Crop response-driven intelligent coordination and optimization control of greenhouse microclimate factors

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Abstract: How to achieve precise and coordinated control of greenhouse microclimate factors under strong coupling and nonlinear conditions remains a key challenge in protected agriculture. To address this issue, this study integrates intelligent control and multi-objective optimization to regulate greenhouse temperature and humidity in a coordinated manner. A mechanistic model of a Venlo-type greenhouse was first developed in Matlab R2022a. Then, three control methods, namely LQR, MPC, and NMPC, were compared, and NMPC showed the best performance. Finally, NSGA-II was introduced to optimize the objective function weights of NMPC, further improving the control results. Compared with NMPC alone, the optimized method reduced the RMSE and MAE by 0.3366 and 0.0812 for temperature control, and by 0.2192 and 0.6853 for humidity control, respectively. The proposed method improves the precision and coordination of greenhouse environmental control and provides support for efficient greenhouse production. Ultimately, this study offers a promising technical paradigm for transitioning traditional greenhouse management towards highly autonomous and sustainable precision agriculture.

Keywords: intelligent greenhouse, crop response, environmental regulation, coordinated optimization
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1 Introduction

Greenhouse technology plays an important role in modern agriculture by extending production periods, increasing yield, and supporting year-round crop supply[1-3]. Among greenhouse microclimate factors, temperature, humidity, light, and carbon dioxide concentration have significant effects on crop growth and quality, making their precise regulation essential for efficient production[4-6]. However, traditional greenhouse environmental control mainly relies on empirical adjustment and simple feedback mechanisms, which often suffer from limited accuracy, slow response, and poor adaptability under complex operating conditions[7]. In particular, conventional Single-Input Single-Output (SISO) strategies are inadequate for handling the strong coupling among greenhouse variables. For example, ventilation for temperature reduction may simultaneously decrease humidity, while independent control loops may lead to actuator conflicts, system oscillation, and energy waste. In addition, such reactive methods cannot effectively compensate for external disturbances or satisfy strict growth constraints.

To overcome these limitations, a variety of advanced control methods have been applied to greenhouse regulation, including PID[8], fuzzy control[9], adaptive control[10-14], neural network control[15], hierarchical optimization control[16,17], and model predictive control (MPC)[18-20]. Compared with conventional methods, intelligent control strategies offer better adaptability to nonlinear, coupled, and time-varying greenhouse systems, and are more suitable for coordinated optimization of multiple environmental factors[21]. Among them, nonlinear model predictive control (NMPC) is particularly promising because it can explicitly handle multivariable coupling and system constraints. However, its control performance strongly depends on the appropriate selection of objective function weights.

Therefore, this study proposes an intelligent coordinated optimization control method for greenhouse environmental factors. A mechanistic model of a Venlo-type greenhouse is first established, and LQR, MPC, and NMPC are compared for temperature and humidity regulation. On this basis, the NSGA-II algorithm is introduced to optimize the objective function weights of NMPC, thereby improving coordinated control performance. The feasibility and effectiveness of the proposed method are verified through simulation analysis.

2 Materials and methods

2.1 Analysis and modeling of greenhouse environments

This study focuses on a common Venlo-type greenhouse for tomato cultivation[22-24]. Temperature and humidity, being two of the most critical environmental factors in a greenhouse, significantly affect plant growth and development. Thus, this study aims to regulate the greenhouse system to control temperature and relative humidity, providing an optimal environment to maintain healthy plant growth and enhance agricultural production efficiency. Although this study validates the strategy using a Venlo-type greenhouse model, the proposed algorithm is highly adaptable to other greenhouse structures by simply recalibrating the physical parameters such as volume, air density, and transmittance.

