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Development of Energy Saving and Rapid Temperature Control Technology for Intelligent Greenhouses

XIAO FEI[1,2], WU XIAO-LONG[1], AND XIA YONG[1]
[1]School of Information Engineering, Nanchang University, Nanchang 330031, China
[2]Department of Mechanical and Electrical Engineering, Yiyang Vocational and Technical College, Yiyang 413000, China
Corresponding author: Wu Xiao-Long (wxl6895209@gmail.com)

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ABSTRACT Modern greenhouses need a certain equipment to achieve the expected environmental temperature in a short time while saving energy. To achieve greenhouse temperature management and energy savings through intelligent control, a greenhouse mechanism model is first built to study the controller design for a greenhouse located in Yiyang city in this paper. Then, the model accuracy is verified by experimental data. Based on the verified model, two intelligent control technologies are proposed, namely, active disturbance rejection control and fuzzy active disturbance rejection control. Methods are adopted to adjust skylight opening and thermal air conditioning for greenhouse temperature control and energy savings. In 60 hours of continuous working time, fuzzy active disturbance rejection control takes 10 hours less than active disturbance rejection control to make the greenhouse temperature reach the ideal steady state, and the temperature overshoot is reduced by 60%. Through analysis, the proposed fuzzy active disturbance rejection control method for greenhouse temperature management can achieve 15% energy savings. The proposed intelligent control technology can also be applied to temperature management for real greenhouses.

INDEX TERMS Greenhouse environment, temperature control, fuzzy active disturbance rejection controller, energy savings, agriculture.

I. INTRODUCTION

Modern intelligent greenhouses must not only enhance the growth of a single crop but also meet the growth needs of many crops. Therefore, the flexibility of temperature control in intelligent greenhouses is very important [1], [2]. In addition, modern greenhouse management must focus on energy savings and temperature [3], while traditional greenhouse management only focuses on temperature control. Therefore, it is important to develop multitemperature stable working conditions and energy-saving greenhouses. At present, a feasible method is to use existing equipment with a greenhouse environment model and to develop a control system to achieve temperature control and energy savings.

Many scholars have done much work in the development of greenhouse models. For example, Aji *et al.* [4] proposed an intelligent method to address the difficulty in modeling and analyzing the physiological and ecological processes of plants. A nonlinear autoregressive neural network with exogenous input was used to establish a dynamic model of the plant growth response to root zone temperature. Based on the noncontinuous response of pepper root growth to temperature, a weighing system was used to measure plant growth. The result was satisfactory. Escamilla-García *et al.* [5] reviewed the applications of artificial neural networks in greenhouse technology and presented how this type of model could be developed by adapting to new technologies such as the Internet of Things (IoT) and machine learning. Riahi *et al.* [6] built a photovoltaic generator model with the aim of reducing the costs of agricultural production and obtained good results. Wang and Wang [7] successfully built a greenhouse model by using a system identification toolbox to identify the assumed parameters in the model process with 90 datasets to obtain the transfer function of the greenhouse model. Rasheed *et al.* [8] used a transient system simulation program

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to build a multispan greenhouse building-energy-simulation model. Then, a detailed model was built for the greenhouse thermal environment under different design parameters. The results showed that the proposed model was worth popularizing. Márquez-Vera *et al.* [9] used a greenhouse climate to measure data, built a greenhouse internal temperature fuzzy model, and obtained a fuzzy model. The model performance was not good. Zarei and Behyad [10] used an artificial neural network to predict greenhouse gases from solar water to examine the parameters of the greenhouse effect on fresh water; then, the parameter effect on freshwater production was evaluated by using an optimized neural network model. Shamshiri *et al.* [11] proposed two greenhouse microclimate parameter models to evaluate a crop production system. The model was implemented in MATLAB/Simulink with a flexible architecture and self-adjusting reference input to adapt for different crops and cultivation practices, in which modeling and analysis could be carried out for different growth stages. Guo *et al.* [12] built a three-dimensional symmetry model for the cooling problem of greenhouses in summer and included a k–ε turbulence model and discrete coordinate irrationality model. Guo also used a semi-implicit pressure connection equation algorithm to study roof sprinklers in the thermal environment of a greenhouse; the accuracy of the model was verified by numerical calculations. These models were helpful in optimizing greenhouse environments. Zhang *et al.* [13] built a mathematical model to quantitatively evaluate the greenhouse light environment; this model considered the shape parameters of the greenhouse, the optical properties of the material, and the evolution of indoor solar radiation, including beam radiation, diffuse reflection, and multiple reflection; it was verified under different weather conditions, and the average error of sunny and cloudy weather was 1.67% and 10.30%, respectively. In the above literature, although the greenhouse model has achieved high accuracy, there are two shortcomings for the comprehensive study of greenhouse temperature and energy saving control. First, the model is not combined with an actual greenhouse, and thus the model has not been verified. Second, a high-dimensional model is not suitable for temperature control. The higher the dimension of the model is, the more unfavorable the control work. Therefore, it is necessary to develop a model suitable for greenhouse energy savings and temperature control.

