# Optimization of parameters of Fuzzy PID controller using grey wolf algorithm

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## ABSTRACT

To enhance the precision of greenhouse air temperature regulation, this paper introduces an optimization approach for fuzzy Proportional-Integral-Derivative Controller (PID) control parameters utilizing the Grey Wolf Algorithm (GWO). Initially, a dynamic mathematical model for temperature control is formulated. Subsequently, GWA is employed to fine-tune the three key parameters of the fuzzy PID controller: proportional gain ($K_p$), gral gain ($K_i$) and derivative gain ($K_d$) thereby identifying the optimal controller settings. Further, the MATLAB/Simulink platform is leveraged to conduct comparative simulation studies against traditional PID control, fuzzy PID control, fractional-order PID control methodologies. The paper culminates with an evaluation of the improved GWA against other optimization techniques such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Bat Algorithm (BA) for the parameter tuning of the fuzzy PID controller. The findings indicate that the fuzzy PID control system, refined through the enhanced GWO, exhibits swift response characteristics, minimal overshoot, commendable robustness, and robust stability.

**Keywords:** Temperature control, fuzzy PID control, gray wolf algorithm, optimization algorithms

## 1. INTRODUCTION

The greenhouse temperature control system is an integrated assembly comprising sensors, actuators, and a control unit. These three integral components work in concert to regulate temperature, with the overarching goal of sustaining an optimal growth environment conducive to the robust development of flora[1]. The efficacy of the temperature control is contingent upon the precision of the sensors, the swiftness of the actuators' response, and the accuracy of the control algorithms. In scenarios characterized by abrupt temperature fluctuations, achieving precise control can be challenging. The internal ambiance of a greenhouse is significantly influenced by a multitude of external factors, including meteorological conditions and the physiological state of the plants. These factors impart a nonlinear and time-variant nature to the greenhouse environment, thereby amplifying the intricacy and the inherent intricacy of the control system's design.

At present, dealing with the matter of temperature governance, domestic and foreign researchers mainly use PID and fuzzy PID to adjust key parameters and achieve accurate control of the system[2-4]. However, the PID control approach has inherent limitations, particularly when dealing with complex control systems. Its intrinsic anti-interference capabilities are insufficient to withstand the impact of external disturbances, which can impede the attainment of the desired control outcomes. To address these limitations, alternative control strategies have been explored, including intelligent control methods. These encompass fuzzy control, which leverages the principles of fuzzy logic to handle uncertainties[5], neural network control, known for its adaptability and learning capabilities[6-8], and advanced techniques such as active disturbance rejection control and flexible control, which are designed to enhance system robustness and adaptability[9,10]. For control objects characterized by nonlinearity and time-variability, fuzzy control not only demonstrates superior performance but also exhibits substantial robustness against uncertainties and varying conditions. However, the efficacy of fuzzy control is significantly contingent upon the expertise and acumen of the designer, which introduces the potential pitfall of tending to settle on local best solutions instead of the overall best solution. The hybrid Fuzzy-PID control strategy amalgamates the swift response attributes of PID control with the adaptive flexibility inherent in fuzzy logic, thereby facilitating expedited convergence and bolstered robustness. This approach advantageously preserves the simplicity of the control structure, making it an appealing option for complex control scenarios. This methodology can often fall short of fulfilling the stringent performance criteria demanded by modern control systems. Zhang and Zhou et

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al.[12] optimized the PID control parameters for the servo system of an unmanned vehicle using a Backpropagation Neural Network (BPNN), thereby enhancing the control performance. Zhang[13] designed an infusion temperature control system by integrating a fuzzy control strategy with PID control technology. Wang and Zhou et al.[14] proposed a fuzzy temperature control method with a variable universe of discourse, effectively addressing the challenges posed by nonlinear and time-varying control systems. Qu and Qi[15] employed a genetic algorithm to optimize the parameters of the fuzzy PID controller, thereby enhancing the accuracy of motor speed regulation. Balakrishna and Arun[16] applied the Ziegler-Nichols reaction curve tuning method for the design of a linear PI controller. Subsequently, a genetic algorithm was applied to fine-tune the objective function, with the aim of optimizing the parameters for a fuzzy PI controller. Jegatheesh and Agees Kumar[17] implemented a fractional order PID controller for the precise control of liquid levels within an Integrated Chemically Sensitive Total System (ICSTS).

