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Event-Based PID Control for Greenhouse Environment

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Abstract: This paper is concerned with the proportional-integral-derivative (PID) control problem for a greenhouse environmental system under the event-triggered mechanism (ETM) using the decomposition-based multi-objective evolutionary algorithm (MOEA/D). To reduce network resource consumption, ETM is implemented in the communication channels between the sensors and the controller. Firstly, a greenhouse environmental system model based on temperature variations is adopted. Secondly,the energy consumption and accuracy are used as performance metrics to construct the objective functions. Furthermore, the MOEA/D is employed under the ETM to optimize the established objective functions, obtaining the Pareto optimal solutions, and subsequently tuning the parameters of the PID controller. Finally, the simulation results validate the effectiveness of the proposed event-based PID control strategy using MOEA/D.

Keywords: PID control; event-triggered mechanism (ETM); decomposition-based multi-objective evolutionary algorithm (MOEA/D)

1. Introduction

Greenhouse environmental control, with temperature regulation as its core objective, aims to enhance the system's dynamic response performance while optimizing energy consumption. The variation of internal temperature is not only driven by external climatic conditions but also depends on the accuracy of actuator adjustments, rendering the control process highly complex and time-varying. Greenhouse temperature control is subject to multi-objective conflict constraints between control accuracy and energy consumption [1]. Therefore, it is necessary to design an efficient and robust temperature control strategy to achieve a balance between accuracy assurance and energy optimization under complex dynamic environments.

The PID control is widely applied in greenhouse environmental control due to its simple structure, good stability, reliable operation, ease of adjustment, and straightforward implementation. In previous studies, various methods have been proposed for tuning PID controllers in greenhouse environmental systems. Among them, a control system based on a single-neuron PID algorithm, by incorporating neural network technology, can effectively improve the accuracy and stability of greenhouse temperature and humidity control [2]. Meanwhile, the parameter self-tuning PID control method adapts PID parameters through self-adjustment, enabling it to better cope with dynamic changes in the greenhouse environment, thereby improving the system's response speed and stability [3]. Additionally, some studies have attempted to optimize PID parameters through intelligent control methods and applied them to greenhouse environmental control [4, 5]. However, these methods often fail to fully consider the interactions between various factors in the greenhouse and overlook the conflicts between control accuracy and energy consumption. Therefore, conducting research on PID control for greenhouse environmental systems under the context of multi-objective conflicts holds significant theoretical value.

Optimizing greenhouse environmental control is essentially a multi-objective optimization problem [6]. To address this issue, it is essential to consider the interrelationship between system response speed and accuracy. Traditional methods, such as the weighted sum approach [7] and the constraint method [8], simplify multi-objective problems but are limited by subjective weight selection and uncertain constraint boundaries. Recently, evolutionary algorithms have been widely applied in greenhouse environmental control as effective multi-objective optimization tools. These algorithms generate Pareto-optimal solutions, providing decision-makers with multiple balanced options. For example, the NSGA-II has optimized the balance between photosynthesis rate and control costs in greenhouses [9], and PSO has been applied to optimize PID controller parameters, effectively enhancing system response speed and reducing overshoot [10]. By integrating evolutionary algorithms with PID control, these methods overcome traditional limitations and significantly improve control system precision and response speed.

With the continuous development of smart agriculture and wireless communication technologies, greenhouse environmental systems have attracted widespread research attention, particularly under resource-constrained conditions such as limited communication bandwidth and energy. In such networked greenhouse systems, traditional periodic (time-triggered) sampling transmits sensor and control data at fixed intervals regardless of whether the greenhouse state has significantly changed. This rigid transmission pattern often results in redundant communication, increased network load, and unnecessary actuator operations, which waste bandwidth and power resources [11]. By contrast, event-triggered mechanisms (ETMs) update control signals only when predefined state-dependent conditions are violated, enabling adaptive communication and computation schedules that focus resources on critical moments [12]. Over the past decades, event-triggered mechanism (ETM) perform excellently in greenhouse temperature and humidity control [13], and also demonstrate the potential to reduce water usage and improve control accuracy in greenhouse irrigation systems [14]. Beyond greenhouse applications, recent studies in networked and cyber-physical control further show that event-/protocol-aware designs can enhance resource efficiency and resilience while maintaining control performance [15, 16]. The integration of the PID controller under the ETM not only enhances system efficiency but also reduces communication and computational burdens [17, 18]. Therefore, researching the PID control problem for the greenhouse environmental system under the ETM using evolutionary algorithms is of practical significance.