In addition, to make the greenhouse environment reach an ideal level, it is of important to carry out parametric control. In terms of controlling the greenhouse environment, various scholars have carried out relevant research. Shamshiri *et al.* [14], Galvan *et al.* [15] and Ramírez-Arias *et al.* [16] summarized the critical and failure air temperature, root zone temperature, relative humidity and vapor pressure deficit of tomato greenhouses in detail and the hierarchical control structure of advanced multiobjective optimization control. There are many similar articles that provide guidance for the environmental control of greenhouses. Qin *et al.* [17] proposed a hybrid system approach to control a greenhouse climate. According to the indoor temperature and operational constraints, considering the interaction dynamics between the ventilation window and the output (temperature) of the control system, combined with the predictive control algorithm, good results were obtained, but the energy saving problem was ignored. Wang and Zhang [18] proposed an adaptive fuzzy control method for managing greenhouse temperature to meet the growth needs of tomatoes. Chen and You [19] proposed a new data-driven robust model predictive control framework for the automatic control of greenhouse temperature and CO_2 concentration. The basic concept was to combine the dynamic model of greenhouse temperature and CO_2 concentration with the data-driven model to identify the uncertainty of weather forecast error.

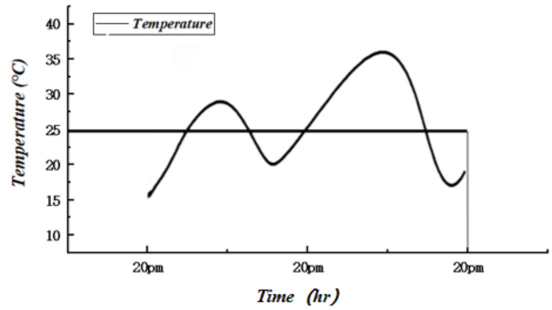
Some scholars have realized the management of greenhouse environments by adding more auxiliary equipment, which undoubtedly increases the greenhouse cost. Yang *et al.* [20] applied an earth-to-air heat-exchanger system in a greenhouse temperature control system. Compared with a greenhouse without an earth-to-air heat exchanger, the cost of the equipment was 35.3% higher when considering energy savings. Under an extreme environment, Villarreal-Guerrero and Pinedo-Alvarez [21] added varying frequency driving into a greenhouse to control transpiration, which achieved good results. Rahul *et al.* [22] combined a traditional receding horizon control algorithm with multiple operating ranges to adjust greenhouse temperature. Jin *et al.* [23] proposed a recreation-gene algorithm based on an engineering constraint rule, which not only effectively solved the nonlinear greenhouse programming problem but also greatly improved the effectiveness and feasibility of solving the optimal greenhouse environment dynamic control problem. Lin *et al.* [24] adopted the relative average deviation and most relative deviation to compare MPC and open-loop control tracking performance under three different system disturbance levels (2%, 5%, 10%). Simulation results showed that the proposed strategy could effectively reduce the operating cost of the greenhouse while maintaining temperature, humidity, and concentration within the required range. Riahi *et al.* [25] connected a photovoltaic generator to a DC/AC inverter in a greenhouse. At the same time, Riahi connected a wind turbine to a permanent magnet synchronous generator and used maximal power-point tracking control based on fuzzy logic to power the greenhouse. In the MATLAB/Simulink environment, Riahi simulated and verified the system performance. The results showed that this system could effectively control the greenhouse environment at different times of the year. Sumalan *et al.* [26] proposed remote monitoring based on an embedded platform for greenhouse control software installation, deployment, integration, maintenance, and crop-control strategy formulation and built a distributed sensing and control network with integrated wired and wireless nodes. Through the realization of sensing control nodes, Sumalan verified the application of configuration visualization software and, through deployment in a typical greenhouse, the operation effect of the platform. Subahi and Bouazza [27] provided an energy efficiency scalable system design, which uses a dynamic graphical data model to process a large amount of IoT big data captured from sensors for future analysis and prediction of yield, crop growth rate, energy consumption and other related issues. The above literature, which focused on greenhouse control, was mostly realized by adding auxiliary equipment but did not focus on greenhouse control without auxiliary equipment. The purpose of energy savings was not reflected in the above literature.

Although the abovementioned literature has done much work on greenhouse control, related research literature on temperature control and energy savings has not been published based on a small amount of equipment. In addition, there are many limitations in the use of adaptive control, sliding mode control, and predictive control in industrial applications. Considering the transient overshoot and power consumption in the greenhouse temperature control process, active disturbance rejection control (*ADRC*) is adapted in this paper. *ADRC* has been widely applied and is the evolution of PID through data-driven modification. In an *ADRC* controller, all the differences between the assumed linear model and the actual device are concentrated into the total disturbance under the "unified concept", including nonlinearity, external load disturbance and internal modeling uncertainty. The design concept can be expressed as a controller-rejector pair. The suppressor estimates the interference in real time and performs anti-interference through the analysis of the controller output and process output data. Due to the cancellation effect of the suppressor, the controller designed for the nominal model can be fixed and simple but highly efficient.