In response to the issue that existing algorithmic strategies for optimizing controller parameters necessitate extensive parameter tuning, this paper introduces the GWA[18-20] as an enhancement to the fuzzy PID control methodology. The PID controller parameters, namely proportional $K_p$, $K_i$, $K_d$ are optimized by parameter iteration. MATLAB/Simulink software is used to establish the model, and Grey Wolf algorithm, PSO[21], GA[22] and Bat Algorithm[23] are employed to optimize the parameters of the fuzzy PID controller. These methods are compared to verify the performance of the optimized control system. The comparison yields an enhanced Grey Wolf fuzzy PID controller, which demonstrates superior performance.

## 2. MATHEMATICAL MODELING OF THE SYSTEM

### 2.1 Data Sources

The experimental data are from Yanchi County, Wuzhong City, Ningxia Province (107°41’ E, 37°79’ N), and the greenhouse type is arched three sides (left side, right side, back side) earth wall and one side (front side) greenhouse film. The data set contains information on environmental parameters (such as temperature, humidity, $CO_2$ concentration, etc.) and soil properties (such as N, P, K content, etc.). The data is collected roughly 14 times an hour, and all the data is monitored in real time and automatically stored in the database.

### 2.2 Data Processing

Check the data for missing values. After data preprocessing found. There are 42,635 rows of data with 21 columns each. Among them. There are 26262 missing values in the “soil_NH_1(mg/kg)” and “soil_NH_2(mg/kg)” columns, 16373 missing values in the “soil_N_1” and “soil_N_2” columns, and 2 missing values in the “date” column. To address the missing-values problem, the following methods are used:

(1) Direct deletion method

Because “date” is a date, it can’t be filled in, so we delete both rows where the date value is missing, leaving 42,633 rows in the table.

(2) Choose the filling method

Since the number of missing values in columns “soil_NH_1(mg/kg)” and “soil_NH_2(mg/kg)” is more than one-half of the sample size of the data in the table, the number of missing values in columns “soil_N_1” and “soil_N_2” is more than one-third of the sample size of the data in the table, you cannot simply delete the data in the row with the four missing columns as a whole. Therefore, these four columns of missing values are filled in by the following method.

First, the correlation with missing values is found by Pearson correlation analysis. For columns with values<=-0.8 or >=0.8 and no missing values, calculate the mean of the columns with the same attribute and create soil_P_mean, respectively. Multivariate linear regression equations for soil_K_mean, soil_EC_mean with soil_NH_mean and soil_N_mean, pre-measured. The values of soil_NH_mean and soil_N_mean, and the model evaluation data are exhibited in Table 1. It is found that the multivariate linear regression equation cannot be used to predict the values of soil_NH_mean and soil_N_mean.

Table 1. Model evaluation results.

| Dependent variable | Independent variable | Intercep | Coefficient | MSE | MAE | $R^2$ |
|---|---|---|---|---|---|---|
| Soil_NH_mean | Soil_P_mean | -3.73 | -0.08 | 953.14 | 28.39 | 0.14 |
| | Soil_K_mean | | 0.14 | | | |
| | Soil_EC_mean | | 0.02 | | | |
| Soil_NH_mean | Soil_P_mean | 5.06 | 0.24 | 955.73 | 28.58 | 0.12 |
| | Soil_K_mean | | -0.09 | | | |
| | Soil_EC_mean | | 0.03 | | | |

Therefore, the median of soil_NH_mean and soil_N_mean is calculated, the number of bits and modes is shown in Table 2.

Table 2. Median mode.

| Method | Column name | Result |
|---|---|---|
| Median | Soil_NH_mean | 67.5 |
| | Soil_N_mean | 62.5 |
| Mode | Soil_NH_mean | 68.0 |
| | Soil_N_mean | 0.0 |

According to the results in Tables 1 and 2, the median values of soil_NH_mean and soil_N_mean were finally selected to fill the missing values in the columns "soil_NH_1(mg/kg)" and "soil_NH_2(mg/kg)", "soil_N_1" and "soil_N_2" of the sample data.

The complete dataset was supplemented with the help of MATLAB/Identification pairs. Through identification, the transmission of the temperature control system as in equation (1) is calculated Recursive function:

$$H(s) = \frac{1.7}{71s+1} \tag{1}$$

# 3. RELATED WORK

## 3.1 Fuzzy PID controller

Zadeh proposed fuzzy control theory in 1965 by simulating human Class decision process, dealing with the uncertainty and fuzziness of the system[22-24]. Fuzzy control is frequently employed in modern control systems due to its benefits in addressing uncertainty and challenges exhibiting non-linearity. Through a fuzzy rule base and a fuzzy inference system, the controller adjusts its variables to adjust for various operating environments and disturbance situations. The fuzzy controller achieves the target task by simulating the experience of experts and forming strict control rules in the form of language, and then controlling its calculation through the control rules. Figure 1 shows the schematic.

