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Managing energy-water-carbon-food nexus for cleaner agricultural greenhouse production: A control system approach

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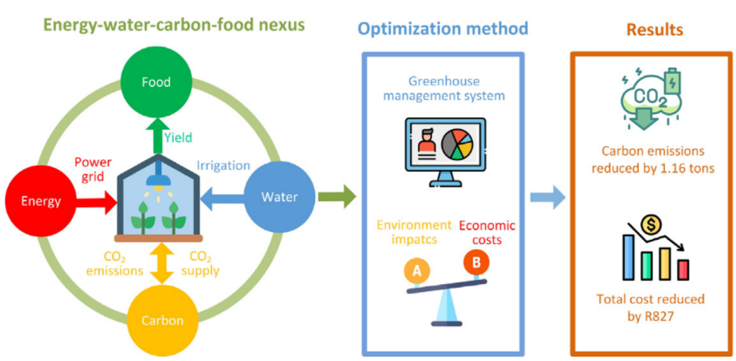
HIGHLIGHTS

- An economic model predictive control method for managing greenhouses is proposed.
- Both economic costs and environmental impacts of carbon emissions are considered.
- A sensitivity analysis of prices is carried out.
- The total cost and carbon emissions are reduced.

GRAPHICAL ABSTRACT



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ABSTRACT

Poverty, food insecurity and climate change are global issues facing humanity, threatening social, economic and environmental sustainability. Greenhouse cultivation provides a potential solution to these challenges. However, some greenhouses operate inefficiently and need to be optimized for more economical and cleaner crop production. In this paper, an economic model predictive control (EMPC) method for a greenhouse is proposed. The goal is to manage the energy-water-carbon-food nexus for cleaner production and sustainable development. First, an optimization model that minimizes the greenhouse's operating costs, including costs associated with greenhouse heating/cooling, ventilation, irrigation, carbon dioxide (CO_2) supply and carbon emissions taking into account both the CO_2 equivalent (CO_2-eq) emissions caused by electrical energy consumption and the negative emissions caused by crop photosynthesis, is developed and solved. Then, a sensitivity analysis is carried out to study the impact of electricity price, supplied CO_2 price and social cost of carbon (SCC) on the optimization results. Finally, a model predictive control (MPC) controller is designed to track the optimal temperature, relative humidity, CO_2 concentration and incoming radiation power in presence of system disturbances. Simulation results show that the proposed approach increases the operating costs by R186 (R denotes the South African currency, Rand) but reduces the total cost by R827 and the carbon emissions by 1.16 tons when compared with a baseline method that minimizes operating costs only. The total cost is more sensitive to changes in SCC than that in electricity price and supplied CO_2 price. The MPC controller has good tracking performance under different levels of system disturbances. Greenhouse environmental factors are kept within specified ranges suitable for crop growth, which increases crop yields. This study can provide effective guidance for growers' decision-making to achieve sustainable development goals.

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1. Introduction

Global issues such as poverty, energy crisis, food insecurity, climate change and global warming affect social, economic and environmental sustainability (Lipper et al., 2014). During the COVID-19 epidemic, the impact of these issues is increasing, especially in some low-income countries (Laborde et al., 2020). Agricultural production is critical to deal with these issues (Nie et al., 2019). According to the World Bank, agriculture can help 80 % of the world's poor reduce poverty, increase incomes and improve food security (Bank, 2022). However, the growth of crops is greatly affected by the weather under the traditional open-field cultivation mode. Crops cultivated with this mode have low yields (Lin et al., 2021). In recent years, with a growing population and decreasing arable land, the traditional open-field cultivation mode is facing many challenges in providing sufficient food (Ouammi, 2021). Moreover, some cultivation modes cause problems such as soil erosion, land degradation and pesticide residues, which restrict the sustainable development of agriculture (Su et al., 2021). Compared with traditional open-field cultivation, modern precision agriculture has many advantages, such as environmentally friendly and high crop yields, which can help to achieve cleaner production and sustainable development (Tahery et al., 2021).

Greenhouse cultivation is one of the most popular modern agricultural technologies (Hesampour et al., 2022). A greenhouse is an enclosed agricultural building covered with transparent materials such as plastic or glass to allow sunlight to pass through. Greenhouses can provide a suitable environment for crops and protect them from adverse external environmental conditions such as extreme temperatures, heavy rain and hail, etc. (Xu et al., 2019). Therefore, the crops under greenhouse planting mode can obtain higher yield and better quality than those under traditional outdoor planting mode (Ouammi et al., 2019).

Greenhouses consume a lot of resources, which leads to high operating costs and adverse environmental impacts (Golzar et al., 2019). Firstly, greenhouses consume a lot of energy and the energy efficiency of greenhouse systems under some traditional operation modes is low (Zhang et al., 2020). About 65 % to 85 % of the energy consumed by greenhouses is used for heating (Ahamed et al., 2019). Greenhouse heating is generally done by using electric heaters or burning fossil fuels, which will increase carbon dioxide (CO_2) emissions (Ouammi et al., 2020). The increasing CO_2 emissions contribute to global warming, which has a great impact on environmental sustainability (Nižetić et al., 2019). Secondly, the greenhouse irrigation process needs to be optimized to reduce water consumption while meeting the water demand for crop growth (Ramírez-Arias et al., 2012). Thirdly, greenhouse CO_2 supply and shading control also should be considered in the optimization of greenhouse operations to reduce operating costs (Li et al., 2018).

Some studies focus on reducing greenhouse energy consumption or costs. In (Ramírez-Arias et al., 2005), a model predictive control (MPC) method is proposed to improve the energy efficiency of the greenhouse heating system. A simplified linearized model of the system around the predefined set points is adopted. The designed controller tracks the optimized reference trajectory to reduce energy consumption. The results show that the proposed method can improve the system performance without modifying the system. In (Zhang et al., 2015), the use of a solar soil heat storage system for greenhouse heating is studied. The solar energy stored in the soil under the greenhouse can be used to reduce the energy demand of extreme cold and continuous overcast days in winter. Results reveal that 27.8 kWh of electricity can be saved per square meter of greenhouse per year. In (van Beveren et al., 2020), an optimal control method for the energy utilization of a semi-closed greenhouse is proposed. All available equipment is used under optimal conditions. The energy cost is reduced by 29 % compared with the grower's situation. In (Attar et al., 2014), the use of ground thermal energy for greenhouse heating is studied. During the day, the air suspension exchanger recovers excess solar energy. At night, excess energy stored in storage tanks is used to heat the greenhouse air. The obtained results indicate that the energy stored in the ground can increase the temperature by 6°C at night.

Some studies focus on reducing greenhouse water consumption. Water is critical for agricultural crop production (Lovarelli et al., 2016). Methods to reduce water consumption by improving water efficiency have been discussed in many studies. A predictive control approach for reducing greenhouse energy and water consumption is presented in (Blasco et al., 2007). In (Tsafaras et al., 2021), a method of reducing water use for evaporative cooling is studied. Results reveal that increasing the temperature of the extracted air can effectively reduce water consumption. In (Parada et al., 2021), the irrigation of a rooftop greenhouse is optimized to reduce water consumption and environmental impact while maintaining the water requirements of the grown tomatoes.