Greenhouse temperature is typically controlled by factors such as heating, cooling, ventilation, lighting, and solar radiation, while

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greenhouse humidity is influenced by crop transpiration, water vapor condensation, and ventilation[5]. A mechanistic model of the Venlo-type greenhouse is constructed based on energy transfer and material exchange, with the differential equations for temperature and humidity variables in the greenhouse as follows:

$$\begin{cases} \dfrac{\mathrm{d}T_{\mathrm{in}}(t)}{\mathrm{d}t} = \dfrac{1}{C_{\mathrm{cap}}}\left(Q_{\mathrm{sun}}(t) + Q_{\mathrm{lamp}}(t) - Q_{\mathrm{cov}}(t) - Q_{\mathrm{trans}}(t) - Q_{\mathrm{vent}}(t) + Q_{\mathrm{c}}(t)\right) \\ \dfrac{\mathrm{d}H_{\mathrm{in}}(t)}{\mathrm{d}t} = \dfrac{1}{h}(H_{\mathrm{trans}} - H_{\mathrm{vent}} - H_{\mathrm{cov}}) \\ RH_{\mathrm{in}} = \dfrac{H_{\mathrm{in}}}{H_{\mathrm{in,sat}}} \times 100\% \end{cases} \tag{1}$$

where, T_{in} is the temperature inside the greenhouse, °C; C_{cap} is the thermal capacity of the greenhouse, J/(m²·°C); Q_{c} is the heating or cooling power, W/m²; Q_{sun} is the incident solar radiation, W/m²; Q_{cov} is the energy exchange through the covering material, W/m²; Q_{trans} is the energy exchange caused by crop transpiration inside the greenhouse, W/m²; Q_{lamp} is the heating power from lights, W/m²; Q_{vent} is the energy change due to ventilation, W/m²; RH_{in} is the relative humidity inside the greenhouse, %; H_{in} is the water vapor pressure inside the greenhouse, Pa; $H_{\mathrm{in,sat}}$ is the saturation water vapor pressure inside the greenhouse, Pa; h is the average height of the greenhouse, m; H_{trans} is the vapor pressure produced by plant transpiration, Pa; H_{cov} is the loss caused by condensation of water vapor in the greenhouse, Pa; and H_{vent} is the exchange of water vapor inside and outside the greenhouse due to ventilation, Pa.

2.2 Research on multi-objective coordinated optimization control methods for greenhouses

Greenhouse environmental control is a complex and critical task that requires balancing and coordinating multiple factors. The core of multi-objective optimization is to find a set of solutions that bring all objective functions as close as possible to their optimal values[25]. This study needs to simultaneously consider the appropriate ranges for both temperature and humidity, which can sometimes conflict. For example, increasing temperature can raise the evaporation rate, affecting humidity, while decreasing temperature can increase condensation, also affecting humidity.

Multi-objective optimization algorithms aim to resolve these conflicts by finding the optimal trade-off solutions among multiple objective functions. These algorithms search for a set of optimal solutions in the decision space and coordinate the optimal solutions of each objective function so that each part of the objective function is as close as possible to its optimal value. Therefore, multi-objective optimization problems do not have a single global optimal solution but rather a set of solutions known as the Pareto front. The Pareto front refers to a set of solutions where no objective can be improved without sacrificing another objective. Because different objectives may conflict with each other, these solutions represent the best balance among the objectives, typically resulting in Pareto optimal solutions that satisfy different objective weights[26]. In multi-objective optimization, a solution is said to be dominated if another solution performs better in some objectives. A solution that outperforms another solution in all objective functions is called a dominating solution, indicating that no other solution can surpass it in all objectives, thus holding an advantageous position in overall optimization.

The general mathematical expression for multi-objective coordinated optimization control is as follows:

$$\min f(x) = \left[f_1(x), f_2(x), \ldots, f_n(x)\right] \tag{2}$$

$$\text{subject to: } g_n(x) \le 0,\ \ h(x) = 0 \tag{3}$$

where, x represents the control variables of the optimization problem, $f1(x), f2(x), \ldots, fn(x)$ represents the n objective functions, $g(x)$ represents n inequality constraints, and $h(x)$ represents p equality constraints.