Motivated by the above discussions, this paper focuses on PID control in the greenhouse environmental system using an evolutionary algorithm under the ETM.The novelties of this paper lie in the following: (1) the adoption of the ETM reduces the data transmission frequency and significantly saves computational resources; (2) a PID controller structure is constructed based on the ETM to meet the control requirements of the greenhouse environment system; (3) an effective optimization scheme is proposed to address the trade-off between control accuracy and energy consumption under resource-constrained conditions, offering both theoretical significance and practical application potential.

The structure of this paper is as follows. Section 2 introduces the greenhouse environmental system model and designs the discrete PID controller structure based on the ETM. Section 3 formulates the objective functions related to energy consumption and control accuracy. Section 4 outlines the multi-objective evolutionary algorithm employed in this study. A simulation example is provided in Section 5. The conclusions are summarized in Section 6.

2. Greenhouse Environmental System Model

The model of greenhouse environmental system needs to comprehensively consider various factors. The description methods can generally be divided into two categories: one is based on physical processes, and the other is data-driven. This paper adopts the first approach, drawing on the greenhouse environmental system model presented in the literature [19]. In the modeling process, several reasonable simplifications are made to improve computational efficiency while preserving the dominant thermal dynamics of the greenhouse. First, it is assumed that the temperature inside the greenhouse is spatially uniform, so horizontal and vertical temperature gradients could be ignored. Second, since dynamic changes in air temperature are the main factor in short-term greenhouse control, the effects of soil heat transfer and humidity are ignored. Third, since the mechanical and electrical time constants of the actuators are much faster than the thermodynamic response of the greenhouse system, its dynamic characteristics are simplified to a quasi-static response. Finally, to reduce model complexity, the air mixing process is idealized, assuming that the mixing efficiency reaches an ideal state under a given ventilation configuration. The corresponding differential equations are as follows:

$$\frac{dT_{in}(t)}{dt} = \frac{1}{\rho C_p V}\left[q_{heater}(t) + S_i(t)\right] - \left(\frac{V_{cap}(t)}{V} + \frac{G_{wall}}{\rho C_p V}\right)\left[T_{in}(t) - T_{out}(t)\right] \tag{1}$$

where T_{in} and T_{out} denote the indoor and outdoor air temperatures (K), respectively. ρ denotes the air density, taken as 1.2 kg·m^{-3}, and C_p is the specific heat of air, valued at 1006 J·(kg·K)$^{-1}$. V denotes the greenhouse volume (m^3). q_{heater} represents the heat supplied by the greenhouse heater (J·s^{-1}), S_i the intercepted solar radiant energy (J·s^{-1}), V_{cap} the ventilation rate (m^3·s^{-1}), and G_{wall} the overall heat transfer coefficient (J·s^{-1}·K^{-1}). Moreover, the applicability of the simplified heating-ventilation model is mainly limited to short-term temperature control under moderate environmental fluctuations. The model accurately captures the dominant thermal dynamics when the greenhouse operates in a well-mixed air regime with relatively uniform temperature distribution and moderate ventilation rates. However, under strong radiation gradients, high humidity variations, or non-uniform air circulation conditions, additional physical factors such as spatial temperature stratification, latent heat exchange, and soil heat transfer may become significant. Nevertheless, for the purpose of control design and performance optimization, this simplified formulation provides a tractable and sufficiently accurate representation of the main dynamic behavior.

The inside temperature is denoted as the dynamic state variable $x(t)$; the greenhouse heater and the ventilation rate are denoted as the control inputs $u_1(t)$ and $u_2(t)$, respectively; and the solar radiation and outside temperature are denoted as the disturbances $v_1(t)$ and $v_2(t)$, respectively. Then, Equation (1) can be rewritten in the following form:

$$\dot{x}(t) = \frac{1}{\rho C_p V}(v_1(t) + u_1(t)) - \frac{G_{wall}}{\rho C_p V}(x(t) - v_2(t)) + \frac{1}{V}u_2(t)v_2(t) - \frac{1}{V}u_2(t)x(t) \tag{2}$$

For the purpose of reducing the communication burden, an event-triggered communication mechanism is taken into consideration. Define the event generator function $\mathcal{J}(t)$ as follows:

$$\mathcal{J}(t) \triangleq e(t)^2 - \zeta_1 \cdot y(t)^2 - \zeta_2 \tag{3}$$

where $e(t) = r(t) - x(t)$, $r(t)$ represents the reference temperature, ζ_1 and ζ_2 are given positive scalars used to weight the previous error and set the triggering threshold, respectively.