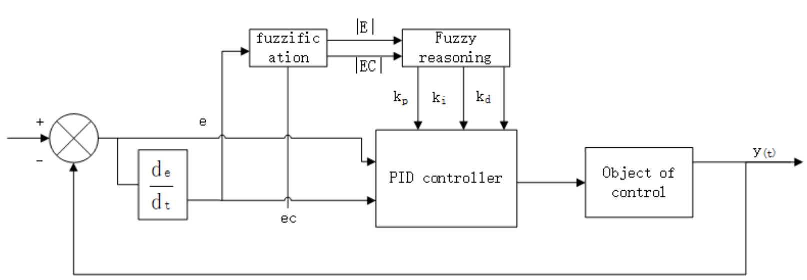


Figure 1. Principle diagram of fuzzy controller.

The usual structure of the transfer function of a fuzzy PID controller is detailed subsequently.

$$G(s)=K_p+\frac{K_i}{s}+K_d\frac{N}{1+N/s} \tag{2}$$

Among $K_i$ is integral gain, which serves the purpose of correct the constant error in the system's final state and adjust output according to the accumulated amount of error. When the system deviates from the target for a long time, the integral control will increase the output to decrease the persistent deviation in the system's equilibrium condition. $K_d$ is the differential gain, used to suppress system overshoot and oscillation, regulate the output in response to the error's rate of alteration in comparison to the difference, when the system quickly approaches the target value, the differential control can reduce the output to smooth the response of the system. N is the parameter of the differential filter to reduce the sensitivity of the differential operation to high-frequency errors, thereby reducing the response of the controller to noise. It usually takes a positive integer value. The larger the value is, the stronger the effect of the filtering is and the smaller the response to high-frequency noise is, but it may lead to the delay of the response. This form of transfer function takes into account the proportion, integral and differential three control modes, and introduces the concept of fuzzy control, The differential part is adjusted by the parameter $N$ of the differential filter Response features, allowing for more flexible control.

### 3.2 Grey Wolf optimization algorithm

GWO is developed by Mirjalili et al.[25], a scholar from Griffith University in Australia, proposed a swarm intelligence optimization algorithm[26] according to group hunting behavior of grey wolves in nature in 2014. The algorithm, taking cues from grey wolves' hunting practices, is a sophisticated optimization search mechanism boasting potent convergence, a sparse parameter set, and user-friendly application.

The level and hunting behavior are used to guide the moving strategy in the search process, so as to realize the rapid explore in quest of the superior answer. The update formula for the gray Wolf population of $\alpha,\beta,\delta$ is as follows.

$$D=\left|C\cdot X_p(t)-X(t)\right| \tag{3}$$

$$X(t+1)=X_p(t)-A\cdot D \tag{4}$$

$$A=2a\cdot r_1-a \tag{5}$$

$$C=2\cdot r_2 \tag{6}$$

Among them:D represents the position distance within the dynamic of the grey wolf and its prey; t represents the current number of iterations; A、C is the vector of synergy coefficients, $X_p$ is the position vector of the prey*;* *X(t)*is the position vector of the prey; a is the step size factor. It diminishes from 2 to 0 with an increasing number of iterations. $r_1$, $r_2$ take a random value in the range [0,1].

Grey wolves can identify potential prey locations, and search relies on grey wolves to guide. To simulate gray Wolf search, it is presupposed that there is a robust capacity to detect possible locations of prey. The iteration phase consistently preserves the foremost three grey wolves, with the positions of other search agents being updated in accordance with their locational details. In GWO, $\alpha,\beta,\delta$ are optimal solutions, other gray wolves are called $\omega$, moving closer to $\alpha,\beta,\delta$. The search process can be articulated through a mathematical model, outlined below

$$D_\alpha=\left|C_1\cdot X_\alpha-X\right| \tag{7}$$

$$D_\beta=\left|C_2\cdot X_\beta-X\right| \tag{8}$$

$$D_\delta=\left|C_3\cdot X_\delta-X\right| \tag{9}$$

Among them: $X_\alpha$ denotes the location vector of the leading grey wolf; $X_\beta$ Represents the coordinates of $\beta$. $X_\delta$

denotes the position vector of δ grey Wolf; $C_1$, $C_2$, $C_3$ is a random value; X represents the current solution position (the grey Wolf's position vector). Equations (7)-(9) were used to calculate the space between the ω Wolf and the $a, \beta, \delta$ gray Wolf positions, in sequence. ω the final position of the grey Wolf's final position is calculated as follows:

$$X_1 = X_\alpha - A_1 \cdot (D_\alpha) \tag{10}$$

$$X_2 = X_\beta - A_2 \cdot (D_\beta) \tag{11}$$

$$X_3 = X_\delta - A_3 \cdot (D_\delta) \tag{12}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{13}$$