Some studies focus on the optimization of the greenhouse CO_2 supply. Using CO_2 as fertilizer for crops in greenhouses can not only improve crop yields but also increase CO_2 sink (Ghiat et al., 2021). This technology has been widely used in greenhouse production and achieved good economic benefits. In (Chalabi et al., 2002), two optimal control methods of CO_2 supply for greenhouse tomato planting are proposed. In (Oreggioni et al., 2019), the technology of CO_2 by-product applied to tomato production in an agricultural greenhouse is evaluated. Results show that CO_2 utilization technology has better economic benefits than CO_2 storage.

For the greenhouse production, energy, water, carbon emissions and food are highly inter-connected, which is called the energy-water-carbon-food (EWCF) nexus. Energy, water and food are essential for human well-being, poverty reduction and sustainable development (FAO, 2014). The management of the EWCF nexus helps to achieve social, economic and environmental objectives with limited resources (Xu et al., 2020). However, the EWCF nexus approach has been rarely discussed in previous studies on greenhouse operation optimization. Most previous studies focus on resource utilization such as reducing energy and water consumption, or economic aspects, such as reducing greenhouse operating costs or increasing greenhouse production profits, while few studies consider the environmental impact of carbon emissions. To fill these gaps, an optimization method that takes into consideration both economic costs and carbon emissions of greenhouse systems is studied in this paper. The proposed method is studied based on meteorological data from South Africa. South Africa is a country short of electricity (Zhang et al., 2021). The vast majority of electricity in South Africa is generated by burning coal. Fig. 1 shows the energy mix of South Africa from 1990 to 2018. It can be observed that coal accounts for more than 80 % of South Africa's total energy, while renewable energy accounts for a small part of the overall mix. Due to its heavy reliance on coal, South Africa has become the 14th largest carbon emitter in the world and the largest carbon emitter in Africa.

In this study, an economic model predictive control (EMPC) method for a greenhouse under the climate of South Africa is proposed. The objective is to manage the EWCF nexus for low-cost and cleaner crop production. The proposed method has a two-layer structure consisting of an optimization layer and a control layer. At the optimization layer, an optimization method is adopted to minimize the total cost including the operating costs and the cost of carbon emissions while keeping greenhouse environmental factors

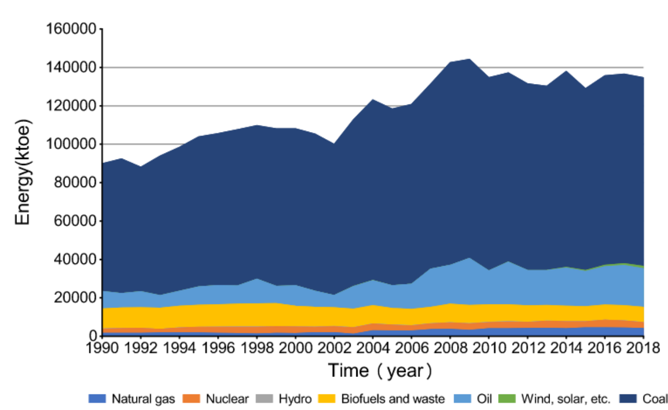

Fig. 1. Energy mix of South Africa.

including temperature, relative humidity, CO_2 concentration and incoming solar radiation power within required ranges. The calculation of operating costs takes into account heating/cooling, ventilation, CO_2 supply and irrigation. The carbon emissions include the CO_2 equivalent (CO_2-eq) emissions from electricity consumed by greenhouse operation and the negative emissions from crop photosynthesis. The cost of carbon emissions is determined by the amount of CO_2-eq emissions and the social cost of carbon (SCC) which is a commonly used indicator to measure the expected economic loss caused by one ton of CO_2 emissions (Ricke et al., 2018). Moreover, a sensitivity analysis is carried out to study the impact of the electricity price, supplied CO_2 price and SCC on the total cost. At the control layer, an MPC approach is used to deal with system disturbances. The control performance of the designed controller is analyzed.

The main contributions of this study can be summarized as: 1) Most studies on greenhouse operation optimization consider energy consumption or economic costs but ignore the environmental impacts of carbon emissions. In this paper, both operating costs and carbon emissions are considered. The proposed method helps to achieve cleaner crop production and sustainable development. 2) Most previous studies on the optimization of greenhouse operation only considered one or some of the environmental factors (temperature, relative humidity, CO_2 concentration and incoming solar radiation power), while this study considered all of them. Compared with previous studies, this study can provide a better environment for crop growth and obtain a higher crop yield. 3) The impact of climatic factors on the CO_2 absorption rate of crop photosynthesis is analyzed. The feasibility of reducing the CO_2 emission of the greenhouse system by adjusting the climate environment inside the greenhouse is studied. 4) The SCC and the grid emission factor are introduced to calculate the cost of carbon emissions. The multi-objective optimization problem considering two conflicting objectives of greenhouse operating costs and CO_2 emissions are transformed into a single-objective optimization problem that minimizes the total cost of operating costs and carbon emissions costs. The computational complexity of the greenhouse operation optimization problem is reduced. 5) A sensitivity analysis of the electricity price, supplied CO_2 price and SCC is conducted. A deeper insight into the effects of uncertainty in model parameters on the optimization results is obtained. 6) An MPC method is introduced to deal with system disturbances and the complex interactions between different environmental factors.

The rest of this paper is organized as follows. Section 2 presents the greenhouse system model. Section 3 discusses the proposed optimization methods. Section 4 designs the EMPC controller. Simulation results are shown in Section 5. Section 6 concludes this paper and gives future work.

2. System description

2.1. Greenhouse system

The growth of crops in the greenhouse requires suitable temperature, relative humidity, CO_2 concentration and light intensity, which needs to be achieved through the cooperation of multiple systems including a power supply system, ventilation system, carbon supply system and irrigation system (Achour et al., 2021).

Fig. 2 is the schematic diagram of greenhouse production. The production process can be summarized as follows: First, farmers set optimization goals and system constraints based on their own experience and needs. Then, the controller, that is, the control centre, gives corresponding instructions to each system based on the received information. Finally, each system operates based on the control signal received from the control centre.

2.2. Greenhouse environmental factors model

In this study, four environmental factors (temperature, relative humidity, CO_2 concentration and incoming radiation power) affecting crop growth are considered. The model adopted is derived from (Van Beveren et al., 2015a; Van Beveren et al., 2015b) and has been verified to have good prediction performance.

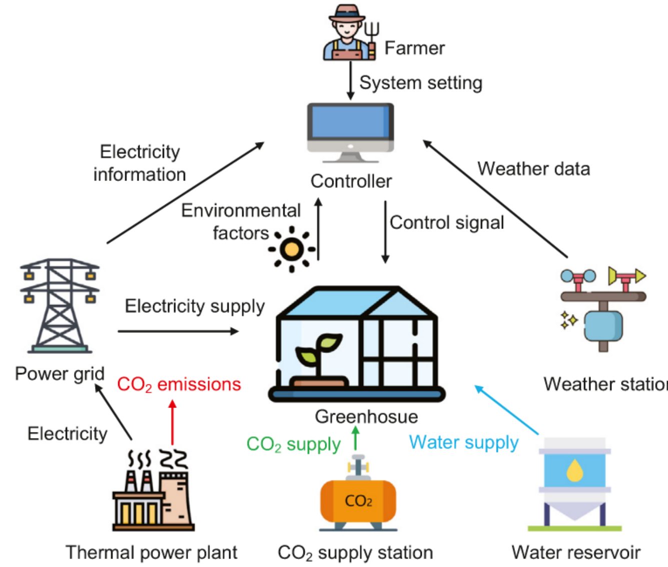

Fig. 2. Schematic diagram of greenhouse production.