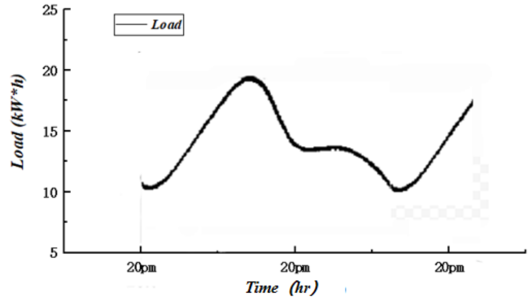
However, the change in greenhouse temperature is often different due to the different greenhouse work conditions. To more efficiently realize greenhouse temperature control, this paper introduces fuzzy control with *ADRC* according to the different work conditions so that the controller can adopt different *ADRC* strategies under different work conditions to realize highly efficient greenhouse temperature control and achieve energy savings. The innovations of this paper are as follows:

1. Fuzzy-ADRC (FADRC) is first used for greenhouse temperature control.
2. With less auxiliary equipment, efficient control and energy savings of greenhouse temperature are successfully realized.
3. The proposed method successfully shortens the time required for greenhouse temperature tuning.

The main goal of this paper is to develop a rapid constant temperature and energy-saving control system for greenhouses while reducing the cost of running a greenhouse. Based on the verified greenhouse model, the development of a greenhouse control system is more conducive to the rapid control of greenhouse temperature and energy savings.



(a) Temperature result.



(b) Electricity-load consumption.

FIGURE 1. Greenhouse control result under current controller.

II. PROBLEM DESCRIPTION OF GREENHOUSE TEMPERATURE CONTROL

A. GREENHOUSE TEMPERATURE CONTROL PROBLEM

It is very difficult to simulate temperature changes inside a greenhouse. The greenhouse environment is a complex system with many factors. In addition, different crops have different environmental characteristics, with different times and locations for respiration and light cooperation, which influence the temperature factor. In fact, the greenhouse environment can be controlled in a reasonable range by accurate modeling and complete energy savings.

At present, the environment also varies with different crops or with the same crop at different times of the day. Therefore, greenhouse temperature is difficult to accurately control but can be kept within a reasonable characteristic climate value to meet the requirements.

Our researched greenhouse adopts bang-bang control, which can only meet the greenhouse temperature in a set range, to ensure the normal operation of greenhouse temperature control equipment, but the performance of greenhouse temperature control at a constant value is poor. Under the current control strategy, greenhouse measurement points of temperature and power-load conditions, as shown in Figure 1, were obtained in a 48-hour operation cycle. Figure 1 shows that the greenhouse temperature control result was unstable, and the electricity load fluctuated greatly. The reason is that the setting parameters of bang-bang control are unreasonable, and the greenhouse external environment is complex and changeable, which leads to the temperature control equipment not being adjusted at the time it should be adjusted. Therefore, a new control method is necessary.

TABLE 1. Agricultural electricity price of Yiyang.

Electricity Classification	Electricity Price (yuan/kW·h)		
	Below 1 kV	1–10 kV	35–110 kV
0–170 kW·h monthly	0.4225	0.4125	0.3825

B. EQUIPMENT FOR GREENHOUSE TEMPERATURE CONTROL

There are two common ways to control greenhouse temperature: skylight opening (Figure 2a) and thermal air conditioning (Figure 2b). Opening skylights is the cheapest way to decrease greenhouse temperature, but skylights can only be opened when greenhouses are at high temperatures. If the temperature drops too fast when the skylights are open, the skylights need to be immediately shut to prevent damage to the greenhouse crops because the temperature is too low.

Thermal air conditioning is the main way to quickly raise the temperature. The thermal air flow rate and temperature should be strictly controlled to prevent the environmental temperature from becoming too high.

The studied greenhouse is shown in Figure 2c, which consisted of four thermal air conditioners and four skylights.

To save energy and reduce electricity costs, it is also necessary to control the local tiered electricity price. This paper took the electricity price of the city of Yiyang, China, as an example and considered an air heater (0.75 kW) and the motor power of a skylight (0.75 kW). The temperature of Yiyang on a certain day is shown in Figure 3.

At the same time, this paper takes tomato growth requirement temperature as a case; the most suitable temperature for its growth and development is 20 ∼ 30 °C in the daytime and 15 ∼ 20 °C at night. To facilitate control, the temperature was controlled at a constant temperature of 25 °C (day) and 15 °C (night).

(a) Greenhouse skylight.

(b) Greenhouse air heater.

(c) Composition of greenhouse.

FIGURE 2. Greenhouse temperature-controlling equipment.

