspects. (1) Use a hybrid energy system composed of PV panel, wind generator, power

Fig. 17. Comparison of open loop control and MPC under 2% system disturbances.

grid, diesel generators and battery bank to power the greenhouse system. (2) The greenhouse optimization process considers some long-term objectives such as crop yields and greenhouse production profits. (3) Distributed control of large-scale greenhouse systems. (4) To verify the effectiveness of the proposed strategies through relevant experimental studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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