2.2.1. Temperature

The temperature is determined by the energy balance of the system. Fig. 3 shows the energy, water and CO_2 flow. It can be seen that the energy mainly comes from solar radiation and heating. The energy loss is caused by greenhouse ventilation, heat exchange with outdoor air, crop transpiration and greenhouse cooling. Therefore, the temperature can be calculated 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 power, and Q_{lamp} is the lamp heating power. Q_{cov} is the heat loss through the cover, Q_{trans} is the energy absorbed by crop transpiration. Q_{vent} represents the energy loss through ventilation. Q_c represents the heating or cooling power. When the value of Q_c is positive, the greenhouse is being heated, and the heating power is Q_c. When the value of Q_c is negative, the greenhouse is being cooled, and the value of cooling power is the absolute value of Q_c.

Q_{sun} is determined by:

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

where α_1 represents the transmission coefficient of the cover, s_r is the shading rate, Q_{rad} represents the solar radiation power.

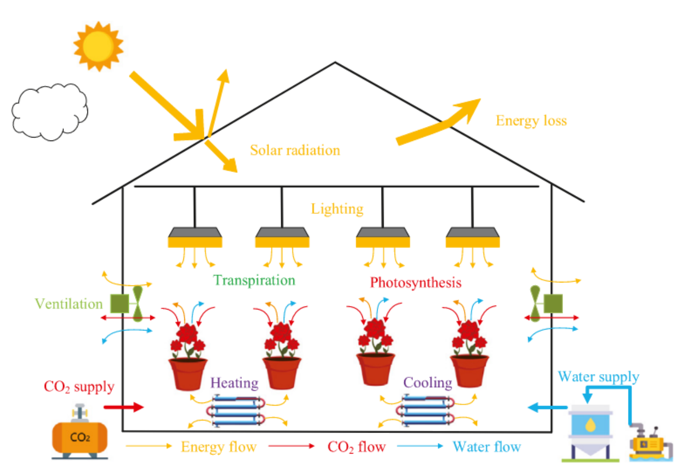

Fig. 3. Energy, water and CO_2 flow.

Q_{cov} can be calculated by:

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

where α_2 is the cover heat transfer coefficient, T_{out} is the outdoor 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, and L is the energy consumed to evaporate water from a leaf. H_{crop} is the absolute water vapour concentration at the crop level. H_{air} is the absolute water vapour concentration.

Nomenclature

T_{air}	greenhouse temperature, °C
T_{out}	outdoor temperature, °C
Q_c	controlled heating or cooling power, W/m^2
Q_{sun}	incoming radiation power, W/m^2
Q_{lamp}	lamp heating power, W/m^2
Q_{cov}	heat transfer through the cover, W/m^2
Q_{rad}	solar radiation power, W/m^2
Q_{trans}	transpiration endothermic power, W/m^2
Q_{vent}	heat loss through ventilation power, W/m^2
H_{air}	greenhouse humidity, g/m^3
H_{trans}	vapour evaporated by the crop, g/m^{2}s
H_{cov}	vapour condensation to the cover, g/m^{2}s
H_{crop}	vapour concentration at crop level, g/m^3
H_{out}	humidity outside the greenhouse, g/m^3
H_{vent}	vapour flux due to ventilation, g/m^{2}s
RH_{air}	greenhouse relative humidity, %
C_{air}	greenhouse CO_2 concentration, g/m^3
C_{out}	CO_2 concentration outside the greenhouse, g/m^3
C_{inj}	CO_2 injection into the greenhouse, g/m^{2}s
C_{assi}	CO_2 assimilation by the crop, g/m^{2}s
C_{vent}	effect of ventilation on CO_2 concentration, g/m^{2}s
C_{cap}	greenhouse heat capacity, J/°Cm^2
$C_{p,\,air}$	air heat capacity, J/kg°C
C_{oper}	operating costs, R
C_{elec}	electricity cost, R
C_{carb}	cost of supplemental CO_2, R
C_{equi}	equivalent carbon emissions of energy consumed, ton
RH_{air}	greenhouse relative humidity, %
SCC	social cost of carbon, $/ton
s_r	shading rate
α_1	transmission coefficient
α_2	heat transfer coefficient, W/°Cm^2
g_e	transpiration conductance, m/s
LAI	leaf area index
L	energy needed to evaporate water from a leaf, J/g
ϵ	ratio of latent to sensible heat content of saturated air
r_b	boundary layer resistance parameter, s/m
r_s	stomatal resistance, s/m
γ	crop specific parameter
P_E	artificial lighting power, W/m^2
η	lighting thermal conversion coefficient
g_v	ventilation rate, m/s
s	the greenhouse area, m^2
ρ_{air}	density of air, kg/m^3
h	average height of greenhouse, m
g_c	the condensation conductance, m/s
p_{gc}	parameter related to the properties of the condensation surface, $m^\circ C^{-\frac{1}{3}}s^{-1}$
p_o	off-peak electricity price, R/kWh
p_s	standard electricity price, R/kWh
p_p	peak electricity price, R/kWh
p_c	supplied CO_2 price, R/ton

g_e is obtained by:

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

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 and r_s is the stomatal resistance.

H_{crop} is given 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. $H_{air,\,sat}$ is determined by:

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

ϵ and r_s can be obtained by:

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

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

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

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

where P_E is the power of lighting.

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

where η is the lamp heating coefficient.

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

where g_v represents the ventilation rate, ρ_{air} represents the air density, $C_{p,\,air}$ represents the air heat capacity.

2.2.2. Relative humidity

The relative humidity RH_{air} is determined as follows:

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

where H_{air} is the air vapour concentration and 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 and H_{vent} is the vapour flux caused by ventilation. h is the greenhouse height.

H_{trans} can be described by:

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

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:

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

where p_{gc} is a coefficient determined surface characteristics.

H_{vent} can be obtained by:

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

where g_v is the ventilation rate.

2.2.3. CO_2 concentration

For the greenhouse system, CO_2 supplement is through greenhouse ventilation and CO_2 injection. CO_2 loss is due to the assimilation of crops. The CO_2 concentration model is given by:

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

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

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

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

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

2.2.4. Incoming radiation power

Solar radiation power is an important environmental factor affecting crop growth. The calculation of incoming radiation power Q_{sun} can be found in Eq. (2) and will not be repeated in this section.

2.3. Greenhouse irrigation model

In this study, the drip irrigation method is used. The amount of water consumed for irrigation is equal to the evapotranspiration of crops. The dynamic model of the greenhouse irrigation can be expressed as:

$$\frac{dI_{con}}{dt} = ET, \tag{22}$$

where I_{con} represents the amount of water consumed for irrigation, ET represents the crop evapotranspiration.

$$ET = k_c \times \frac{0.408\Delta R_n + \gamma \frac{1713}{T_{air} + 273}(e_s - e_a)}{\Delta + 1.64\gamma}. \tag{23}$$

where k_c is the crop factor, Δ is the slope of the vapour pressure curve, γ is the psychometric constant, e_s is the saturation vapour pressure, e_a is the average vapour pressure.

$$\Delta = \frac{4098 \times e_s}{(T_{air} + 237.3)^2}, \tag{24}$$

$$e_a = e_s \times RH_{air}, \tag{25}$$

$$e_s = 0.6108 \times exp\left(\frac{17.27 \times T_{air}}{T_{air} + 237.3}\right). \tag{26}$$

2.4. Model analysis

The validation of the greenhouse climate model used can be found in (Van Beveren et al., 2015a; Van Beveren et al., 2015b). The performance analysis of the crop reference evapotranspiration model can be found in (Qiu et al., 2011). The authors collected data from greenhouses and compared it with the results predicted by the model. The results show that the predicted values can follow the actual values well. The model is verified to have good performance and can be used for optimization and control of greenhouse systems.