2.2.1 Design of greenhouse temperature and humidity controller based on NMPC

MPC combines predictive models, rolling time-domain optimization, and feedback correction mechanisms to achieve precise control of complex systems[27]. NMPC is an extension of MPC that uses nonlinear models for prediction, making it suitable for nonlinear, multivariable, time-varying, and constrained systems, allowing for more precise regulation of nonlinear processes.

To control NMPC, an accurate mathematical model describing the controlled system must be established to predict future behavior. This study uses the nonlinear greenhouse temperature and humidity model established in Section 2.1 and converts it into the differential equations shown in Equation (4) for prediction. Here, x represents the state parameters, which are indoor temperature and relative humidity; u represents the output parameters, which are the heating power, supplementary light power, and ventilation rate; and d represents the disturbance variables during the control process, including outdoor temperature and relative humidity, and solar radiation. NMPC recalculates the optimization problem based on the current state during each sampling period, but only the first step (i.e., the control input at the current moment) is applied to the system, and the next optimization step is performed in the new state of the system, completing the rolling optimization.

$$x(k+1) = f(x(k), u(k), d(k)) \tag{4}$$

The core of NMPC lies in its optimization solving steps. NMPC transforms the control problem into an optimization problem and uses numerical optimization methods to find the optimal solution. The goal of this optimization problem is to find an optimal control input sequence that meets the system constraints and achieves the optimal system performance over a future period. This involves selecting and setting the optimization objective function, which typically includes tracking errors and the cost of control inputs, while also considering various system constraints such as physical limits and safety requirements. Appropriate optimization algorithms, such as Sequential Quadratic Programming (SQP) and interior point methods, can be used to solve this optimization problem and obtain the optimal control input sequence. For this study, Matlab's fmincon function with the SQP algorithm was used to solve the optimization problem. A well-designed objective function is crucial for ensuring the performance of the NMPC controller. Equation (5) shows the objective function used to calculate the error between the predictive model and the reference model, where λ_1' is the weight vector for the temperature and humidity errors, λ_2' is the weight vector for the control output change rates, $\lambda_1' \sum_{i=1}^{tp} [x(k+i) - x_d(k+i)]^2$ represents the temperature and humidity errors, and $\lambda_2' \sum_{i=2}^{tp} [u(k+i) - [u(k+i-1)]]^2$ represents the change rate of control outputs. Minimizing the rate of change of control outputs not only ensures smoother control actions but also directly reduces energy consumption and mechanical wear of the actuators. By adjusting the values of λ_1' and λ_2', the weights of temperature and humidity errors and the weights of control output change rates can be regulated. Equation (6) sets constraints on control inputs and system states. Setting limits on control inputs can effectively avoid violating physical or safety operating conditions to ensure stable system operation, while setting physical or operational constraints on system states can ensure the feasibility of the optimal solution, further enhancing system performance and stability, helping to ensure the entire system operates safely and efficiently.

$$J = \lambda_1' \sum_{i=1}^{tp} [x(k+i) - x_d(k+i)]^2 + \lambda_2' \sum_{i=2}^{tp} [u(k+i) - [u(k+i-1)]]^2 \tag{5}$$

$$\begin{cases} u_{\min} \le u(i) \le u_{\max} \\ x_{\min} \le x(i) \le x_{\max} \\ i,\ \ k = 1, 2, \ldots, tp \end{cases} \tag{6}$$

Due to external disturbances and model limitations, predictive models may not fully reflect actual dynamics. Therefore, NMPC introduces a feedback correction mechanism to correct the model with real-time feedback information, reducing prediction errors and making control more precise. Continuous feedback and correction enable NMPC to constantly optimize control strategies, improving the robustness and stability of the system. Thus, NMPC strategies demonstrate more robust advantages and application potential when dealing with systems with high uncertainty and difficult-to-match precise models.