III. GREENHOUSE ENVIRONMENTAL MODELING AND ADRC ALGORITHM

A. GREENHOUSE ENVIRONMENTAL MODELING

Trends in greenhouse temperature are a combination of physical processes, including energy transfer and mass balance. The air within the greenhouse temperature model, which links output variables to external climate and control variables, is considered uniform for modeling purposes. The temperature model based on energy conservation is described as follows [28]:

$$\frac{dT_{in}(t)}{dt} = \frac{1}{C_g}(u_q(t) + c_{rad}S_r(t) - (c_{cap}u_v + c_{ai})(T_{in}(t) - T_{out}(t)) \quad (1)$$

where T_{in}(°C) and T_{out}(°C) are the inside and outside temperature, respectively; C_{g} is the greenhouse thermal capacity, $C_{\text{g}} = 30,000$ J/(m^{2}K); u_q(W/m^2) is thermal capacity provided by the heater; C_{rad} is the thermal load factor caused by solar radiation, $C_{\text{rad}} = 0.2$; S_{r}(W/m^2) is the outdoor solar radiation; C_{cap} is the thermal capacity volume of the greenhouse, $C_{\text{cap}} = 1290$ J/(m^{3}K); u_v(m/s) is the rate of skylight opening through the vent; and c_{ai} is the overall heat-transfer parameter through mulch, $c_{ai} = 6.1$ W/(m^{2}K).

In addition, $u_{q,\%} = u_q/u_{q,\max}$ and $u_{v,\%} = u_v/u_{v,\max}$ for control are used; $u_{q,\max}$ indicates the maximal thermal capacity, and $u_{v,\max}$ indicates the maximal skylight opening. Therefore, model (1) can be written as follows:

$$\frac{dT_{in}(t)}{dt} = \frac{1}{C_g}(u_{q,\max}u_{q,\%}(t) + c_{rad}S_r(t) - (c_{cap}u_{v,\max}u_v + c_{ai})(T_{in}(t) - T_{out}(t))) \quad (2)$$

Equation (2) shows that the greenhouse temperature system is nonlinear but has a linear relation with the control input, with state variable $x = T_{in}$, control variable $u = [u1, u2] = [u_{q,\%}, u_{v,\%}]$, $v = [v1, v2] = [S_r, T_{out}]$, and

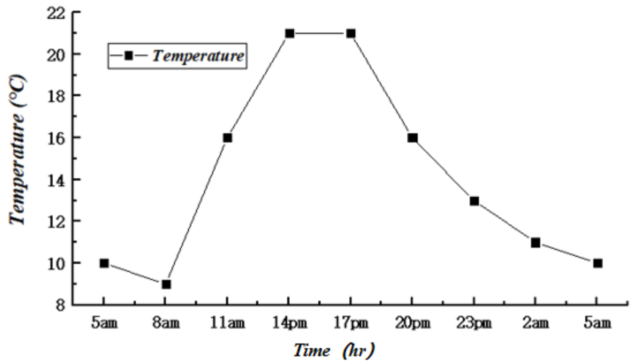


FIGURE 3. Temperature change over 24 hours in November in Yiyang.

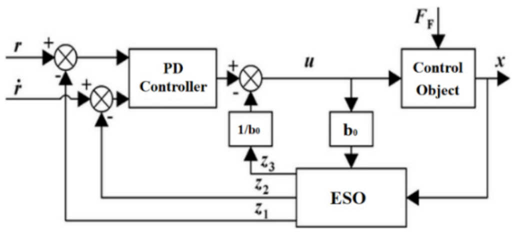


FIGURE 4. Controller structure of ADRC.

T being an external disturbance variable. A general form of the greenhouse temperature system with a SISO nonlinear system is obtained, as Equation (3) shows:

$$\begin{cases} \dot{x} = -\frac{c_{ai}}{C_g}x + \frac{c_{rad}}{C_g}v_1 + \frac{c_{ai}}{C_g}v_2 \\ +\left(\frac{u_{q,max}}{C_g} - \frac{c_{cap}u_{v,max}}{C_g}(x - v_2)\right)u \\ y = x \end{cases} \tag{3}$$

where y is the greenhouse system temperature output, and $-\frac{c_{ai}}{C_g}x + \frac{c_{rad}}{C_g}v_1 + \frac{c_{ai}}{C_g}v_2$ is a state function to express the relationship of the gain vector and system state variables $\dot{x}$. $\frac{u_{q,max}}{C_g} - \frac{c_{cap}u_{v,max}}{C_g}(x - v_2)$ is the gain vector.

B. ADRC ALGORITHM

ADRC is a kind of algorithm that does not have to rely on an accurate mathematical model, curbs the global error of a more advanced control method through local error, and has good robustness and anti-noise performance [29], [30]. A traditional *ADRC* controller commonly comprises a differential tracker (TD), extended state observer (ESO), a nonlinear combination (N-PD), and other components. The TD tracks the system to the input signal and gives the exact differential signal; the ESO estimates the state and disturbance of the system; and the N-PD obtains the control quantity and compensates for the disturbance.

The *ADRC* controller structure is shown in Figure 4; it does not use TD for the delay of trajectory time.