According to Eq. (20), we can find that the CO_2 assimilation rate is related to the incoming solar radiation power and the CO_2 concentration. Fig. 4 shows that the assimilation rate, i.e. crop CO_2 absorption rate, increases with the increase of temperature and radiation power. Therefore, the following methods can be used to increase the assimilation rate and reduce the CO_2 emissions of the greenhouse system: increasing the radiation power and CO_2 concentration. The incoming solar radiation power can be adjusted by controlling the greenhouse shading system. The CO_2 concentration can be adjusted by the CO_2 supply system. It should be noted that the effect of radiation power on the assimilation rate is greater than that of CO_2 concentration.

3. Optimization

The greenhouse operation optimization problem can be formulated as the optimization of greenhouse heating/cooling, ventilation, CO_2 supply and shading to achieve the set goals of reducing costs and carbon emissions while providing the desired environment for crop growth. The following will explain the optimization problem from four aspects: decision variables, objectives, constraints and optimization methods.

3.1. Decision variables

This study takes into consideration the control of greenhouse heating, ventilation, CO_2 supply and shading systems. Decision variables include Q_c, g_v, C_{inj} and s_r.

3.2. Objectives

The proposed optimization method considers economic costs and the environmental impact of greenhouse operation. Greenhouse operation planning considers two objectives: greenhouse operating costs and carbon emissions.

3.2.1. Operating costs

The calculation of greenhouse operating costs C_{oper} takes into account greenhouse heating, ventilation, CO_2 supply and irrigation. These costs can be divided into two categories: the cost of electricity consumed and the cost of CO_2 supplied. C_{oper} can be calculated by:

$$C_{oper} = C_{elec} + C_{carb} \tag{27}$$

where C_{elec} is the cost of electricity consumed, C_{carb} is the cost of CO_2 supplied. C_{elec} can be calculated by:

$$C_{elec} = C_h + C_v + C_i, \tag{28}$$

where C_h is the cost of greenhouse heating and cooling, C_v is the cost of ventilation, C_i is the cost of irrigation.

$$C_h = \int_{t_i}^{t_f} Q_c(t)p(t)Sdt, \tag{29}$$

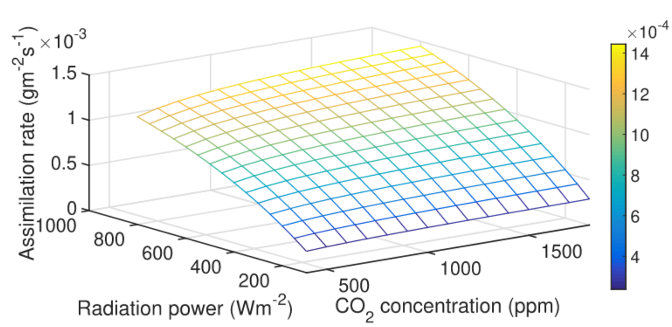

Fig. 4. Crop assimilation rate.

$$p(t) = \begin{cases} p_o & t \in [0,6] \cup [22,24] \\ p_s & t \in [9,17] \cup [19,22], \\ p_p & t \in [6,9] \cup [17,19] \end{cases} \tag{30}$$

where S is the greenhouse area, p is the electricity price. It should be pointed out that the time-of-use (TOU) tariff is used. p_o, p_s and p_p represent electricity price during the off-peak, standard and peak period, respectively.

$$C_v = \int_{t_i}^{t_f} g_v(t) p(t) \frac{Q_f S}{V_f} dt, \tag{31}$$

where Q_f is the rated power of the ventilation fan, V_f is ventilation volume per hour at rated power.

In this study, the irrigation uses free groundwater. The irrigation cost refers to the operating cost of the water pump. As shown in Fig. 3, the water pumped from the ground will first be stored in a reservoir and then supplied to the greenhouse according to the needs of the crops. It should be pointed out that the storage capacity of the reservoir can meet the water needs of the crops in the greenhouse for one day. Therefore, the water pumping is carried out during the off-peak period to reduce the irrigation cost. C_i can be calculated by:

$$C_i = p_o Q_p \frac{I_{con}}{V_p}, \tag{32}$$

$$I_{con} = \int_{t_i}^{t_f} ET(t) dt, \tag{33}$$

where Q_p is the rated power of the pump, V_p is the volume of water pumped by the pump per hour at rated power, I_{con} is the volume of water consumed by the greenhouse irrigation.

C_{carb} can be obtained by:

$$C_{carb} = \int_{t_i}^{t_f} p_c C_{inj}(t) S dt, \tag{34}$$

where p_c is the price of supplied CO_2.

3.2.2. CO_2 emissions

This study focuses on carbon emissions caused by energy use in the greenhouse system, while other greenhouse gases such as N_2O and CH_4 produced are not considered. Carbon emissions are determined by the CO_2-eq emissions from electricity consumed, negative emissions from CO_2 absorbed and soil respiration. The impact of soil respiration on carbon emissions is small compared to other factors considered. To simplify modeling, soil respiration is not included. The CO_2 emissions model can be expressed as:

$$C_{emis} = C_{equi} - C_{abso}, \tag{35}$$

$$C_{equi} = k_{eq} E_{elec}, \tag{36}$$

$$E_{elec} = \int_{t_i}^{t_f} \left(Q_c(t) S + Q_v(t) S + \frac{Q_p ET(t)}{V_p} \right) dt, \tag{37}$$

$$C_{abso} = \int_{t_i}^{t_f} C_{assi}(t) S dt, \tag{38}$$

where C_{equi} is the CO_2-eq emissions of the consumed energy, which is determined by the electrical energy consumed E_{elec} and the grid emission factor k_{eq}. k_{eq} represents the CO_2 emissions per kilowatt-hour of electricity generated.

3.3. System constraints

For greenhouse cultivation, the greenhouse environmental factors (state variables) should be maintained within appropriate ranges, otherwise the yield of crops will decrease. For example, too high temperature will cause crop wilting or even death, and too low CO_2 concentration will reduce the rate of photosynthesis of crops. The constraints of these state variables can be set by growers according to their own experience, and can also be obtained through the optimization of greenhouse crop yields or profits.

3.3.1. State constraints

The state constraints are as follows:

$$T_{air}^{min} \le T_{air} \le T_{air}^{max}, \tag{39}$$

$$RH_{air}^{min} \le RH_{air} \le RH_{air}^{max}, \tag{40}$$

$$C_{air}^{min} \le C_{air} \le C_{air}^{max}, \tag{41}$$

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

It should be pointed out that greenhouse shading is only carried out when the incoming solar radiation power is greater than the set lower limit value Q_{sun}^{min}. Moreover, the incoming solar radiation power value after shading control should be greater than Q_{sun}^{min}. The constraints of the shading rate can be given by:

$$\begin{cases} s_r = 0 & \text{if } Q_{sun} \le Q_{sun}^{min} \\ 0 < s_r \le 1, Q_{sun}^{min} \le Q_{sun}(1 - s_r) & \text{if } Q_{sun} > Q_{sun}^{min} \end{cases} \tag{42}$$

3.3.2. Input constraints

The input constraints are as follows:

$$Q_c^{min} \le Q_c \le Q_c^{max}, \tag{43}$$

$$g_v^{min} \le g_v \le g_v^{max}, \tag{44}$$

$$C_{inj}^{min} \le C_{inj} \le C_{inj}^{max}, \tag{45}$$

$$s_r^{min} \le s_r \le s_r^{max}, \tag{46}$$

where Q_c^{min}, g_v^{min}, C_{inj}^{min} and s_r^{min} are the lower limits of heating/cooling power, ventilation rate, CO_2 supply rate and shading rate, respectively. Q_c^{max}, g_v^{max}, C_{inj}^{max} and s_r^{max} are the upper limits of heating/cooling power, ventilation rate, CO_2 supply rate and shading rate, respectively. k represents the kth sampling interval.