2.2.2 Multi-objective optimization control of greenhouse environment based on the NSGA-II Algorithm

The control of greenhouse environments requires coordinated optimization of multiple parameters, such as temperature and humidity, to improve crop yield and quality. As an efficient multi-objective optimization algorithm, NSGA-II has been widely used in engineering applications because of its good convergence, solution diversity, and stability[28]. Compared with other algorithms such as MOPSO and MOGA, NSGA-II is more suitable for constrained multi-objective optimization problems. Given the strong coupling, nonlinearity, and variability of greenhouse systems, this study employs NSGA-II to optimize the objective function weights for coordinated greenhouse environmental control, and its workflow is shown in Figure 1.

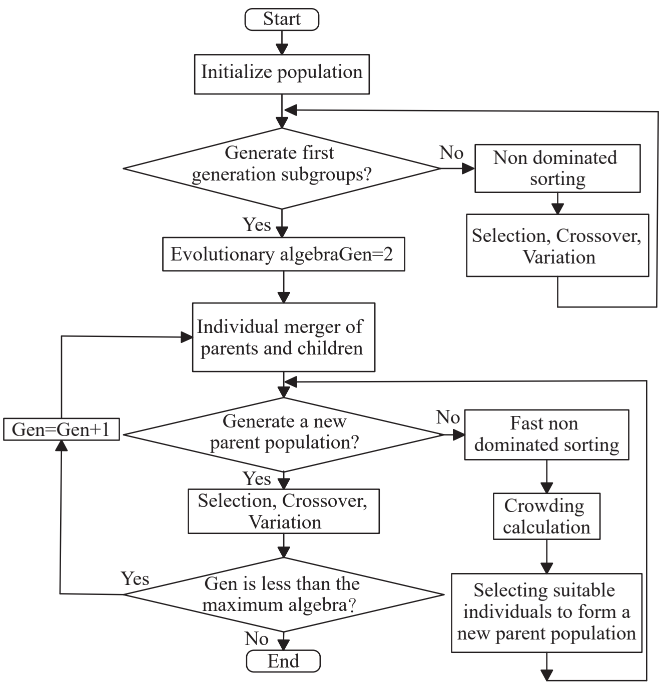


Figure 1 Flowchart of how NSGA-II works

NSGA-II ranks individuals by non-dominated sorting and maintains population diversity through crowding distance, thereby gradually approaching the Pareto-optimal solution set during iterative evolution. Its basic procedure includes population initialization, fitness evaluation, non-dominated sorting, crowding distance calculation, selection, crossover, mutation, and population update.

In greenhouse temperature and humidity control, the weighting design of the objective function in Equation (5) is critical, since improper weights may degrade control performance. Therefore, NSGA-II is employed to optimize the weights by jointly considering temperature and humidity errors as well as the variation rate of control outputs. Specifically, the algorithm initializes the population, evaluates individual fitness, performs non-dominated sorting and crowding distance calculation, and then generates new populations through selection, crossover, and mutation. Through iterative updating, the Pareto-optimal solution is obtained for coordinated greenhouse environmental control.

3 Results and discussion

The simulation experiments were implemented using Matlab R2022a. The crop selected was tomato seedlings, which thrive at daytime temperatures of 20°C-25°C and nighttime temperatures of 10°C-15°C during the seedling stage[29-31]. Consequently, the reference model was set with a daytime temperature of 23°C and a nighttime temperature of 13°C. The validation of the greenhouse mechanism model was conducted over 1440 sampling points, with an interval of 5 min per sampling point, totaling 7200 min or 5 d. For the simulation of the greenhouse temperature and humidity controller, the simulation time was set to 800 sampling points with a 5-min interval, totaling 4000 min.