The purpose of the tracking differentiator is to address the contradiction between the rapidity and accuracy of the controlled object. Its function principle is to track the reference input signal and arrange the transitional process. The tracking differentiator is constructed by $fh(\cdot)$, the fast optimal synthesis function of the second-order discrete system:

$$\begin{cases} fh(k) = fhan(v_1(k) - v_0(k), v_2(k), r, h) \\ v_1(k+1) = v_1(k) + T \cdot v_1(k) \\ v_2(k+1) = v_2(k) + T \cdot fh(k) \end{cases} \tag{4}$$

where T is the sampling period; v_0 is the expectation input, which is $\Delta x \cdot f$, $\Delta y \cdot f$, or $\Delta z \cdot f$; r is the speed coefficient; h is the filter coefficient; and $fhan(\cdot)$ produces $v_1(k)$ fast and smooth tracking of desired signals $v_0(k)$.

As the core part of the *ADRC*, the extended state observer can estimate the sum of the perturbations in real time and compensate for it to achieve the effect of integrating the errors. Disturbance here includes the disturbance of external factors and uncertainty inside the model. The estimation principle of the extended state observer is only related to output y and input u of the system, and nonlinear function fe is constructed to obtain that the extended state observer is:

$$\begin{cases} e = z_1(k) - x_1(k) \\ fe_1 = fal(e, \alpha_1, \delta) \\ fe_2 = fal(e, \alpha_2, \delta) \\ z_1(k+1) = z_1(k) + T \cdot (z_2(k) - \beta_1 e) \\ z_2(k+1) = z_2(k) + T \cdot (z_3(k) - \beta_2 fe_1 + b_0 u(k)) \\ z_3(k+1) = z_3(k) - T \cdot \beta_3 fe_2 \end{cases} \tag{5}$$

where x_1 is the relative error between two machines on a single channel; function $fal(\cdot)$ is the extended state observer; parameters α_1 and α_2 are 0.5 and 0.25, respectively; δ determines the smoothness of the output signal; and $\beta_1\beta_3$ indicates the feedback gain of the state error, which affects the convergence rate of the ESO.

The observation precision of the ESO directly affects the design of the controller, so it is necessary to reasonably adjust the parameters of the observer. After that, the particle swarm algorithm adopted in this paper mainly targets specific parameters in the ESO.

Nonlinear error feedback control finds an appropriate combination form in the nonlinear field to form an error feedback law. Its ability to suppress uncertain factors is much better than that of linear feedback, and it can reach specified error attenuation in a finite time. Its structure is as follows:

$$\begin{cases} e_1 = v_1(k) - z_1(k) \\ e_2 = v_2(k) - z_2(k) \\ u = u_0 - z_3/b_0 \end{cases} \tag{6}$$

where b_0 is the input coefficient of a single channel; u_0 is the error feedback control law; and $u_0 = fhan(e_1, e_2, r, h)$.

In conclusion, the tracking differentiator (TD), extended state observer (ESO), and nonlinear state error feedback (NLSEF) compose a complete *ADRC* nonlinear control system i, and its control structure is shown in Figure 5.

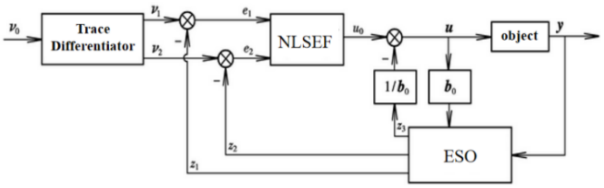


FIGURE 5. ADRC structure.

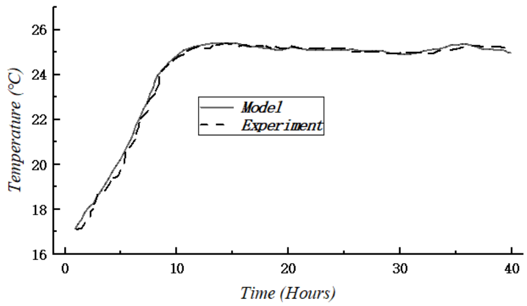


FIGURE 6. Model simulation results.

IV. RESULTS AND DISCUSSION

A. MODEL SIMULATION RESULT VALIDATION

According to the input mechanism model of greenhouse environmental parameters, the output of the mechanism model is consistent with the temperature detected by the temperature sensor installed in the greenhouse, as shown in Figure 6. The fitting degree between the model accuracy and the actual greenhouse temperature is 97%. Figure 6 shows that the greenhouse temperature enters a relatively stable working interval after running for approximately 10 hours, but it still fluctuates, which is not conducive to vegetation that needs a constant temperature environment to grow. Therefore, the greenhouse temperature needs to be further controlled, so controlling measures need to be applied to the model obtained above to make it reach the desired set value quickly and remain stable.

To achieve effective control, the environmental temperature outside the greenhouse, the environmental temperature inside the greenhouse, the opening of the skylight and the operating power of the air conditioner are regarded as the controller inputs. The temperature measured by the sensor shown in Figure 2 is used as the output to observe the control effect of the greenhouse system.