To reduce the actuator wear caused by frequent changes, the rate of change constraints should be considered.

$$\left| \frac{Q_c}{dt} \right| \le k_1, \tag{47}$$

$$\left| \frac{g_v}{dt} \right| \le k_2, \tag{48}$$

$$\left| \frac{C_{inj}}{dt} \right| \le k_3, \tag{49}$$

$$\left| \frac{s_r}{dt} \right| \le k_4, \tag{50}$$

where k_1, k_2, k_3 and k_4 are the maximum change rates of Q_c, g_v, C_{inj} and s_k, respectively.

3.4. Optimization methods

3.4.1. Analysis of optimization methods

This study considers two conflicting objectives: operating costs and carbon emissions. Therefore, a multi-objective optimization method can be used. The multi-objective optimization problem is formulated as:

Minimize:

$$F\left(\overleftarrow{x}\right) = \left[f_1\left(\overleftarrow{x}\right), f_2\left(\overleftarrow{x}\right)\right]^T, \tag{51}$$

subject to:

$$\begin{cases} g_i\left(\overleftarrow{x}\right) \le 0, i = 1, 2, \ldots, p \\ h_j\left(\overleftarrow{x}\right) = 0, j = 1, 2, \ldots, q \end{cases}, \tag{52}$$

where $\overleftarrow{x} = [x_1, x_2, \ldots, x_n]^T$ represents the decision variables, f_1 and f_2 are objective functions, g_i is the function of the inequality constraint, h_j is the function of the equality constraint.

It should be pointed out that solving a multi-objective optimization problem could be computationally complex. If the multi-objective optimization method is adopted, the greenhouse should be equipped with a powerful control system that can deal with complex calculation problems. In addition, if the weighted sum method is used, growers will be required to have extensive experience in determining weight factors of different objectives.

3.4.2. Single objective (total cost) optimization

In this study, a single objective optimization approach is proposed to reduce the total cost including the operating costs and the cost of carbon emissions. This method solves the problems of computationally intensive for obtaining the Pareto frontier of a multi-objective optimization problem and the difficulty of selecting weights for different objectives in the weighted sum method.

The grid emission factor is introduced to calculate the CO_2-eq emissions of the electrical energy consumed by the greenhouse system. The SCC is used to quantify the impact of carbon emissions on the environment as cost. The objective function can be expressed as:

$$J = C_{oper} + C_{emis} SCC. \tag{53}$$

It should be pointed out that the calculation of SCC is not the focus of our research. In this paper, a value of \$50 per ton, which is very close to the value given by the US government (\$51 per ton), is adopted. The optimization problem can be formulated as: to minimize J and subject to constraints (39) to (50).

4. Economic model predictive control

In this paper, an EMPC method for greenhouse operation management is studied. The EMPC strategy is widely used in building energy management and has achieved good economic and control performance (Ma et al., 2012).

4.1. Hierarchical control structure

The proposed method consists of an optimization layer and a control layer. At the optimization layer, an optimization strategy is proposed to minimize the total cost including the operating costs and the cost of carbon emissions. The optimization results are taken as reference trajectories of the control layer. At the control layer, an MPC controller is designed to follow the reference trajectories obtained from the optimization layer.

4.2. Open loop controller

The state-space model can be expressed as:

$$x_o(k+1) = f_o(x_o(k), u_o(k)), \tag{54}$$

where x_o is the state variable, u_o is the input variable, $u_o(k) = [Q_c(k), g_v(k), C_{inj}(k), s_r(k)]^T$, $x_o(k) = [T_{air}(k), RH_{air}(k), C_{air}(k), Q_{sun}(k)]^T$, k represents the current time kT_o, T_o is the optimization sampling interval, $f_o(\cdot)$ is the nonlinear functions that represent the greenhouse system model obtained from Eqs. (1) to (26). The optimization objective function J_o is derived from Eq. (53) and can be expressed as:

$$J_o = \sum_{k=1}^{N_o} \left((|Q_c(k)| + \lambda_v g_v(k)).p(k)S + p_o Q_p \frac{ET(k)}{V_p} + C_{inj}(k) p_c S + SCC\left(k_{eq}\left(Q_c(k)S + \frac{Q_f}{V_f} g_v(k)S + \frac{Q_p ET(k)}{V_p}\right) - C_{assi}(k)S\right), \tag{55}$$

where N_o is the total number of samples for the optimization. Please note that how ET is affected by the decision variable s_r can be found in Eqs. (2) and (23) to (26).

The rate of change constraints for the optimization can be given by:

$$\begin{aligned} |Q_c(k+1) - Q_c(k)| &\le k_1 T_o \\ |g_v(k+1) - g_v(k)| &\le k_2 T_o \\ |C_{inj}(k+1) - C_{inj}(k)| &\le k_3 T_o \\ |s_r(k+1) - s_r(k)| &\le k_4 T_o \end{aligned} \tag{56}$$

The total cost optimization controller solves the following problem:

$$u_o^* = \arg\min_{u_o} \ J_o, \tag{57}$$

subject to the constraints (39) to (46) and (56). It should be pointed out that the corresponding state x_o^* can be calculated according to the obtained input u_o^* and the model (4.2). The obtained x_o^* will be taken as the reference trajectories x_{ref} for the controller at the control layer.

4.3. MPC controller

The state-space model is given by:

$$x_m(m+1) = f_m(x_m(m), u_m(m)), \tag{58}$$

where x_m is the state variable, u_m is the input variable, $x_m(m) = [T_{air}(m), RH_{air}(m), C_{air}(m), Q_{sun}(m)]^T$, $u_m(m) = [Q_c(m), g_v(m), C_{inj}(m), s_r(m)]^T$. m represents the current time mT_m, T_m is the sampling interval for MPC. $T_m = T_o/N_s$, N_s is a positive integer. The total number of samples N_m can be calculated by: $N_m = N_s \times N_o$.

