Application of dynamic programming algorithm in winter heating control of greenhouse

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Abstract: In order to solve the immaturity of decision-making methods in the regulation of winter heating in greenhouses, this study proposed a solution to the problem of greenhouse winter heating regulation using a dynamic programming algorithm. A mathematical model that included indoor environmental state variables, optimization decision variables, and outdoor random variables was established. The temperature is kept close to the expected value and the energy consumption is low. The model predicts the control solution by considering the cost function within the next 10 steps. The two-stage planning method was used to optimize the state of each moment step by step. The temperature control strategy model was obtained by training the relationship between indoor temperature, outdoor temperature, and heating time after optimization using a regression algorithm. Based on a typical Internet of Things (IoT) structure, the greenhouse control system was designed to regulate the optimal control according to the feedback of the current environment. Through testing and verification, the optimized control method could stabilize the temperature near the target value. Compared to the threshold control (threshold interval of 2.0°C) under similar weather conditions, the optimized control method reduced the temperature fluctuation range by 0.9°C and saved 7.83 kW·h of electricity, which is about 14.56% of the total experimental electricity consumption. This shows that the dynamic programming method is feasible for environmental regulation in actual greenhouse production, and further research can be expanded in terms of decision variables and policy models to achieve a more comprehensive, scientific, and precise regulation.

Keywords: greenhouse, dynamic programming, heating control, model predictive control, Internet of Things

DOI: 10.25165/j.ijabe.20241704.8221

Citation: Gao F, Tu H B, Zhu D L, Liu M Y, Shi C Y, Zhang R, et al. Application of dynamic programming algorithm in winter heating control of greenhouse. Int J Agric & Biol Eng, 2024; 17(4): 60–66.

1 Introduction

The optimization and regulation methods and techniques for the greenhouse environment can effectively improve the production conditions of greenhouse crops, increase the utilization efficiency of resources, and achieve high-quality production of greenhouse crops[1,2]. The control methods based on setpoints, such as PID control[3-6] and predictive control[7-9], are currently commonly used environmental regulation methods and are relatively mature in research. With the "Internet+" strategy, the combination of intelligent control algorithms and optimization control algorithms has become a research hotspot.

The emergence of numerous optimization algorithms and the maturity of machine learning and deep learning algorithms have greatly promoted the conditions required for optimization control. Su et al.[10] used three neural network algorithms to estimate the cost functions and control input and compensate for the dynamic greenhouse environment that was not modeled. Zhu et al.[11] used a genetic algorithm to solve the multi-objective optimization problem that includes crop status, external weather, and resource cost. Although the research on greenhouse production optimization control by Chinese scholars started relatively late, certain achievements have still been made. Li et al.[12] used singular perturbation theory to study greenhouse hierarchical control, used simulations to solve calculations, and verified the effectiveness of the method. Jin et al.[13] proposed an improved genetic algorithm with engineering constraint rules to achieve an effective solution to the dynamic optimisation problem of greenhouse environment. Optimization control is rapidly developing and continuously evolving towards multi-objective optimization in domestic research[14-16]. The greenhouse production system is complex, and most scholars have only verified the feasibility of algorithms through simulation technology, there may be phenomena such as time delay and large lag in actual applications[17]; At the same time, the calculation period of optimization algorithms is generally longer and does not consider the dynamic changes of the greenhouse environment.

In production and scientific experiments, there is a kind of activity whose process can be divided into several interrelated stages, each of which requires decision-making so as to achieve the

Received date: 2023-03-07 **Accepted date:** 2023-11-30

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best results of the whole process. Decision-making at each stage depends on the current situation and affects the subsequent development. When the decision of each stage is determined, a decision sequence is formed, and thus an activity route of the whole process is determined. This type of problem is called a multi-stage decision process[18]. American mathematician R. Bellman and others put forward the famous optimization principle when they studied the optimization problem of a multi-stage decision process. They believed that the sub-strategy of an optimal strategy must also be optimal for its initial state and final state, and then created dynamic programming[19]. This process of solving multi-stage decision optimization is called dynamic programming.

In winter, the greenhouse can not meet the needs of crop growth only by its own heat storage and heat preservation capacity[20]. Especially at night, the temperature will drop to the lowest level of the day. In order to ensure the normal growth of crops, it is necessary to use greenhouse heating equipment for active heating[21]. In this study, the greenhouse heating control problem is discretized into a multi-stage decision-making problem, and the mathematical model is established. Combined with the basic idea of a dynamic programming algorithm[22,23], the continuously changing greenhouse environment is decomposed into a number of interrelated stages (sub-problems). After arranging the stages in a certain order, the sub-problem is solved for each given stage state. Then, the solution of the original problem is obtained from the solution of these sub-problems, and the optimal control strategy of the greenhouse environment is obtained, so as to realize the scientific control of the greenhouse environment.