This study, based on an in-depth examination of the interaction mechanisms among greenhouse environmental factors, considered elements such as temperature and humidity. The physical principles were employed to model the microclimate factors of a Venlo-type greenhouse. To verify the feasibility of this model, the modeling results were compared with actual greenhouse conditions using the Matlab R2022a platform. The model's effectiveness was evaluated using root mean square error (RMSE) and mean absolute error (MAE) as metrics.

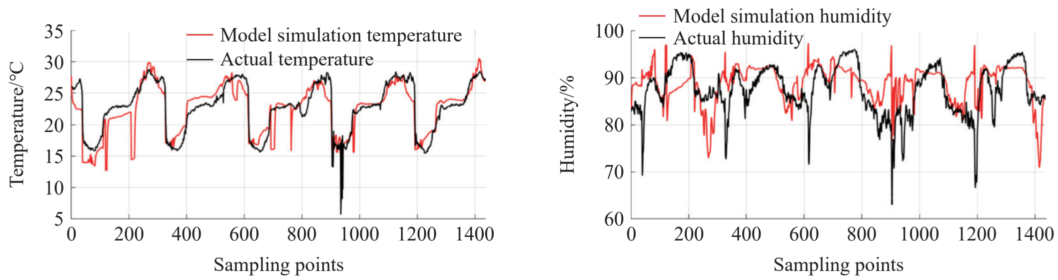
Table 1 presents the comparison of errors between the actual temperature and humidity data and the simulated data from the mechanism modeling of a Venlo-type greenhouse. Figure 2 shows the comparison on the left side between the actual temperature inside the greenhouse and the temperature simulated by the mechanism model, and on the right side, the comparison between the actual relative humidity and the simulated relative humidity. The simulation results indicate that the deviation between the predicted and actual values for temperature is smaller than that for relative humidity. Thus, the temperature model's simulation performance is superior to that of the relative humidity model.

Table 1 Temperature and humidity error of the mechanistic model

Model	RMSE	MAE
Temperature model	2.2235	1.5689
Humidity model	5.3498	4.0035

In achieving the coordinated optimization control of greenhouse temperature and humidity, intelligent regulation of these factors is crucial for the efficient management of enclosed environments like greenhouses. Addressing the intelligent control problem of temperature and humidity in greenhouse microclimates, this study conducted comparative experiments using LQR, MPC, and NMPC methods[32,33]. The simulation results demonstrate that NMPC performs best in temperature and humidity control. For temperature control, the RMSE value is only 1.3889, and the MAE value is as low as 0.8446. For humidity control, the RMSE value is 3.0192, and the MAE value is 2.8314. The significant reduction in RMSE indicates that the greenhouse microclimate is maintained more consistently within the optimal growth range for tomato seedlings (20°C-25°C), which is critical for preventing heat stress and ensuring high seedling quality. Therefore, NMPC is chosen as the primary control strategy for further research.

Table 2 displays the errors in greenhouse temperature and humidity control for the LQR, MPC, and NMPC controllers, with the smallest root mean square error (RMSE) and mean absolute error (MAE) values highlighted in bold. The error analysis shows that NMPC has the smallest RMSE and MAE for both temperature and humidity, indicating superior control performance over LQR and MPC.



a. Comparison chart of the actual simulation of greenhouse temperature

b. Comparison diagram of the actual simulation of the relative humidity of the greenhouse

Figure 2 Mechanistic modeling and actual data comparison of Venlo-type greenhouses