For time $t_m \in [m_1T + m_2T_m, m_1T + (m_2 + 1)T_m]$, $m_1 = 0,1,2, \cdots, N_o - 1$, $m_2 = 0,1,2, \cdots, N_m - 1$, the MPC controller is to follow the reference trajectories $x_{ref}(m_1 + 1)$. The objective function can be expressed as:

$$J_m = \sum_{i=1}^{N_p} (\Delta x_m(k+i|k))^T Q (\Delta x_m(k+i|k)) + \sum_{i=0}^{N_c-1} (\Delta u_m(k+i|k))^T R (\Delta u_m(k+i|k)), \tag{59}$$

where N_p and N_c represent the prediction horizon and control horizon, respectively. $|k$ means that the predicted value is based on the information up to time k. Δx_m represents the tracking error. Δu_m represents the control effort. Q and R are the weighting matrices that penalize the future tracking and control efforts, respectively (Coelho et al., 2005). $\Delta x_m(k + i| k)$ and Δu_m

$(k + i|k)$ can be calculated by:

$$\Delta x_m(k+i|k) = x_m(k+i|k) - x_{ref}(k+i), \tag{60}$$

where x_{ref} represents the reference trajectories.

$$\Delta u_m(k+i|k) = \begin{cases} u_m(k+i|k) - u_m(k-1), i = 0 \\ u_m(k+i|k) - u_m(k+i-1|k), \\ i = 1, 2, \cdots, N_c - 1. \end{cases} \tag{61}$$

The rate of change constraints can be given by:

$$\begin{aligned} |Q_c(k+1) - Q_c(k)| &\le k_1 T_m \\ |g_v(k+1) - g_v(k)| &\le k_2 T_m \\ |C_{inj}(k+1) - C_{inj}(k)| &\le k_3 T_m \\ |s_r(k+1) - s_r(k)| &\le k_4 T_m \end{aligned} \tag{62}$$

Define vector $U = [u_m(k|k), u_m(k+1|k), u_m(k+2|k), \cdots, u_m(k+N_c-1)|k]^T$. The MPC controller solves the following problem:

$$U^*(k) = \arg\min_U \ J_m(k), \tag{63}$$

subject to the constraints (39) to (46) and (62).

The greenhouse EMPC procedure can be described by the pseudo code of Algorithm 1.

Algorithm 1: EMPC algorithm for the greenhouse control.

```
Solve the open loop optimization problem
  formulated in Equation (57);
Take the optimization results as the reference
  trajectories of model predictive control;
while k ≤ N_m − N_p do
    Calculate the value of U by solving the
      optimal problem (63);
    Implement the first element in U and
      ignore the rest;
    Calculate the state of next interval;
    k = k + 1;
end
while k > N_m − N_p do
    N_p = N_p − 1;
    Calculate the value of U by solving the
      optimal problem (63);
    Implement the first element in U and
      ignore the rest;
    Calculate the state of next interval;
    k = k + 1;
end
```

5. Simulation

5.1. Simulation data

The meteorological data used comes from a weather station at the University of Pretoria. The weather data for July 1, 2020, is adopted and shown in Fig. 5. The system constraints are listed in Table 1. The model parameters are listed in Table 2.

5.2. Optimization results

The optimization problems are solved by the 'fmincon' function with the 'interior-point' algorithm in the MATLAB environment.

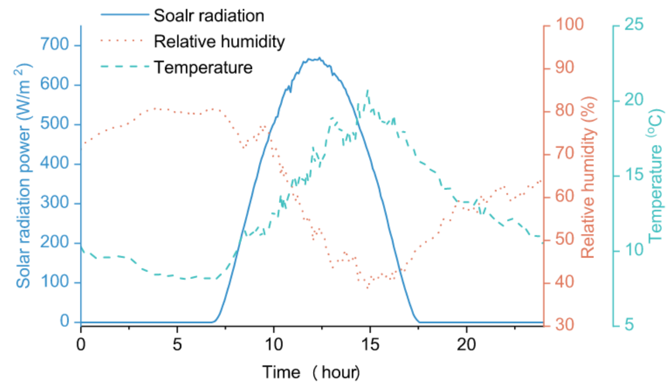

Fig. 5. Meteorological data for July 1, 2020.

Table 1
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	Wm^{-2}
Q_c^{max}	200	Wm^{-2}
g_v^{min}	0	ms^{-1}
g_v^{max}	0.02	ms^{-1}
C_{inj}^{min}	0	$gm^{-2}s^{-1}$
C_{inj}^{max}	0.02	$gm^{-2}s^{-1}$
k_1	0.17	$Wm^{-2}s^{-1}$
k_2	1.67×10^{-5}	ms^{-2}
k_3	1.67×10^{-5}	$gm^{-2}s^{-2}$
k_4	3.33×10^{-4}	s^{-1}

5.2.1. Optimization results of the proposed method

The optimization results of the proposed method are shown in Fig. 6. Sub Figs. 1 to 4 show the heating/cooling power, ventilation rate, CO_2 injection rate and shading rate, respectively. Sub Figs. 5 to 8 show the temperature, relative humidity, CO_2 concentration and incoming solar radiation power, respectively.

From sub-Fig. 1, we can find that greenhouse heating mainly occurs in the morning when the greenhouse temperature has gradually decreased to the set lower limit and the solar radiation power during this period is low. Therefore, the greenhouse should be heated to maintain the temperature within the specified range (between 14°C and 26°C). From sub-Fig. 2, we can see that the ventilation mainly occurs at noon when the outdoor

Table 2
Greenhouse model parameters.

Parameter	Value	Unit	Parameter	Value	Unit
α_1	0.7	–	p_{gc}	1.8×10^{-3}	$m^{o}C^{-1/3}s^{-1}$
α_2	10	$Wm^{-2°}C^{-1}$	p_o	0.5157	R/kWh
Γ	0.008	–	p_s	0.9446	R/kWh
LAI	2.6	–	p_p	3.1047	R/kWh
C_{cap}	30,000	$Jm^{-2o}C^{-1}$	λ	0.06	Wm^{-3}
h	7	m	η	0.75	–
s	40,709	m^2	g	9.8	ms^{-2}
L	2450	Jg^{-1}	h_w	7	m
r_b	150	sm^{-1}	ω_3	1000	R/ton
ρ_{air}	1.225	kgm^{-3}	K_c	0.7	–
$C_{p,\ air}$	1003	$J^{o}C^{-1}kg^{-1}$	SCC	50	$/ton
k_{eq}	0.879	kg/kWh	Q_p	3	kW
V_p	10	m^3	Q_f	0.3	kW
V_f	5000	m^3			

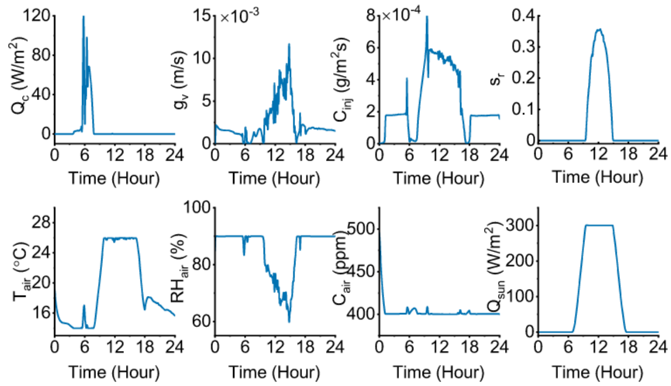

Fig. 6. Optimization results of the proposed method.

temperature is high. The energy loss caused by the ventilation process can be reduced. From sub-Fig. 3, we can see that the CO_2 injection rate is low. The CO_2 concentration in the greenhouse is kept at a low level that is close to the lower limit of 400 ppm. The reason is that the low CO_2 supply rate helps achieve the goal of reducing operating costs. From sub-Fig. 4, we can find that the shading control is only performed when the solar radiation power is greater than 300 W/m^2. From sub-Figs. 5 to 8, we can see that temperature, relative humidity, CO_2 concentration and incoming solar radiation power are kept within specified ranges.

5.2.2. Comparison between the proposed method and the baseline

In this study, a greenhouse operation method to minimize the operation cost, which is often used in greenhouse management, is taken as the baseline. The study of the baseline method can be found in (Xu et al., 2018; Lin et al., 2020). The objective function of the baseline method can be expressed as Eq. (27). The optimization results are shown in Fig. 7. Table 3 shows the comparison between the proposed method and the baseline method.