The execution is triggered as long as the condition $\mathcal{J}(t) \geq 0$ is satisfied. Therefore, the sequence of event-triggered instants $0 \leq s_0 < s_1 < \cdots < s_n < \cdots$ is determined iteratively by

$$s_{n+1} = \inf\{t \in \mathbb{N} | t > s_n, \mathcal{J}(t) \geq 0\} \tag{4}$$

PID control is a classical feedback control approach widely used in industrial process control and automation. Equation (5) is introduced here not merely as a general definition but as the specific control law implemented in the greenhouse temperature regulation model and later simulations. In the subsequent simulations, this control law serves as the core temperature controller under the event-triggered framework, directly determining actuator updates at each triggering instant. It combines the proportional, integral, and derivative actions of the system error to achieve precise regulation of the target variable. Within the greenhouse environment, these three actions correspond to distinct physical processes of heat exchange and energy balance. The basic control law is given by:

$$u(t) = k_p e(t) + k_i \int_0^t e(\tau)d\tau + k_d \frac{de(t)}{dt} \tag{5}$$

where k_p is the proportional gain, k_i is the integral gain and k_d is the derivative gain. The proportional term responds instantly to the temperature deviation, producing a heating or ventilation adjustment proportional to the magnitude of the error. The integral term reflects the system's cumulative thermal imbalance: it compensates for the slow accumulation of heat loss or gain through the greenhouse walls and ventilation gaps, thereby eliminating residual offset between the actual and desired temperature. The derivative term anticipates the rate of temperature change caused by variations in solar radiation and airflow, providing a predictive damping effect that suppresses overshoot and stabilizes the transient response.

Let $\hat{u}_1(t)$ and $\hat{u}_2(t)$ denote the zero-order hold (ZOH) versions of the event-based control signals, which satisfy:

$$\hat{u}_j(t) = u_j(s_n), \quad t \in [s_n, s_{n+1}), \quad j = 1, 2. \tag{6}$$

In this work, the ZOH mechanism is adopted to maintain the last control signal constant between two consecutive triggering instants. This method is widely employed in digital control systems owing to its simplicity and robustness in preserving the stability of sampled-data systems [20, 21]. Alternative holds such as first-order or predictive schemes can offer smoother signal reconstruction but require derivative estimation or future state prediction, which increase computational cost and may amplify noise under irregular triggering intervals. In contrast, ZOH avoids these issues while ensuring reliable operation under the event-triggered framework, making it more suitable for greenhouse control systems with limited computation resources. And using Equations (2) and (8) as the basis, the following is derived:

$$\dot{x}(t) = \frac{1}{\rho C_p V}\big(v_1(t) + \hat{u}_1(t)\big) - \frac{G_{\text{wall}}}{\rho C_p V}\big(x(t) - v_2(t)\big) + \frac{1}{V}\hat{u}_2(t)v_2(t) - \frac{1}{V}\hat{u}_2(t)x(t) \tag{7}$$

The system continuously monitors the temperature inside the greenhouse in real-time using sensors and provides feedback to the controller. The controller evaluates the deviation between the setpoint and the actual measured values to determine whether the ETM conditions are met. Once the triggering conditions are satisfied, the system calculates and updates the PID control input signal to perform the corresponding regulation operation.

During the control execution process, the PID controller is used to regulate the greenhouse temperature, ensuring environmental stability. To further improve control accuracy, an evolutionary algorithm is employed to optimize the PID control parameters. The evolutionary algorithm dynamically adjusts these parameters based on the system response, making the control process more precise and adaptive.

3. Performance Criterion

In greenhouse environmental system control design, minimizing energy consumption while ensuring control accuracy is a typical multi-objective optimization problem. In particular, under the ETM, the control signal update mechanism changes from a fixed periodicity to an aperiodic triggering based on system state changes. This non-periodic nature of updates necessitates adjustments to traditional time-domain performance metrics to better reflect the characteristics of control under ETM.