2 Methods

2.1 Model establishment

The greenhouse environment is easily influenced by external conditions and it is commonly considered that the changes in the greenhouse environment over the next 1 to 2 hours can meet practical production needs. It is divided into several interrelated stages, and decisions are made in each stage to achieve the best results throughout the process. If the greenhouse environment control problem is viewed as a multi-stage process with a chain-like structure and interrelated front and back, then its multi-stage decision-making process can be studied.

The response time of greenhouse environment changes is not a restrictive factor in optimal greenhouse control[24], and a step size of 10 to 20 minutes (regulation period) is usually determined to ensure stable regulation. After dividing the stages by time, the total duration can be discretized using the regulation period (k=1, 2, …, n, k=1 for the first period).

The three factors that affect regulation are the internal environment status, equipment status, and external environment. Taking the heating control in the greenhouse during the winter night (18:00 to the next day 8:00) as an example, heating equipment regulation decisions are made. The step size (regulation period) Δt of the optimization problem is determined to be 15 min; the environment state variable x is the indoor temperature, which is represented by $x^{t\text{-in}}$; the optimization decision variable u is the heat system control time, represented by u^{hot}; the random variable w is the outdoor temperature, represented by $w^{t\text{-out}}$.

The heating temperature must meet the needs of crop growth, so the concept of fuzzy mathematics is introduced in the optimization objective to keep the temperature near the expected temperature[25]. At the same time, the energy consumption of a greenhouse heating system is considered. The mathematical model can be represented as:

$$\min_{u} \mathrm{E}\left[\sum_{k=1}^{n}\left(\left(\frac{x_k^{t\text{-in}}-T_{\text{set}}}{T_{\text{set}}}\right)^2+\frac{P_1}{P_0}\right)\right] \tag{1}$$

where, u is the optimization decision variable; n is the total number of regulation periods. $x_k^{t\text{-in}}$ is the indoor temperature of the greenhouse in the kth stage, °C; T_{set} is the ideal target temperature, °C; P_1 is the actual power consumption in a cycle, kW·h; which can be obtained by calculating the actual working time and heating power; P_0 is the power consumption required for a complete cycle, kW·h; E is the mathematical expectation of the model.

2.2 Decision variables and state transition equation

Decision and state transition are naturally connected. The state transition equation can generally be expressed as $x_{k+1}=z_k(x_k, u_k, w_k)$, where, $z_k(\cdot)$ represents the state transition equation at time k. If the x value of the state variable $x_k^{t\text{-in}}$ at the kth stage is given, once the decision variable u_k^{hot} determined, the value of the state variable $x_k^{t\text{-in}}$ at stage k+1 is also completely determined. Assuming that z_k of all k are the same.

Based on the basic principles of thermodynamics and heat transfer, the heat stored in a greenhouse after heating is equal to the heat entering the greenhouse minus the heat conducted. When the heat entering the greenhouse is greater than the heat conducted, the greenhouse stores heat and warms up until the heat stored is balanced[26]. At night, the only source of heat for the greenhouse is the heating system (Q), and the loss of heat from the greenhouse is through conductive and radiative heat from the roof, ground, windows, and other enveloping structures (R). Within a certain time, the change in heat causes the temperature in the greenhouse to change. The change in heat ΔQ in the greenhouse system is equal to the input heat minus the lost heat, that is,

$$\Delta Q = Q - R \tag{2}$$

where, ΔQ is the heat contained in the temperature change of the greenhouse, W; Q is the heat supply for the air source heat pump, W; R conducts the heat lost to the greenhouse, W.

The heat loss (R) from the greenhouse mainly results from the transfer of heat from the indoor to the outdoor due to the temperature difference between indoor and outdoor air, which can be calculated based on the steady heat transfer theory. The basic equation is as follows:

$$R = K \cdot F \cdot \left(x_k^{t\text{-in}} - w_k^{t\text{-out}}\right) \tag{3}$$

where, K is the comprehensive heat transfer coefficient of the greenhouse enclosure, W/(m²·°C); F is the total heat transfer area of the greenhouse, m²; $x_k^{t\text{-in}}$ is the indoor temperature at the current stage, °C; $w_k^{t\text{-out}}$ is the outdoor temperature at the current stage, °C.

The heat contained in the temperature change in the greenhouse can be calculated according to the specific heat capacity formula, and the calculation formula is as follows:

$$\Delta Q = c_{\text{air}} \cdot \rho_{\text{air}} \cdot V \cdot \Delta m \tag{4}$$

where, c_{air} is the specific heat of air, taking 1003 J/(kg·°C); ρ_{air} is the air density, taken as 1.293 kg/m³; V is the volume of a greenhouse, m³; Δm is the change difference of the temperature in the greenhouse, °C.