It can be observed that the operating costs, carbon emissions and total cost of the baseline method are R12910, 5.05 tons and R17288, respectively. The operating costs, carbon emissions and total cost of the proposed method are R13096, 3.89 tons and R16461, respectively. Compared with the baseline method, the proposed method increases the operating costs by R186 but reduces the total cost by R827 and the carbon emissions by 1.16 tons.

Fig. 8 shows the total cost composition of the proposed method and the baseline. It can be observed that the cost of heating and cooling is the highest among all cost components, followed by the cost of carbon emissions, the cost of CO_2 supply, and the cost of irrigation. Moreover, there is little difference between the ventilation cost, irrigation cost and CO_2 supply cost of the two methods. However, the carbon emission cost and heating/cooling cost of the two methods are quite different. Compared with the baseline method, the proposed method increases the heating/cooling cost by R194 and reduces the CO_2 emission cost by R1011.

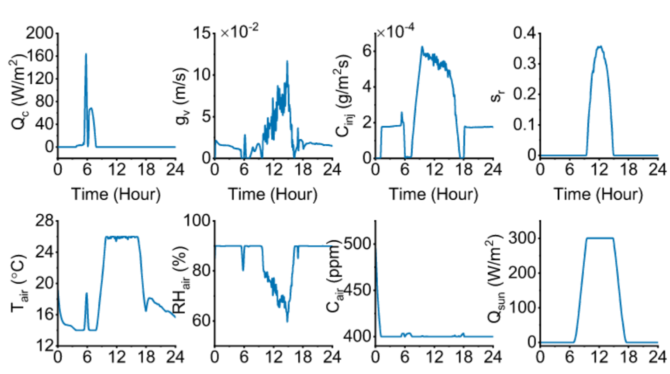

Fig. 7. Optimization results of the baseline method.

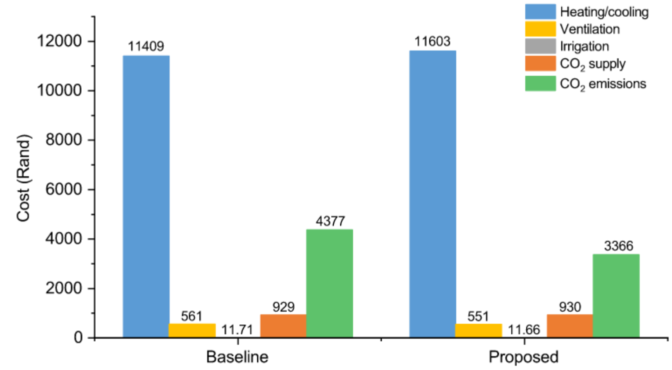

Fig. 8. Total cost composition.

5.2.3. Optimization based on different weather data

To make the conclusion more convincing, we studied the proposed optimization method based on different meteorological data. In this paper, the meteorological data from July 2, 2020 to July 8, 2020 are used and shown in Fig. 9. Fig. 10 shows the optimization results.

We can find that the results obtained are similar to the optimization results shown in Fig. 8. The cost of the greenhouse heating and cooling is the highest, followed by the cost of carbon emissions, the cost of CO_2 supply, the cost of ventilation and the cost of irrigation. It should be pointed out that the total cost of the greenhouse on July 3 and July 4 is lower than the cost on other dates. The reason is that the temperature in these two days is higher than that in other days. Less energy is consumed for heating, which reduces costs.

Table 3
Comparison between the proposed method and the baseline method.

Methods	Operating costs (Rand)	Carbon emissions (ton)	Total cost (Rand)
Baseline	12,910	5.05	17,288
Proposed	13,096	3.89	16,461

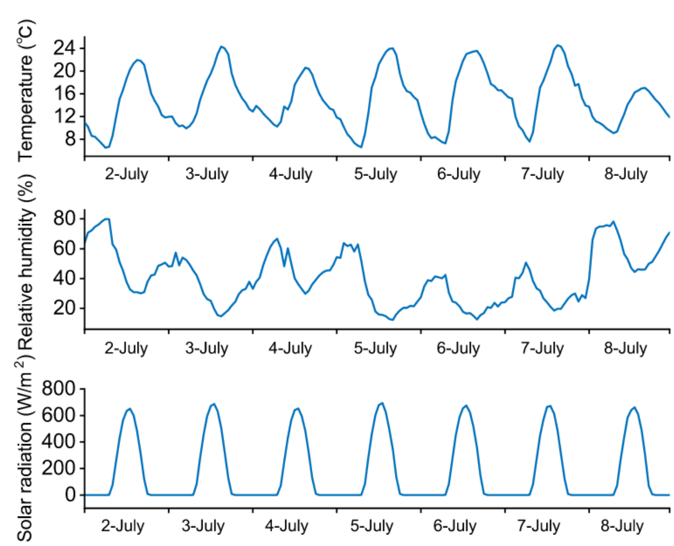

Fig. 9. Meteorological data from July 2, 2020 to July 8, 2020.

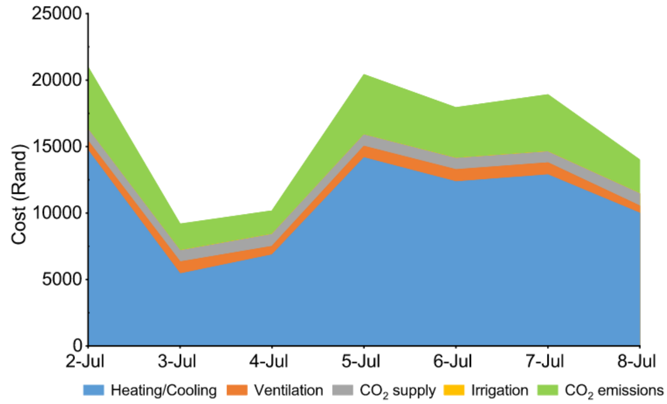

Fig. 10. Optimization results of the proposed method with one week data.

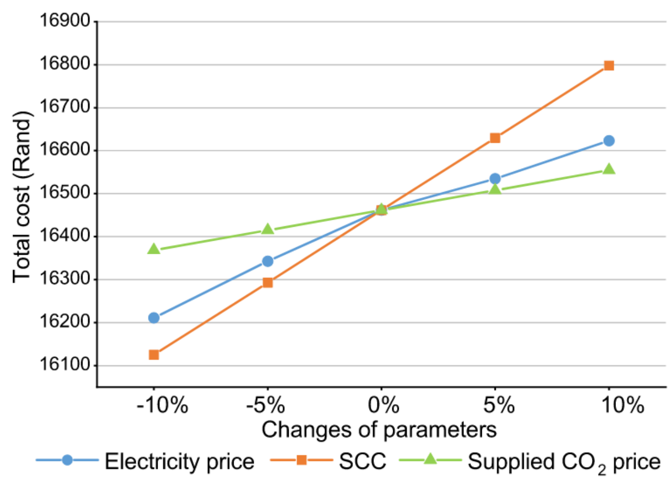

Fig. 11. Results of the conducted sensitivity analysis.

5.3. Sensitivity analysis

Sensitivity analysis can provide insight into the impact of model parameter uncertainty on the optimization results (Guo et al., 2021). In this study, the impact of changes in electricity price, supplied CO_2 price and SCC on the total cost is analyzed. The changes of these parameters are −10 %, −5 %, 5 % and 10 % of the corresponding initial values, respectively. The results of the sensitivity analysis are shown in Fig. 11.