Table 2 Temperature and humidity control error

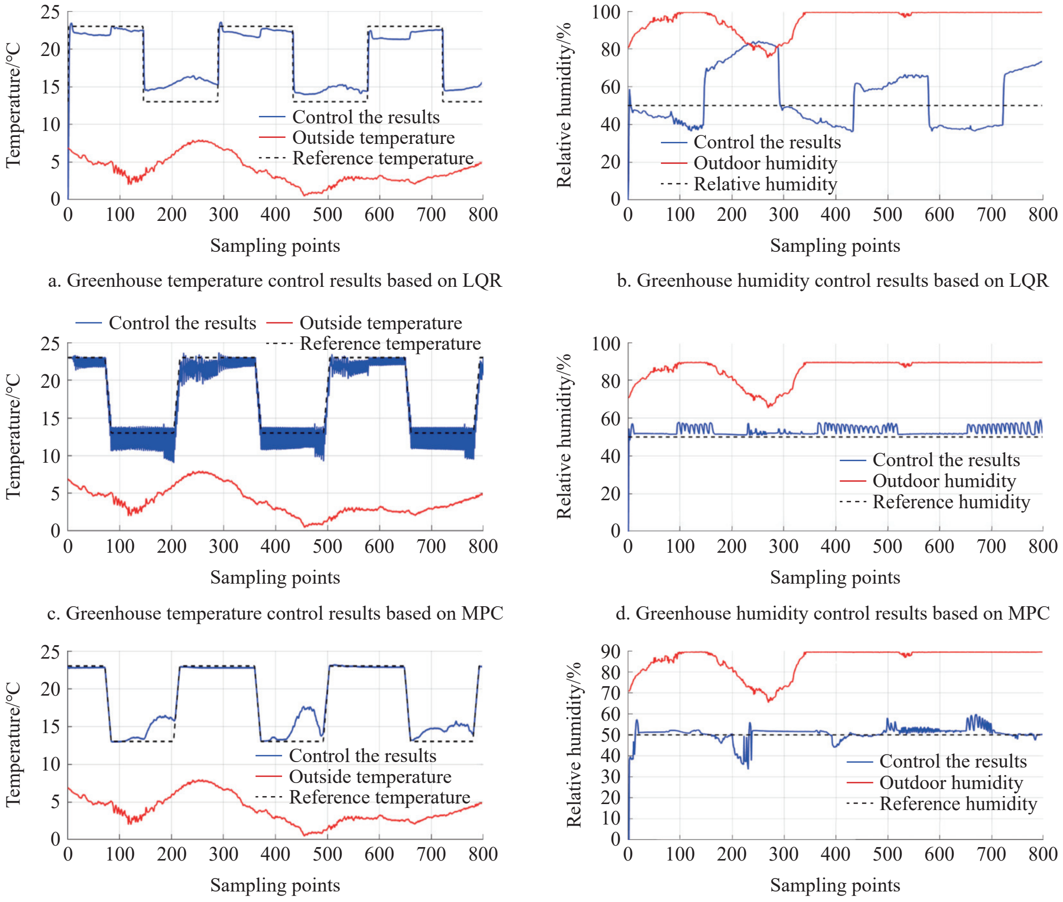
Controller type	Temperature control		Humidity control	
	RMSE	MAE	RMSE	MAE
LQR controller	1.8594	1.4684	18.6617	16.0262
MPC controller	1.6146	1.2957	4.3388	3.3743
NMPC controller	1.3889	0.8446	3.0192	2.8314

Figure 3 illustrates the greenhouse temperature and humidity control results for the LQR, MPC, and NMPC controllers, with temperature control results on the left and humidity control results on the right. Figure 3 shows the output results of greenhouse equipment based on the LQR, MPC, and NMPC controllers. From the greenhouse temperature and humidity control results based on the LQR controller, it is evident that under significant external environmental variations, both temperature and humidity control results exhibit noticeable fluctuations, with temperature control results being significantly better than humidity control results. The poor performance of LQR can be attributed to its high dependence on the accuracy of the system model. If the model cannot accurately reflect the relationships between environmental factors such as light, temperature, and humidity, the controller designed by LQR may not achieve the desired effect. Additionally, LQR is designed for linear systems, and unless it operates near the linearization point of a nonlinear system, it may not provide satisfactory performance. Similarly, MPC, as a linear controller, relies on an accurate system model for prediction and optimization. If the model cannot accurately reflect the complex changes in the greenhouse environment, including the influences of climatic factors, plant physiological responses, and soil conditions, the discrepancies between the model and the actual system may lead to suboptimal control results. The greenhouse system's characteristics of strong nonlinearity, slow time-varying nature, strong coupling, and significant delay further complicate achieving ideal control performance with MPC. In contrast, NMPC improves greenhouse control performance due to its nonlinear nature. The NMPC controller uses the original model for prediction to optimize inputs, providing higher prediction accuracy than MPC since it does not linearize the model. However, NMPC's higher computational complexity can lead to longer running times and real-time issues.