Assuming that the heating performance of the heating system is h, the state transition equation $z(\cdot)$ can be obtained by substituting the Equations (3) and (4) into Equation (2):

$$x_{k+1}^{t\text{-in}} = x_k^{t\text{-in}} + \frac{h \cdot u_k^{\text{hot}} - F \cdot K \cdot (x_k^{t\text{-in}} - w_k^{t\text{-out}}) \cdot \Delta t}{c_{\text{air}} \cdot \rho_{\text{air}} \cdot V} \tag{5}$$

where, $x_{k+1}^{t\text{-in}}$ is the indoor temperature of the next stage, °C.

2.3 Model solution

Assuming the control policy $\pi=\{\mu_1, \mu_2, \mu_3, \ldots, \mu_n\}$, where μ_k maps the environment state variable x_k to the optimal control function $u_k=\mu_k(x_k)$, and for all x_k, $\mu_k(x_k) \in U_k(x_k)$. The expected cost function of the control strategy π starting from the x_1 state can be represented as:

$$J_\pi(x_1) = \mathrm{E}\left[g_k(x_k,\mu_k(x_k),w_k) + J_{k+1}(f(x_k,\mu_k(x_k),w_k))\right] \tag{6}$$

where, J_{k+1} is the cost function of k+1 steps to the global.

Assuming that there is a reasonable approximation to the cost function, the approximate cost function $\tilde{J}_{k+1}$ with a certain step length can meet the actual requirements and make the optimization problem easier to solve. Model predictive control (MPC) is a powerful tool for controlling complex real-world systems, which can predict future behavior. For each encountered state, MPC solves an online optimization problem to select a control action that minimizes future costs[27]. Thus, the cost function can be represented as:

$$\tilde{J}_{k+1}(z_k(x_k,u_k,w_k)) = \sum_{i=1}^{l} g(x_{k+i},u_{k+i},w_{k+i}) \tag{7}$$

Based on the MPC solution concept, at each sampling time, according to the obtained current information, an online finite-time open-loop optimization problem[28] is solved. The continuously changing indoor and outdoor environmental data and equipment state data are discretized according to the control period Δt, giving the solution path s, and finding the optimal control u_k^s.

$$u_k^s \in \arg_{u_k} \min_{u_k,u_{k+1},\ldots,u_{k+l}} g_k(x_k^s,u_k,w_k^s) + \sum_{i=1}^{l} g(x_{k+i},u_{k+i},w_{k+i}^s) \tag{8}$$

Input the indoor temperature $x^{t\text{-in}}$ and outdoor temperature $w^{t\text{-out}}$, for each time step, considering the next 10 steps, step by step solution, the first element of the obtained control sequence is applied to the controlled object, at the next sampling time, repeat the above process: use the new measurement value as the initial condition for predicting the future dynamic of the system at this time, refresh the optimization problem and resolve. The optimization solution approach is shown in Figure 1.

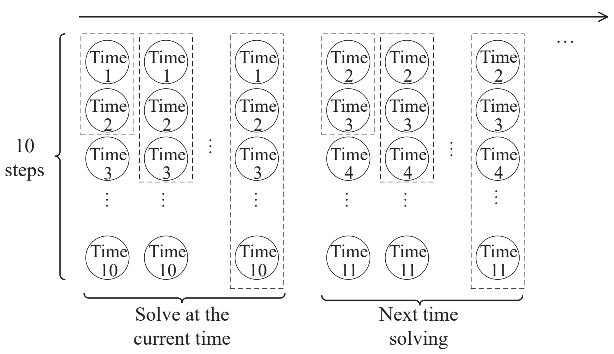


Figure 1 Optimal solution route

Quadratic programming is one of the methods for optimization solutions and it is relatively simple to solve. It is favored by the MPC control framework. In Matlab, quadprog is a solver for a quadratic objective function with linear constraints and it is used for optimization solution. The standardized form of the solution is as follows:

$$\min_{\boldsymbol{m}} \frac{1}{2}\boldsymbol{m}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{m} + \boldsymbol{f}^{\mathrm{T}}\boldsymbol{m}$$
$$\text{s.t}\begin{cases}\boldsymbol{A}\boldsymbol{m} \leq \boldsymbol{b}\\ \boldsymbol{A}_{\text{eq}}\boldsymbol{m} = \boldsymbol{b}_{\text{eq}}\\ \boldsymbol{lb} \leq \boldsymbol{m} \leq \boldsymbol{ub}\end{cases} \tag{9}$$