We can find that the total cost increases with the increase of the electricity price, supplied CO_2 price and SCC. Among the three parameters analyzed, SCC has the greatest impact on the total cost, followed by electricity price, and the supply CO_2 price has the least impact on the total cost. The optimization results are more sensitive to changes in SCC than changes in electricity prices and supply CO_2 prices.

5.4. Model predictive control

The parameters of the proposed MPC are as follows: $N_c = N_p = 5$, $Q = diag\ (100,100,100,100)$, $R = diag\ (1,1,1,1)$. The results of the proposed MPC under three levels (1 %, 5 % and 10 %) of system disturbances are shown in Fig. 12.

In Fig. 12, the red line, the yellow line, and the blue line represent the control results under 1 %, 5 % and 10 % system disturbances, respectively. It can be seen that the designed MPC controller can well track the reference trajectories of temperature, relative humidity, CO_2 concentration and solar radiation power under different levels of system disturbances. The trajectories of the greenhouse environmental factors studied under MPC vary between small ranges around the corresponding reference trajectories.

The MPC tracking errors are listed in Table 4. We can find that the larger the system disturbance, the larger the average tracking error of the MPC controller designed. Moreover, the tracking errors under the three levels of system disturbances are small. For example, under 10 % system disturbances, the average errors of tracking the reference trajectory of temperature, relative humidity, CO_2 concentration and incoming solar radiation power are 8.27 %, 6.90 %, 5.37 % and 5.01 %, respectively. The designed MPC controller is verified to have good control performance. Similar findings can be found in (Chen et al., 2018).

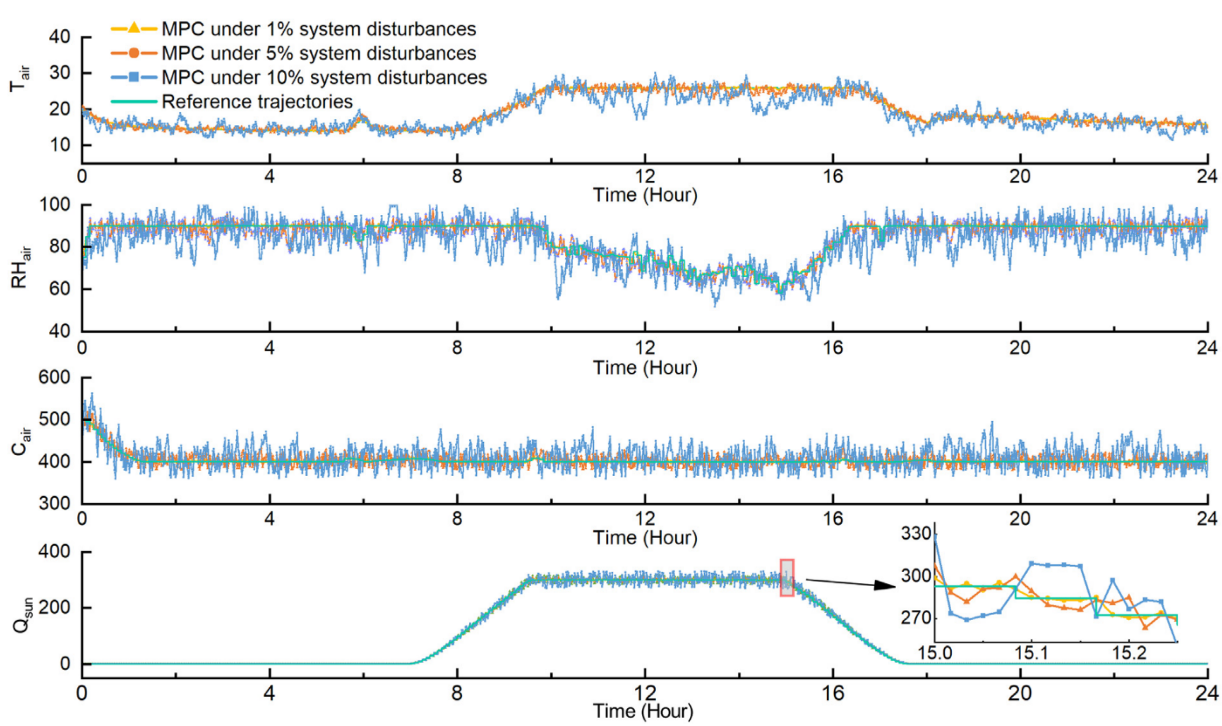

Fig. 12. Results of MPC under different levels of system disturbances.

Table 4
The average tracking error of MPC under different levels of system disturbances.

Environmental factors	Average tracking error		
	1 %	5 %	10 %
Temperature (°C)	0.66 %	3.40 %	8.27 %
Relative humidity (%)	0.70 %	3.22 %	6.90 %
CO_2 concentration (ppm)	0.51 %	2.63 %	5.73 %
Radiation power (W/m^2)	0.52 %	2.50 %	5.01 %

6. Conclusions

In this paper, an economic model predictive control (EMPC) method is proposed for the operation optimization of a greenhouse system. The objective is to manage the greenhouse energy-water-carbon-food (EWCF) nexus for cleaner production and sustainable development. The proposed method consists of an optimization layer and a control layer. At the optimization layer, an optimization method to minimize the total cost of greenhouse heating/cooling, ventilation, carbon dioxide (CO_2) supply and irrigation is studied. A sensitivity analysis is carried out to study the impact of the electricity price, supplied CO_2 price and social cost of carbon (SCC) on the total cost. At the control layer, a model predictive control (MPC) method is used to address system disturbances. The proposed approach is studied based on meteorological data from Pretoria, South Africa.

Simulation results show that the proposed method can effectively reduce the total cost and carbon emissions of greenhouse operations while keeping greenhouse environmental factors (temperature, relative humidity, CO_2 concentration and incoming solar radiation power) within the required ranges. Compared with a baseline method that minimizes the operating costs, the proposed method increases the operating costs by R186 but reduces the total cost by R827 and the carbon emissions by 1.16 tons. In addition, the total cost increases with the increase of the electricity price, supplied CO_2 price and SCC. The optimization is more sensitive to changes in SCC than changes in electricity price and supply CO_2 price. Moreover, the designed MPC controller has good control performance and can deal with system disturbances well.

The proposed method can help achieve low-cost and cleaner greenhouse crop production, which provides a feasible solution to the challenges of poverty, food insecurity and climate change in South Africa. In addition, the proposed approach can be applied to different types of greenhouses in different countries. In future work, we will focus on the following aspects: 1) Energy-water-land-food nexus. Greenhouse operation planning needs to consider trade-offs between economic, resource and environmental concerns. Resources such as energy, water and land are critical to food production. How to use less energy and water resources to get more food in limited land is of great significance for alleviating the resource crisis and achieving sustainable development. 2) Using clean energy to power greenhouses. The use of clean energy such as wind energy and solar energy can not only alleviate the energy crisis but also reduce the adverse impact of greenhouse operations on the environment. 3) Experimental validation of the proposed method. We will verify the effectiveness of the proposed method through experiments in future research.

CRediT authorship contribution statement

Zhiling Ren: Writing - Original Draft. Yun Dong: Software. Dong Lin: Writing - Review & Editing, Supervision. Yuling Fan: Data curation. Lijun Zhang: Review & editing, Supervision. Xiaohua Xia: Supervision.

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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