B. CONTROLLER-PARAMETER OPTIMIZATION BASED ON FUZZY ALGORITHM

The NLSEF rate uses a nonlinear combination of errors to obtain feedback control quantity, estimate the total disturbance by the extended state observer, and then add it to the controller to obtain the virtual controller, thus realizing the linearization of real-time dynamic compensation. $u_0 = k_1 \cdot fal(e_1, \alpha_1, \delta) + k_2 \cdot fal(e_2, \alpha_2, \delta)$ is called the common form of the NLSEF rate (k_1 and k_2 are quasi-proportional and quasi-differential gains). To improve the steady-state performance of the system, class integral items $k_3 \cdot fal(e_3, \alpha_3, \delta)$ and (k_3 is integral-like gain) are introduced. The improved nonlinear state error response rate is as follows:

$$\begin{cases} e_1 = v_1 - z_1, \\ e_2 = 0 = -z_2, \\ e_3 = \int_0^t e_1(\tau) d\pi \\ u_0 = k_1 \cdot fal(e_1, \alpha_1, \delta) \\ \qquad + k_2 \cdot fal(e_2, \alpha_2, \delta) \\ \qquad + k_3 \cdot fal(e_3, \alpha_3, \delta) \\ U = (u_0 - z_3)/b_0 \end{cases} \tag{7}$$

Among them, those normally set are $\delta = h, \alpha_1 = 0.5, \alpha_2 = 1$, and $\alpha_3 = 1.5$.

A problem exists in the initial improved controller: the working condition of the system easily changes under external disturbance, and parameter $\{k_1, k_2, k_3\}$ requires fine-tuning to achieve optimal performance. However, it is not realistic to manually change the *ADRC* controller temporarily. To enhance the adaptive ability of the system, the optimization parameters of the *ADRC* controller should be added. Therefore, fuzzy control is an effective way to improve the tuning of *ADRC* parameters. According to the rules, e_1, e_2 and e_3 are used as input, and online self-tuning is performed to $\{k_1, k_2, k_3\}$ so that it can automatically approach the best value in different states.

When the parameters of *ADRC* are adjusted, it is found that the parameters of TD and ESO will have a wide range of adaptability once they are adjusted, and the control parameters of the nonlinear state error feedback control law need to be adjusted manually. To improve the adaptability and control effect of the active disturbance rejection controller (*ADRC*) for greenhouse temperature control, this paper uses fuzzy logic reasoning to adjust β_1 and β_2 in real time. For β_1, fuzzy inputs e_1 and $\dot{e}_1$ are selected, and the corresponding fuzzy subsets are E_1 and Ec_1, respectively. For β_2, the fuzzy inputs e_2 and $\dot{e}_2$ are selected, and the corresponding fuzzy subsets are E_2 and Ec_2, respectively. Similarly, the case of β_3 can be obtained.

The corresponding fuzzy subsets of β_1, β_2 and β_3 are ΔK_1, ΔK_2 and ΔK_3, respectively. The fuzzy sets of $E_1, Ec_1, E_2, Ec_2, E_3, Ec_3, \beta_1, \beta_2$ and β_3 are {NL, NM, NS, Z, PS, PM, PL}. The domains of $E_1, Ec_1, E_2, Ec_2, E_3, Ec_3, \beta_1, \beta_2$ and β_3 are $\{-6, 5, 4, 3, 2, 1, 0, 1, 2, 3, 4, 5, 6\}$. According to the internal and external environment temperature of the greenhouse (external environment temperature, internal environment temperature and ideal value set by humans) and the parameter setting method of the active disturbance rejection controller, the fuzzy rule table for reasoning ΔK_1, ΔK_2 and ΔK_3 is formulated to realize online parameter setting.

To match the fuzzy sets [31], [32], [33], these variables are classified as e_1, e_2, e_3 and controlling volume U, and the numbers are all 7, which means negative large (NL), negative middle (NM), negative small (NS), zero (Z), positive

TABLE 2. Fuzzy-controlling rules of ΔK_1.

ΔK_1		Ec_1						
		NL	NM	NS	Z	PS	PM	PL
E_1	NL	PL	PM	PS	PS	PS	Z	Z
	NM	PM	PS	PS	PS	PS	Z	Z
	NS	PS	PS	PS	PS	Z	NS	NS
	Z	PS	PS	PS	Z	NS	NS	NS
	PS	PS	PS	Z	NS	NS	NS	NS
	PM	Z	Z	NS	NS	NS	NS	NM
	PL	Z	Z	NS	NS	NS	NM	NL

TABLE 3. Fuzzy-controlling rules of ΔK_2.

ΔK_2		Ec_2						
		NL	NM	NS	Z	PS	PM	PL
E_2	NL	NL	NM	NS	NS	NS	Z	Z
	NM	NL	NM	NS	NS	NS	Z	Z
	NS	NL	NM	NS	NS	Z	PS	PS
	Z	NS	NS	NS	Z	PS	PS	PS
	PS	NS	NS	Z	PS	PS	PM	PL
	PM	Z	Z	PS	PS	PS	PM	PL
	PL	Z	Z	PS	PS	PS	PM	PL

TABLE 4. Fuzzy-controlling rules of ΔK_3.