where, $\boldsymbol{m}$ is the variable to be solved, $\boldsymbol{m}$ is set to $\left[u_1^{\text{hot}}\ x_2^{t\text{-in}}\right]$, and as the rolling solution expands, $\boldsymbol{m}$ becomes $\left[u_1^{\text{hot}}\ x_2^{t\text{-in}}\ u_2^{\text{hot}}\ \ldots\ u_{10}^{\text{hot}}\ x_{11}^{t\text{-in}}\right]$; $\boldsymbol{H}$ is a matrix consisting of coefficients of quadratic terms in the objective function. By substituting the ideal temperature T_{set} and other parameters into the objective function, if the element of the matrix $\boldsymbol{H}$ in the i-th row and j-th column is denoted as $H(i, j)$, and the coefficient of the quadratic term $m_i m_j$ is denoted as $a(i, j)$, then $H(i,j) = \begin{cases}2a(i,j), i=j\\ a(i,j), i \neq j\end{cases}$; $\boldsymbol{f}$ is a vector consisting of coefficients of linear terms in the objective function.

In the constraint condition, $\boldsymbol{A}$ is a matrix consisting of coefficients of inequalities, for this problem, $\boldsymbol{A}$ is taken as an identity matrix; $\boldsymbol{b}$ is a vector consisting of constant terms in the inequalities; $\boldsymbol{lb}$ and $\boldsymbol{ub}$ are determined based on actual limitations of indoor temperature $x_k^{t\text{-in}}$ and heating time u_k^{hot} within the control period; $\boldsymbol{A}_{\text{eq}}$ is a matrix consisting of coefficients in equalities, and $\boldsymbol{b}_{\text{eq}}$ is a vector consisting of constant terms in equalities, $\boldsymbol{A}_{\text{eq}}$ and $\boldsymbol{b}_{\text{eq}}$ are determined based on parameter values in the state transition equation. The aforementioned vectors and matrices expand correspondingly as the rolling optimization step increases.

By solving the optimization problem, the optimal heating control time u_k^{hot} is obtained for each indoor temperature $x^{t\text{-in}}$ and outdoor temperature $w^{t\text{-out}}$. By learning the inherent relationship between them, a control strategy is obtained. The linear model more accurately reflects the inherent relationship and has advantages such as directness, speed, solvability, etc., making it more suitable for practical production activities. It is assumed that the policy function is in the form of Equation (10).

$$\mu(x,w,\theta) = \theta_1 x_k + \theta_2 w_k + \theta_3 x_k w_k + \theta_4 \tag{10}$$

The least square method is used to solve the minimum loss function training model to complete the linear regression solution.

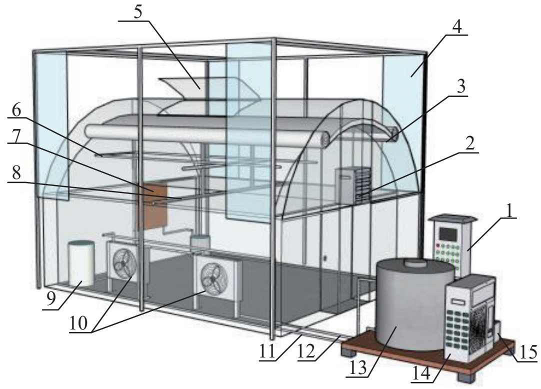
$$\theta_k \in \arg\min_{\theta} \sum_{s=1}^{q} \left\| u_k^s - \mu_k(x_k^s, w_k^s, \theta) \right\|^2 \tag{11}$$

In actual production environment control process, the indoor temperature $x^{t\text{-in}}$ and the outdoor temperature $w^{t\text{-out}}$ are collected in real time through sensors inside and outside the greenhouse, transmitted through the network and synchronized to the intelligent control management system, and through the control strategy calculation analysis, the optimal control u^{hot} under the current conditions is output. The PLC controller adjusts the temperature environment to the expected value by controlling the heating equipment based on the output.

3 Experiments and result analysis

3.1 Overview of greenhouse

The experimental greenhouse is located at China Arid Area Water-saving Agricultural Research Institute, Northwest A&F University (108°4′28″E, 34°16′56″N). The greenhouse is a double-arch and double-film structure, with an outer arch height of 4.0 m, an inner arch height of 3.5 m, an outer frame length of 6.0 m, an inner frame length of 5.6 m, and an outer frame width of 5.2 m and an inner frame width of 4.8 m. The greenhouse structure is shown in Figure 2.