To achieve optimal control of greenhouse environmental systems under the event-triggered mechanism, this study redefined key indicators for measuring system control performance based on the requirements of multi-objective optimization. These indicators not only accurately describe energy consumption and control effectiveness under the event-triggered mechanism but also serve as objective functions in evolutionary algorithm optimization design, guiding the adaptive adjustment of controller parameters.

The first performance metric (J_1) measures system energy consumption, defined as the cumulative amount of control input over the entire control time step, i.e., the total integral of the control input signal. This metric quantifies the energy consumed during the control process. A reduction in the J_1 value implies lower energy usage, thereby improving the overall energy efficiency of the system.

$$J_1 = \sum_{n=1}^{N} \int_{s_n}^{s_{n+1}} (u_1(t) + u_2(t))dt \tag{8}$$

The second performance metric (J_2)measures the system's control accuracy over the entire control period, expressed as the absolute mean error between the indoor environmental variable and the reference value. This metric assesses how closely the greenhouse environmental variable follows the target value at the end of the control period. A lower J_2 value indicates more precise tracking of the reference value. The mathematical formulation is:

$$J_2 = \frac{1}{M} \sum_{l=1}^{M} |e(l)| \tag{9}$$

where M denotes the total number of discrete time instants within the control horizon.

In this study, both J_1 and J_2 are optimized using the MOEA/D to balance energy consumption and control accuracy. This approach ensures that the system can accurately track the reference value while minimizing energy consumption, thereby achieving an efficient and cost-effective greenhouse control strategy.

4. Multi-Objective Evolutionary Algorithms

To optimize the PID controller parameters, this study employs the MOEA/D. Compared with other algorithms, such as NSGA-II, MOEA/D leverages a decomposition strategy in which the multi-objective problem is transformed into several scalar sub-problems, and solutions are collaboratively obtained among neighboring sub-problems. This approach reduces computational complexity and helps generate a well-distributed set of solutions along the Pareto front, thereby providing a more comprehensive trade-off analysis between control accuracy and energy consumption.

In this study, the performance metric J_1 quantifies the total energy consumption of the actuators, while J_2 measures the mean absolute error between the reference and the actual greenhouse temperature, reflecting control accuracy. The set of parameters to be optimized is given by:

$$\Theta = \{K_p^1 K_i^1, K_d^1, K_p^2, K_i^2, K_d^2\},$$

where K_p^1, K_i^1 and K_d^1 are the PID gains of the heating actuator, and K_p^2, K_i^2 and K_d^2 are those of the ventilation actuator. The optimization process using MOEA/D is implemented as follows:

(1) Initialization: A set of weight vectors $\lambda_1, \lambda_2, \ldots, \lambda_N$ is generated to decompose the multi-objective problem into N scalar sub-problems.

The initial candidate solution set Θ is randomly initialized, including all PID controller parameters.

(2) Objective Function Evaluation: For each candidate solution, the performance metrics J_1 and J_2 are calculated based on the greenhouse environmental system model. The multi-objective problem is mapped to scalar sub-problems using Tchebycheff methods and associated with the corresponding weight vectors. The multi-objective problem is mapped to scalar sub-problems using the Tchebycheff method and associated with the corresponding

weight vectors. The Tchebycheff approach is widely adopted in MOEA/D due to its ability to ensure a uniform and well-distributed approximation of the Pareto front while effectively maintaining convergence on non-convex problems [22, 23]. In the Tchebycheff approach, to effectively evaluate the deviation of candidate solutions from the ideal objectives, a reference point vector $z^* = [z_1^*, z_2^*]$ is introduced. Each component z_i^* corresponds to the best-known value of the i-th objective function within the current population. At the initialization stage, the reference point is determined based on the initial population as follows:

$$z_i^* = \min_{x \in \text{initial population}} J_i, \quad i = 1, 2$$

During the evolutionary process, the reference point is dynamically updated. Whenever a newly generated solution achieves a better value in any objective, the corresponding component of the reference point is updated accordingly:

$$z_i^* \leftarrow \min(z_i^*, J_i(\text{new}))$$

where $J_i(\text{new})$ represents the candidate solutions obtained through operations such as crossover and mutation.

(3) Neighborhood Division and Search: Neighborhoods are defined based on the similarity of weight vectors, and each sub-problem is associated with its neighbors. Within each neighborhood, crossover and mutation operations are applied to generate new candidate solutions.

(4) Sub-Problem Update: The newly generated solutions are evaluated and compared with the current solutions. If a new solution improves the value of a sub-problem, it replaces the current solution. Non-dominated solutions are simultaneously updated in the Pareto front.