ΔK_3		Ec_3						
		NL	NM	NS	Z	PS	PM	PL
E_3	NL	PS	NS	NL	NL	NL	NS	PS
	NM	PS	Z	NM	NM	NM	NS	Z
	NS	Z	NS	NS	NS	NS	NS	Z
	Z	Z	Z	NS	NS	NS	Z	Z
	PS	Z	Z	Z	Z	Z	Z	Z
	PM	NS	NS	NS	NS	NS	Z	PS
	PL	NL	NL	NL	NL	NL	Z	PL

small (PS), positive medium (PM), and positive large (PL); in total, 49 fuzzy-controlling rules are formed. The fuzzy controlling rules of ΔK_1, ΔK_2 and ΔK_3 are shown in Tables 2–4, respectively.

The input of the fuzzy inference system is the greenhouse temperature tracking error $Ec = E - \beta$ and the absolute value of the controller parameters α, and the output is the temperature control part ΔK in U. Seven language subsets are defined for input Ec, the domain of input α and output ΔK. All fuzzy sets adopt triangle membership function. The fuzzy rules are based on the following concepts: when the error Ec is large, a larger control effect is needed to reduce E; when the temperature α is large, a smaller control value u should be allocated to the air conditioning equipment and skylight, and when the temperature E exceeds a certain range, $u = 0$.

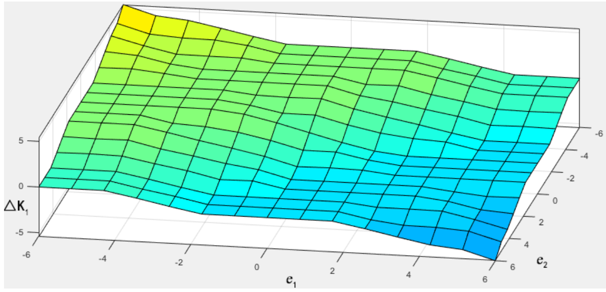


FIGURE 7. Fuzzy-controlling surface of ΔK_1.

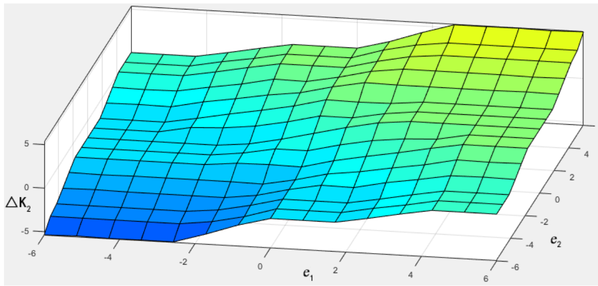


FIGURE 8. Fuzzy-controlling surface of ΔK_2.

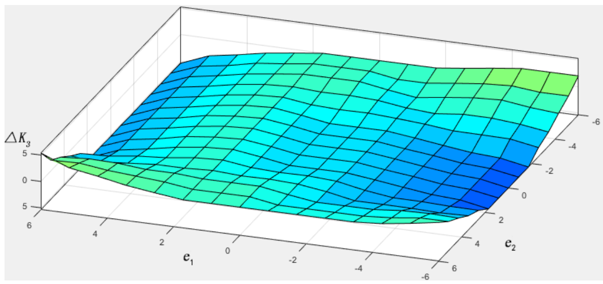


FIGURE 9. Fuzzy-controlling surface of ΔK_3.

According to the fuzzy-controlling rules mentioned above, the corresponding fuzzy-controlling surfaces are drawn as ΔK_1, ΔK_2, and ΔK_3, as shown in Figures 7–9, respectively.

After obtaining ΔK_1, ΔK_2, and ΔK_3 through fuzzy reasoning, the actual control variables can be obtained from Equations (3) $\sim$ (5).

Adding u_0 to the compensation amount of the system disturbance, the control variables u of the fuzzy-*ADRC* (*FADRC*) are obtained:

$$u = u_0 - \frac{z_3}{b} \tag{8}$$

Parameter b is the compensation factor that determines the disturbance compensation strength and is used as an adjustable parameter.

C. CONTROL SIMULATION RESULT

To correct the temperature difference of the above model, the fuzzy-controlling method mentioned above was used, and the *FADRC* and fuzzy algorithms and *ADRC* were combined; the results in Figures 10 and 11 verify the effect.

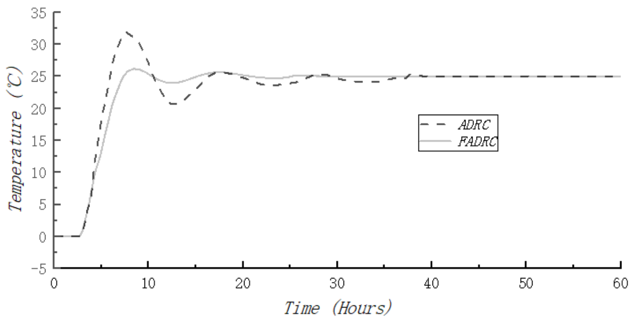


FIGURE 10. Applied control-effect comparison.