# 4. OPTIMIZE THE PARAMETERS OF FUZZY PID CONTROLLER BASED ON GWO ALGORITHM

## 4.1 Fuzzification

According to the schematic of fuzzy PID controller in Figure 2. The outputs are the parameters $K_p$, $K_i$, $K_d$. Based on the accuracy of the variable's input and output, the control syntax will utilize "NB, NM, NS, ZO, PS, PM and PB "to denote 'severely negative, moderately negative, slightly negative, zero, slightly positive, average, and strongly positive', respectively. Furthermore, you must establish the alterations. The domain of the quantity, the domain of the error *e* is [-1, 1], the domain of the error rate of change *ec* is [-2, 2], $K_p$ is set to [-6, 6], $K_i$ is set to [-3, 3], $K_d$ is set this is [-3, 3]. In accordance with practical experience, the fuzzy rule table featured in Table 3 has been designed.

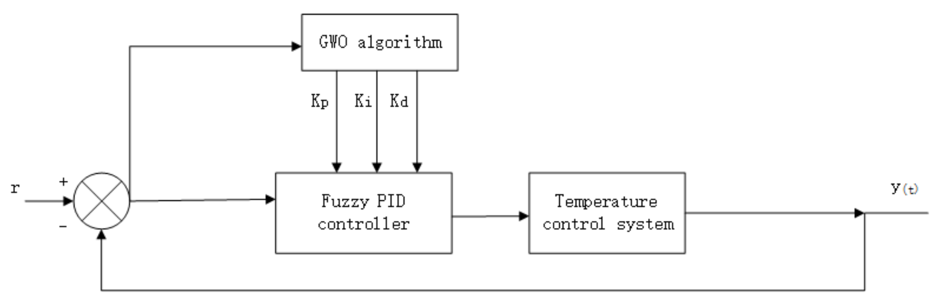


Figure 2. Optimization of fuzzy controller parameters based on GWO.

Table 3. Fuzzy rule table for $K_p$, $K_i$, $K_d$.

| ***e*** | ***ec*** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **NB** | **NM** | **NS** | **ZO** | **PS** | **PM** | **PB** |
| NB | PB/NB/PS | PB/NB/NS | PM/NM/NB | PM/NM/NB | PS/NS/NB | ZO/ZO/NM | ZO/ZO/PS |
| NM | PB/NB/PS | PB/NB/NS | PM/NM/NB | PS/NS/NM | PS/NS/NM | ZO/ZO/NS | NS/PS/ZO |
| NS | PM/NB/ZO | PM/NM/NS | PM/NS/NM | PS/NS/NS | ZO/ZO/NS | NS/PS/NS | NS/PS/ZO |
| ZO | PM/NB/ZO | PM/NM/NS | PS/NS/NS | ZO/ZO/NS | NS/PS/NS | NM/PM/NS | NM/PM/ZO |
| PS | PS/NB/ZO | PS/NS/ZO | ZO/ZO/ZO | NS/PS/ZO | NS/PS/ZO | NM/PM/ZO | NM/PB/ZO |
| PM | PS/ZO/PB | ZO/ZO/NS | NS/PS/NS | NM/PS/PS | NM/PM/PS | NM/PB/PS | NB/PB/PB |
| PB | ZO/Z0/PB | ZO/ZO/PM | NM/PS/PM | NM/PM/PM | NM/PM/PS | NB/PB/PS | NB/PB/PB |

### 4.2 Design based on GWO-Fuzzy PID controller

In addressing the parameter optimization and the problem of minimizing the cost function, a parameter optimization calibration method for the GWO-optimized fuzzy PID control system has been proposed. This method utilizes the GWO algorithm to determine the optimal parameter values. As shown in Figure 3, a GWO-Fuzzy PID controller has been designed.

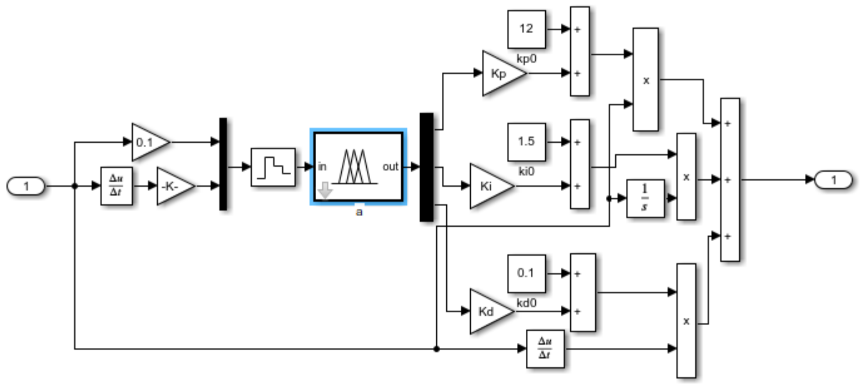


Figure 3. GWO-fuzzy PID controller.