(5) Termination: Determine whether the maximum evolution generation termination is met. If so, the algorithm terminates.

5. Simulations and Results

This study uses the Simulink integrated simulation environment under the Matlab R2022b platform to simulate the greenhouse environmental system model controlled by a PID controller optimized via MOEA/D under the ETM. The model parameters are shown in Table 1.

Table 1. Basic Parameters of the Greenhouse Model.

Parameter Name	Symbol	Value
Greenhouse Dimensions	V	15 m × 10 m × 3 m
Heat Transfer Coefficient	G_{wall}	500 W/K
Air Density	ρ	1.2 kg/m^3
Specific Heat Capacity	C_p	1006 J/(kg·K)

In these basic parameters, v_1 and v_2 represent the external solar radiation and outdoor temperature, all modeled using sinusoidal functions. The solar radiation (v_1) varies in the range of 250 W/m^2 to 500 W/m^2; the outdoor temperature (v_2) varies in the range of 32 °C to 38 °C. These physical quantities directly affect the dynamic changes in temperature inside the greenhouse and serve as input to the system model.

The initial value of temperature in the greenhouse air is 32 °C. The set value for indoor temperature is 25 °C. The MOEA/D parameters are as follows: the population size is 80, the number of generations is 70, the crossover probability is 0.9, the mutation rate is 0.1. The ETM parameters are set as follows: $\zeta_1 = 0.4$ and $\zeta_2 = 0.01$. The parameters ζ_1 and ζ_2 are determined through a simulation-based sensitivity analysis using the performance indices J_1 (energy consumption) and J_2 (control accuracy) as evaluation criteria. Multiple combinations of threshold values are tested to examine their impact on control precision, energy use, and triggering frequency. The chosen values correspond to the range where further reduction in thresholds yielded negligible improvement in J_2 but caused a noticeable increase in J_1 and the number of triggering events. According to event-triggered control theory [24], such parameters achieve a well-balanced compromise between tracking accuracy, communication efficiency, and energy consumption.

The ranges of the PID controller gains are set as $0 \leq K_p^1 \leq 0.5$, $0 \leq K_i^1 \leq 0.1$, $0 \leq K_d^1 \leq 0.1$, $0 \leq K_p^2 \leq 0.2$, $0 \leq K_i^2 \leq 0.1$, $0 \leq K_d^2 \leq 0.1$. These ranges are determined according to practical engineering constraints and actuator characteristics in greenhouse control systems. The chosen intervals follow the parameter settings commonly adopted in greenhouse PID optimization studies, ensuring that the optimization process explores a feasible and physically meaningful region [25].

Figure 1 presents the Pareto front of the simulation results obtained using MOEA/D. The two performance indices represent conflicting objectives: J_1 quantifies the total energy consumption of the actuators, while J_2 measures the mean absolute tracking error between the greenhouse temperature and the reference value. The Pareto front depicts the trade-off between energy efficiency and control accuracy. The individual with the minimum Euclidean distance to the ideal point z^* was selected as the optimal solution for PID parameter tuning. which include $K_p^1 = 0.254$, $K_i^1 = 0.024$, $K_d^1 = 0.002$, $K_p^2 = 0.152$, $K_i^2 = 0.01$, $K_d^2 = 0.03$. As shown in Figure 2, the indoor temperature decreases from 32 °C to the setpoint of 25 °C with well-damped oscillations. The response settles within ±0.2 °C under varying outdoor temperature and solar radiation disturbances. These results indicate a fast and stable response with high tracking accuracy, demonstrating the effectiveness of the proposed event-based PID control strategy using MOEA/D.