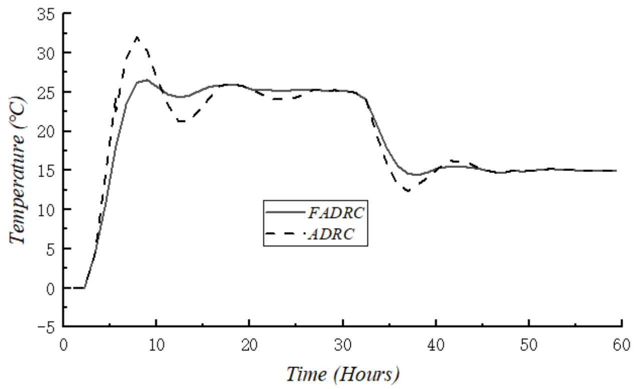


FIGURE 11. Step control-effect comparison.

Figure 10 shows that with the intervention of the control algorithm, we set the initial greenhouse environment to 0°C and introduced the control algorithm when running to the third second.

Compared with the fuzzy-controlling method, *FADRC* is slower, but its overshoot is small. Soon, the greenhouse environmental temperature can be stabilized at 25 °C. The whole process takes 30 hours, while that of the fuzzy-controlling method takes 40 hours. Thus, *FADRC* is fast and stable, which means that it is more suitable for the control of greenhouse temperature. In addition, the overshoot of temperature control is reduced by 60%. The *FADRC* parameters for Figure 10 are obtained as follows:

$$\begin{cases} w_c = 19, \\ w_o = 0.9, \\ K = [9405, 999, 57, 2], \\ L = [4.2, 17.6, 11.2, 1.7] \end{cases} \tag{9}$$

To further prove the accuracy of this controlling algorithm, when the greenhouse temperature enters a steady state, the ideal greenhouse temperature value is 15 °C, as shown in Figure 11. In Figure 11, from the perspective of the consumption market, *ADRC* control still has a large overshoot. Therefore, the *FADRC* is more suitable for controlling greenhouse temperature environments.

In addition, the energy-saving effect of greenhouses is measured by electricity fees. Through the analysis of the electricity fees used, it is found that the proposed *FADRC* control method can save 15% more electricity than *ADRC* in a 60-hour operating cycle (Figure 12).

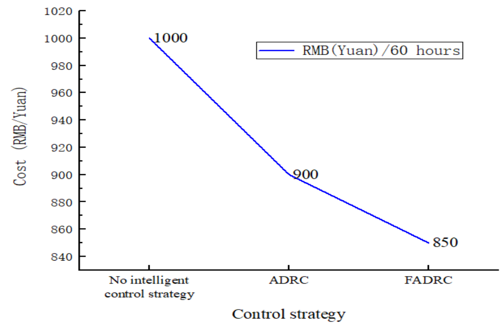


FIGURE 12. Comparing the energy saving effect with electricity fees as an index (RMB).

In Fig. 10 and Fig. 11, it can be concluded that the proposed *FADRC* algorithm can quickly enter the ideal steady state according to the human set ideal preference value. In addition, in Figure 11, the setting change of the artificial ideal preference value is used, and then the control result still shows fast convergence and stability. From this, the novel control strategy can be proven to guarantee the stability of the *FADRC* algorithm proposed in this paper.

Through the study in this paper, we can ensure that the control strategy can maintain the stability of the internal environment temperature of the greenhouse when the external environment temperature is shown in Figure 3. The control strategy will be applied to a real greenhouse environment.

With the continuous acquisition of weather information, the control strategy can be expanded to meet the requirements of energy savings and rapid temperature control in any external environment.

V. CONCLUSION

Based on the validation of the greenhouse model, its accuracy was 97%. This built model combined the developed fuzzy-controlling method with the *ADRC* algorithm to shorten the time needed for greenhouse temperature stability control, which had a better performance on greenhouse temperature overshoot than that of *ADRC*. The proposed method could shorten the time for the greenhouse to reach ideal working conditions by 10 hours. In addition, the overshoot of temperature control was reduced by 60%. The method in this paper can not only effectively control greenhouse temperature but also reduce electricity costs and save energy. The proposed control method is proven to lower energy use by 15% in a 60-hour operation period of the greenhouse.

In the future, the method of this paper can also be applied to real greenhouse systems.

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XIAO FEI was born in Xiantao, Hubei, China, in 1987. He received the M.S. degree in mechanical engineering from the Kunming University of Science and Technology. He is currently a Lecturer with the Yiyang Vocational and Technical College and Nanchang University. His current research interests include greenhouse environments and mechanical automation.

WU XIAO-LONG was born in Danjiangkou, Hubei, China, in 1988. He received the Ph.D. degree in control engineering from the Huazhong University of Science and Technology. He is currently a Lecturer with Nanchang University. His current research interest includes mechanical automation.

XIA YONG was born in Jiujiang, Jiangxi, China, in 1991. He received the Ph.D. degree in industrial engineering from the Huazhong University of Science and Technology. He is currently an Associate Professor with Nanchang University. His current research interest includes mechanical automation.