1. Integrated control cabinet 2. Fan 3. Quilt 4. Shade net 5. Top ventilation 6. Atomizing sprinkler system pipeline 7. Wet curtain 8. Sensor mounting bracket 9. Water tank 10. Plumbing fan 11. Water return pipe 12. Water inlet pipe 13. Hot water storage tank 14. Heat pump host 15. Heat pump system electric control box

Figure 2 Greenhouse structure diagram

The heating of the test greenhouse is provided by an air source heat pump system in combination with a radiator warm air machine. The heating system consists of four parts: an air source heat pump, heat storage tank, hot water pipeline, and radiator warm air machine. The air source heat pump unit model is KJR-51/BMK-A; the heat storage tank has a volume of 1.36 m^3, is made of aluminum zinc plated plate, and has good insulation performance with high-quality polyurethane foam insulation material; the hot water pipeline is made of PVC material and has an outer layer of insulation cotton to prevent heat loss; the radiator warm air machine consists of a finned tube radiator and a fan. The water temperature in the tank is maintained by the air source heat pump unit, and the heating state is switched by controlling the water pump and fan.

3.2 Test method and test index

During the period from December 6th to 20th, 2021, the data for the experiment was collected in the greenhouse using a method based on threshold control. On the one hand, the working parameters h of the heating system were calculated using data analysis, and on the other hand, the collected data was preprocessed by discretizing it according to the cycle. After standardizing the function to be solved, the solution was obtained by inputting it into the program. Finally, the control strategy was obtained through regression. The solution process is shown in Figure 3.

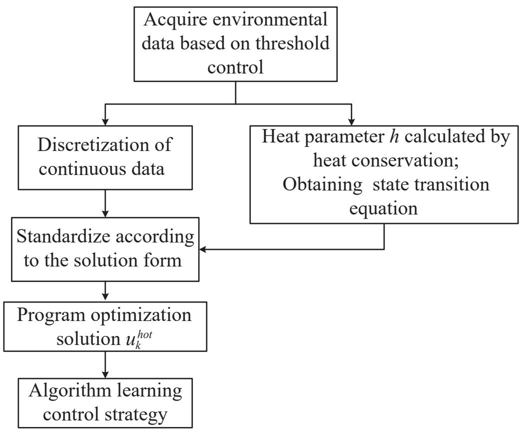


Figure 3 Flow chart of solution process

Considering the crop's nighttime temperature requirements and the minimum temperature change range of 2°C required for threshold regulation, the temperature lower limit and upper limit were set at 15.5°C and 17.5°C, respectively, in the threshold control. The experimental setting of the heat storage tank temperature is (45±2)°C.

Assuming that the distribution of the internal environment in the greenhouse is uniform after the equipment is controlled, and the data at the center of the greenhouse represents the overall situation of the greenhouse, the indoor air temperature was collected once every minute using a light, temperature, and humidity sensor (model ST-GWS-6W, temperature accuracy: ±0.5°C). The outdoor air temperature was collected once every minute using an ultrasonic integrated meteorological station (model RS-FSXCS-N01-1, temperature accuracy: ±0.5°C). The program updates the device status information in real-time and records the heating system's running time and the duration of the operation. The running energy consumption of the heating system was recorded using an electronic energy meter (model DTSU5886, accuracy 0.1 kW·h). The arrangement of the sensors is shown in Figure 4.

a. Outdoor sensors b. Greenhouse interior layout

1. Three-in-one sensor for light, temperature, and humidity 2. Ultrasonic integrated weather station

Figure 4 Greenhouse site layout

3.3 Calculation of relevant parameters

3.3.1 Calculation of comprehensive heat transfer coefficient of enclosure

When the greenhouse is in the night state, when the heating system does not work, the heat dissipation of the greenhouse is equal to the heat generated by the temperature change of the greenhouse. Combining Equations (3) and (4), the comprehensive heat transfer coefficient of the enclosure of the greenhouse can be calculated, that is

$$K = \frac{c_{\text{air}} \cdot \rho_{\text{air}} \cdot V \cdot \Delta m}{F \cdot (x_k^{t\text{-in}} - w_k^{t\text{-out}})} \tag{12}$$

196 groups of data were collected in the experiment, and the measured data were substituted into the Equation (12), and the average value of the single calculation result of the comprehensive heat transfer coefficient was taken, so that the comprehensive heat transfer coefficient K of the greenhouse was 0.266 W/(m^2·°C). The calculations are listed in Table 1.

3.3.2 Calculation of working performance parameters of heating system

When the heating system works at night, the heat provided by the heating system is equal to the sum of the heat dissipation of the greenhouse and the heat of the temperature change of the greenhouse, that is

$$h = \frac{c_{\text{air}} \cdot \rho_{\text{air}} \cdot V \cdot \Delta m + K \cdot F \cdot (x_k^{t\text{-in}} - w_k^{t\text{-out}})}{u^{\text{hot}}} \tag{13}$$

According to the measured test data, the working performance parameter h of the heating system is calculated by substituting the comprehensive heat transfer coefficient K of the greenhouse enclosure obtained by the above calculation, and the working performance parameter of the greenhouse heating system is obtained to be 921.38 W by averaging the single calculation result. The calculations are listed in Table 2.