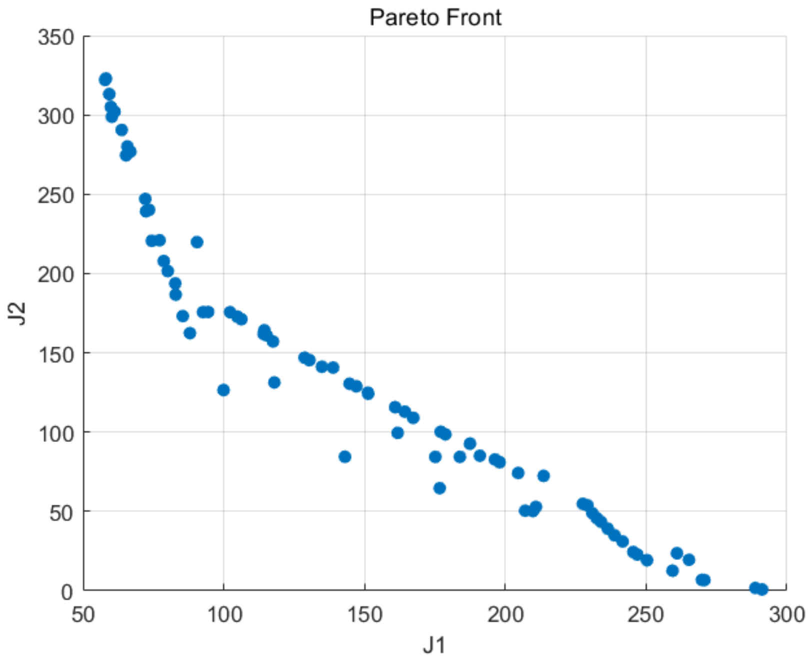

Figure 1. Pareto Front of performance index J1 and J2 under ETM.

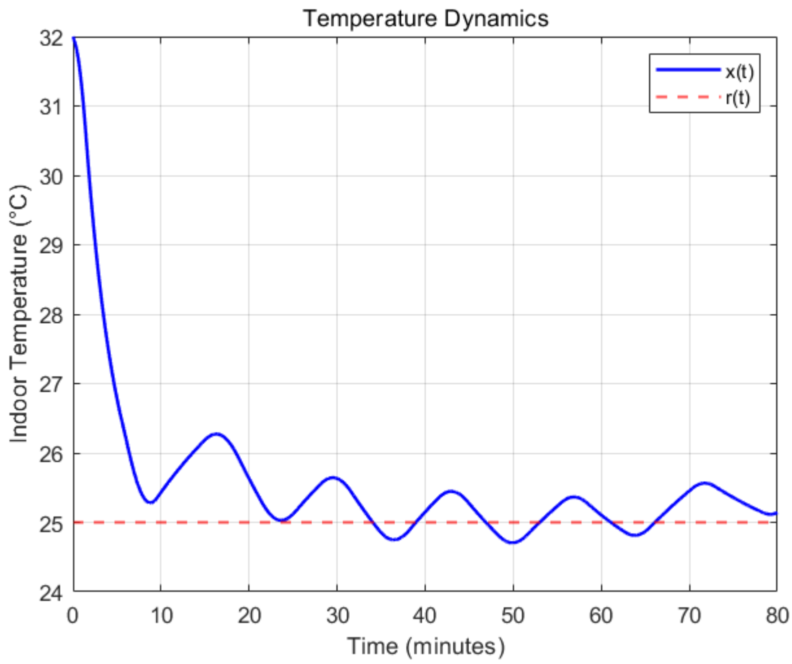

Figure 2. Greenhouse simulation diagram under optimal PID parameters.

6. Conclusions

This paper proposes a PID control method for the greenhouse environmental system based on MOEA/D under an event-triggered mechanism. The method introduces an ETM to regulate the transmission of control signals instead of using purely periodic updates. By updating signals only when necessary, the framework reduces redundant computations and control operations. It improves computational efficiency and optimizes the use of communication and actuator resources. At the same time, it maintains satisfactory control precision and achieves a balanced trade-off between energy efficiency and temperature tracking performance under nonlinear, time-varying, and disturbance-rich conditions.

Although the proposed approach shows promising potential, it still has several limitations. The model established in Section 2 focuses solely on temperature regulation and does not consider the coupled effects of humidity or CO_2 concentration, which may cause the simulated temperature dynamics to differ from those observed in actual greenhouse environments where heat and moisture transfer are strongly coupled. In the design of the event-triggered mechanism, the parameters are determined empirically, so their applicability to different greenhouse scales or climatic conditions may be limited, potentially affecting triggering efficiency. In addition, the experimental results are derived from simulation studies and have not been validated in real greenhouse environments, which may lead to a slight overestimation of control precision due to the absence of model uncertainty and sensor noise. These limitations provide valuable directions for future research. Future work will extend the proposed framework to multi-variable greenhouse systems that jointly control temperature, humidity, and CO_2 concentration. It will also refine the triggering condition design through data-driven or adaptive optimization methods and verify the effectiveness and robustness of the proposed strategy in practical greenhouse applications.

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