Figure 4 shows the greenhouse temperature and humidity control results based on the NMPC controller combined with NSGA-II for objective weight optimization. The RMSE for temperature control is 1.0523, and the MAE is 0.7634. For humidity control, the RMSE is 2.8000, and the MAE is 2.1461. Compared to NMPC alone, the RMSE for temperature control has decreased by 0.3366, and the MAE has decreased by 0.0812. For humidity control, the RMSE has decreased by 0.2192, and the MAE has decreased by 0.6853. The results of greenhouse temperature and humidity control with the combined use of NSGA-II for objective function weight optimization show significant improvement, with noticeable reduction in large fluctuations. However, despite NSGA-II's excellent performance in multi-objective optimization, its inherent limitations, such as the uneven distribution of the Pareto front, might prevent finding the optimal solution. This can lead to fluctuations in the greenhouse control results.

4 Conclusions

To achieve intelligent coordination between the greenhouse environment and crop responses, this paper proposes a regulation method integrating multi-objective optimization with intelligent control. First, a mechanistic model of a Venlo-type greenhouse was constructed, and Nonlinear Model Predictive Control (NMPC) was selected as the foundational control strategy following a comparative evaluation. The core innovation of this study lies in introducing the NSGA-II algorithm to synergistically optimize the objective function weights of the NMPC. The results demonstrate that this strategy effectively overcomes the coupling conflict between temperature and humidity, yielding significantly lower control errors (RMSE and MAE) compared to conventional NMPC. This research provides a robust technical paradigm for the precise regulation of greenhouse environments, contributing to the further enhancement of efficiency and sustainability in modern agricultural production.



a. Greenhouse temperature control results based on LQR

b. Greenhouse humidity control results based on LQR

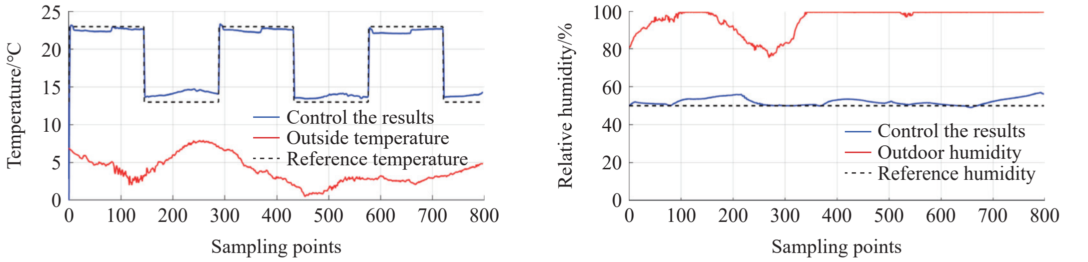
c. Greenhouse temperature control results based on MPC

d. Greenhouse humidity control results based on MPC

e. Greenhouse temperature control results based on NMPC

f. Greenhouse humidity control results based on NMPC

Figure 3 Control results of greenhouse temperature and humidity using LQR, MPC, and NMPC



a. Simulation diagram of greenhouse temperature control

b. Simulation diagram of greenhouse relative humidity control

Figure 4 Greenhouse temperature and humidity control results based on NMPC controller combined with NSGA-II for target weight optimization

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