Table 1 Calculation of the integrated heat transfer coefficient

No.	Time period	Starting temperature /°C	Termination temperature /°C	Average temperature difference between T_{in} and T_{out} /°C	Heat transfer coefficient K /(W·m^{-2}·°C^{-1})	Average heat transfer coefficient /(W·m^{-2}·°C^{-1})
1	Dec. 6 18:59-19:22	19.1	15.2	9.7	0.276	
2	Dec. 6 19:34-19:56	19.0	15.1	10.5	0.267	
…	…	…	…	…	…	0.266
195	Dec. 12 5:48-6:07	18.6	15.1	11.1	0.262	
196	Dec. 12 6:19-6:39	18.7	15.1	11.6	0.245	

Table 2 Calculation of working performance parameters

No.	Time period	Starting temperature /°C	Termination temperature /°C	Average temperature difference between T_{in} and T_{out} /°C	Work time /s	Performance parameters /W	Average performance parameters /W
1	Dec. 8 21:32-21:47	14.9	18.2	13.9	780	916.80	
2	Dec. 8 22:00-22:15	15.0	18.2	14.3	780	917.69	
…	…	…	…	…	…	…	921.38
92	Dec. 8 06:22-06:37	14.5	17.6	16.9	900	860.25	
93	Dec. 8 06:58-07:13	14.7	17.7	19.4	900	923.68	

3.4 Solution process

In practical production activities, "variable temperature management" measures are adopted in temperature management for efficient crop production[29]. Based on the theory of variable temperature management, the ideal target temperature T_{set} from 18:00 to the next day at 04:00 is 15°C, creating a larger diurnal temperature difference, which is beneficial for the transport of assimilates to the fruit; the ideal target temperature T_{set} from 04:00 to 08:00 is 18°C, raising the temperature to increase the temperature of the crop itself, putting the crop in the "preparation" stage of photosynthesis.

Taking the ideal target temperature T_{set} of 15°C as an example, the energy consumption item in the objective function can be replaced by the ratio of the working time of the heating system u^{hot} and the control period Δt. Substituting it into Equation (3) gives the optimized objective function. According to the heating system working performance parameters h calculated above and combined with known parameters, the state transition equation is obtained by substituting into Equation (5).

The initial solve term $\boldsymbol{m} = \left[u_1^{hot} \ x_2^{t\text{-in}}\right]$, according to the quadratic term objective matrix of the objective function $\boldsymbol{H} = \begin{bmatrix} 0 & 0 \\ 0 & 1/76 \end{bmatrix}$, and an initial linear target vector $\boldsymbol{f} = [1/15 - 2/15]$; substituting the measured indoor temperature and outdoor temperature data into the state transition equation for calculation and removing terms to obtain an initial linear equality constraint matrix $\boldsymbol{A}_{eq} = \begin{bmatrix} 0.528 & -1 \end{bmatrix}$, the linear equality constraint vector $\boldsymbol{b}_{eq} = \left[-0.715x_1^{t\text{-in}} - 0.285w_1^{t\text{-out}}\right]$; In this problem, the boundary constraint of the solution quantity m has no coefficient term, $\boldsymbol{A} = \mathrm{eye}(2)$, the upper boundary $\boldsymbol{b}$ and $\boldsymbol{ub}$ vectors are equal, which is determined according to the regulation cycle and the desired target temperature (plus 1°C temperature fluctuation) as [15, 16]; The lower boundary $\boldsymbol{lb}$ is based on the minimum temperature for crop growth [0, 10].

Input the initial greenhouse temperature $x_1^{t\text{-in}}$ and the outside temperature $w_1^{t\text{-out}}$-$w_{10}^{t\text{-out}}$ into the initial matrix of standardized parameters. 10 steps are considered for the state at each moment, the state is continuously solved from front to back, the initial matrix and the initial vector are automatically expanded along with the step, and the temperature and control results solved at each moment are iterated and input for the next calculation. For each time step up to 10 steps, the solution is a 1×20 matrix, and the solution of u_1^{hot} at the corresponding position is the indoor temperature $x_1^{t\text{-in}}$ and the outside temperature $w_1^{t\text{-out}}$ is the optimal control at the current time. Ten steps of data are needed at each moment, and the same solving steps are repeated to obtain a series of optimal controls. The solution flow of the algorithm is shown in Figure 5.

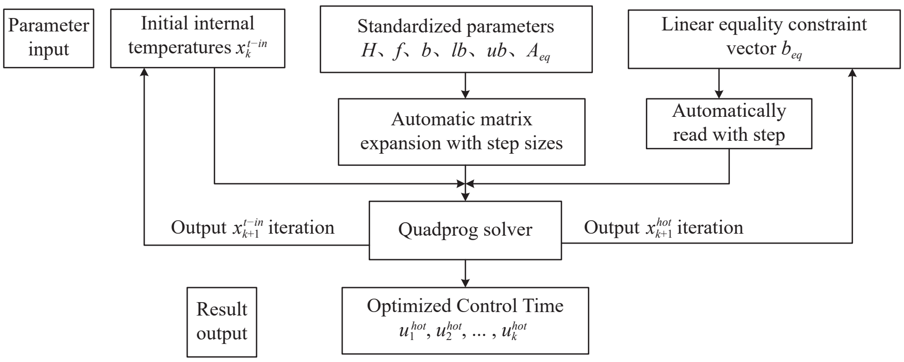


Figure 5 Algorithm flowchart for series optimal control

Through the test data, 1034 groups of control time for heating system optimization under given indoor temperature and outdoor temperature are solved, and the representative data with differences are selected for display, as listed in Table 3.

The regression algorithm is used to train the relationship between indoor temperature $x^{t\text{-in}}$ and outdoor temperature $w^{t\text{-out}}$ with the optimal control u^{hot} using 70% of the sample data, and the control strategy function $\mu(\cdot)$ is obtained as shown in Equation (14), with the fitting determination coefficient R^2 being 0.895.

Table 3 Optimal control calculation result

No.	Date	Moment	Room temperature $x^{t\text{-in}}$/°C	Outdoor temperature $w^{t\text{-out}}$/°C	Optimal control u^{hot}/min
1	2021-12-01	22:30	15.5	2.7	6.12
2	2021-12-02	01:30	17.8	0.8	6.90
3	2021-12-02	04:15	14.5	−0.4	8.76
…	…	…	…	…	…
1033	2021-12-27	05:15	15.6	−1	7.95
1034	2021-12-27	05:30	17.6	−1	7.37

$$u^{hot} = -0.0141x^{t\text{-in}} + 0.5911w^{t\text{-out}} - 0.0644x^{t\text{-in}}w^{t\text{-out}} + 8.7753 \quad (14)$$

The model was validated using the remaining 30% of the sample data, and the predicted values and actual values were shown to have a 1:1 linear relationship in Figure 6. The average absolute error of the model was 0.27 and the root mean square error was 0.45, indicating that the control prediction model is relatively reliable.

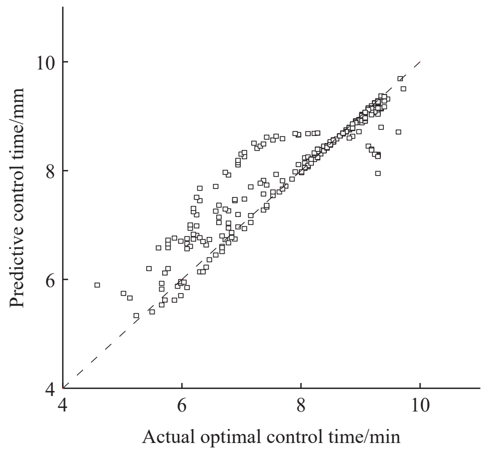


Figure 6 Comparison between predictive value and actual value

When the expected target temperature T_{set} is 18°C, changing the corresponding parameters, the optimization solution was obtained using the same method and resulted in the control strategy as given by Equation (15).

$$u^{hot} = -0.0054x^{t\text{-in}} + 0.2524w^{t\text{-out}} - 0.0396x^{t\text{-in}}w^{t\text{-out}} + 7.32 \quad (15)$$

3.5 Application and result analysis

The environmental information is collected by the air temperature and humidity sensor and the outdoor weather station, and transmitted to the cloud server through the PLC and the cloud box of the Internet of Things (Figure 7). Python reads the cloud data, optimizes the design of the control strategy, and feeds back the calculation results through the API interface. The system reads the data every 15 min calculates according to the optimization strategy, and feeds back the optimal working time of the heating system under the current environmental conditions in real-time. The control information is updated in real-time to realize the synchronization of local and remote. The local terminal subsystem PLC controller receives the information of the optimized heating time and controls the switch of the heating system to adjust the temperature to the desired temperature value.

The validation test was conducted on January 10th and 11th, 2022 with the temperature ranging from −4.0°C to 8.0°C. The temperature changes inside and outside the greenhouse are shown in Figure 8. As demonstrated in the figure, the optimized control ensures that temperatures in different stages are well stabilized near the target temperature, with a maximum temperature fluctuation of only 1.4°C. The heating power consumption was 53.78 kW·h. The threshold control was applied in the early stage of the greenhouse to ensure normal operation. To further illustrate the improvement of the control effect, the comparison was made with the temperature control result inside the greenhouse from January 1st to 2nd, 2022 (when the temperature was −4.0°C to 10.0°C). The threshold control could guarantee the temperature inside the greenhouse within the appropriate range, but without real-time feedback from the greenhouse and outdoor environment, the maximum temperature fluctuation could reach 4.3°C, exceeding the difference between the upper and lower limit set (2.0°C) by 2.3 °C. The power consumption was 61.64 kW·h. The optimized control saved 7.86 kW·h, accounting for 14.6% of the total nighttime power consumption.

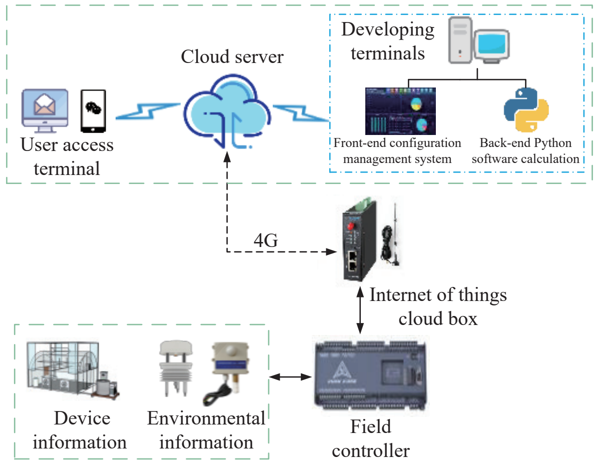


Figure 7 Structure diagram of the control system

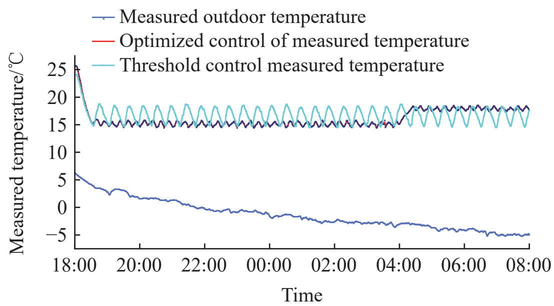


Figure 8 Results of temperature control

4 Discussion

In this study, a mathematical model was established to consider the dynamic characteristics of a greenhouse, and an optimization solution was performed with a focus on the practical application of greenhouse environment control. In the following sections, the generalizability and shortcomings of the model method are discussed.

The 3 major factors affecting environmental regulation are the greenhouse environment state, the control equipment state, and the external environment. Thus, an optimization mathematical model that includes environmental state variables, optimization decision variables, and random variables has a certain generality. The greenhouse control system was designed based on the typical structure of the Internet of Things. In future work, the comparative analysis of the Internet of Things (IoT) and the commonly used environmental control methods such as PID control and predictive control can be carried out; the state variables, optimization decision variables, and random variables can be considered more comprehensively and continuously trained with rich data to achieve more precise and scientific regulation of the greenhouse environment.

However, the greenhouse production system is complex and has a strong coupling in the environment. In this study, only temperature conditions were considered in the environmental state, and in the future, it can be extended to multiple environmental objectives. Meanwhile, as greenhouse control equipment becomes increasingly diverse, decision variables can also be expanded and improved. The selection of the optimization strategy model directly determines the quality of the policy learning. Since there are fewer variables in the case presented in this paper, a linear model can be more accurate. Deep neural networks and other methods can be extended to be used, and the method is scalable.

5 Conclusions

This study explored the application of dynamic programming algorithms in greenhouse environment regulation, taking winter heating regulation in greenhouses as a starting point. It established a mathematical model that includes environmental state variables, optimized decision variables, and random variables, and combined the model prediction and control solution to optimize the results. The main conclusions are as follows:

1) By using quadratic programming algorithms to optimize the solution and train the relationship between the optimization decision variables, environmental state variables, and random variables through regression algorithms, the optimization control model was obtained, proving the feasibility of dynamic programming algorithms in greenhouse environment regulation.

2) Based on the typical structure design of the Internet of Things, an intelligent monitoring system for the greenhouse was established, which is composed of an on-site monitoring subsystem, a cloud box of the Internet of Things, and a remote monitoring subsystem. The experimental results show that the optimal control strategy can maintain the temperature near the target value and the maximum amplitude was only 1.4°C. The power consumption of the optimized control method and the control method of setting the threshold value (the threshold value range was 2.0°C) were compared under similar external weather conditions. The optimized control method reduced the temperature fluctuation range of 0.9°C and saved 7.83 kW·h power, which accounts for about 14.56% of the test power consumption. The optimized control not only reduces the temperature fluctuation range but also saves energy consumption to a certain extent.

Acknowledgements

This work was financially supported by the National Key Research and Development Program (Grant No. 2021YFE0103000); National Key Research and Development Program (Grant No. 2022YFD1900400); Ningxia Hui Autonomous Region Key Research and Development Programme (Grant No. 2022BBF02026).

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