### 4.3 Description of GWO-Fuzzy PID algorithm

The grey Wolf Fuzzy PID control algorithm (GWO-Fuzzy PID) was constructed and applied to the greenhouse temperature control to modify the fuzzy PID parameters automatically. The flow chart of GWO-Fuzzy PID algorithm is shown in Figure 4.

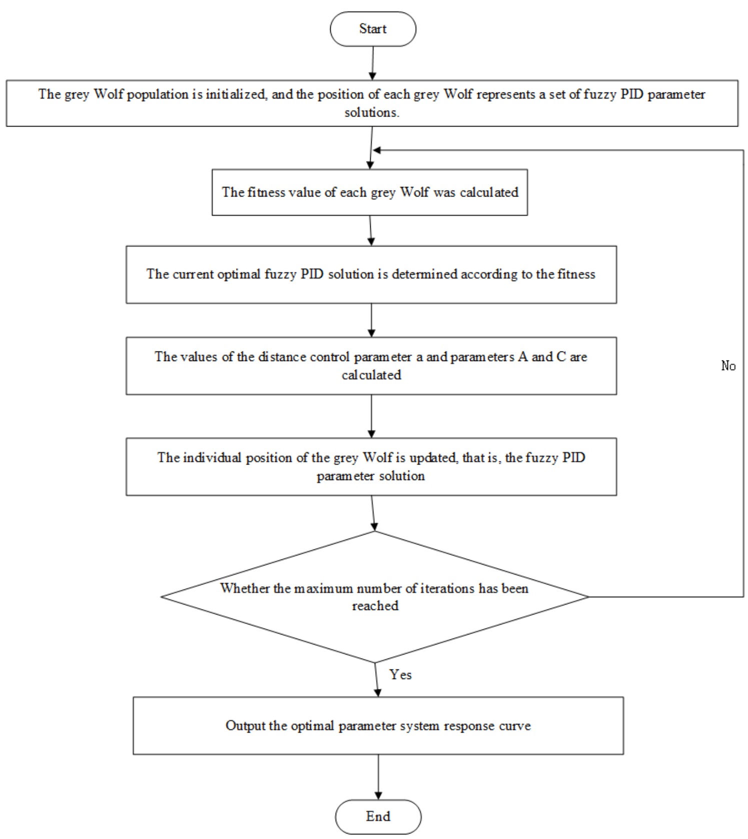


Fig 4. GWO-Fuzzy PID algorithm flowchar.

In the flow chart of GWO-Fuzzy PID algorithm, First define with parameter $K_p$, $K_i$, $K_d$ the fuzzy controller, The position and fitness of $\alpha$, $\beta$ and $\delta$ are updated according to the formula, and the optimal PID parameters are searched through the GWO algorithm to determine the current optimal solution of fuzzy PID, that is, to find the parameter combination that can minimize the value. Then, the distance control parameters a and the values of A, C were calculated. During the iteration process, the algorithm continuously updated the positions of $\alpha$, $\beta$ and $\delta$ Wolf, and adjusted the position of the search agent according to these positions. Finally, it checked whether the amount of iterations was reached or the corresponding termination condition was satisfied. If the termination condition was not reached, steps 2-5 were executed. Otherwise, go to step 6 and output the optimal parametric system response curve.

# 5. EXPERIMENTAL SIMULATION

## 5.1 Ablation experiment

Firstly, the simulation model for the greenhouse temperature control system has been developed, including PID, fuzzy PID and fractional PID and three control modes equation. Then, simulation experiments are carried out in the case of without disturbance and with disturbance, and the performance of various control modes in terms of stability and performance is evaluated. Figure 5 represents the greenhouse temperature control system in PID, fuzzy

Simulation curves in three modes of PID and fractional PID. The sampling period is 1000 seconds. The performance of each control strategy is effectiveness is judged by its capability to stabilize the greenhouse temperature for a specified time. Simulation results show that the performance characteristics of each control strategy are different. The conventional PID control system experiences fluctuations until about 380 seconds and then stabilizes at about 550 seconds.

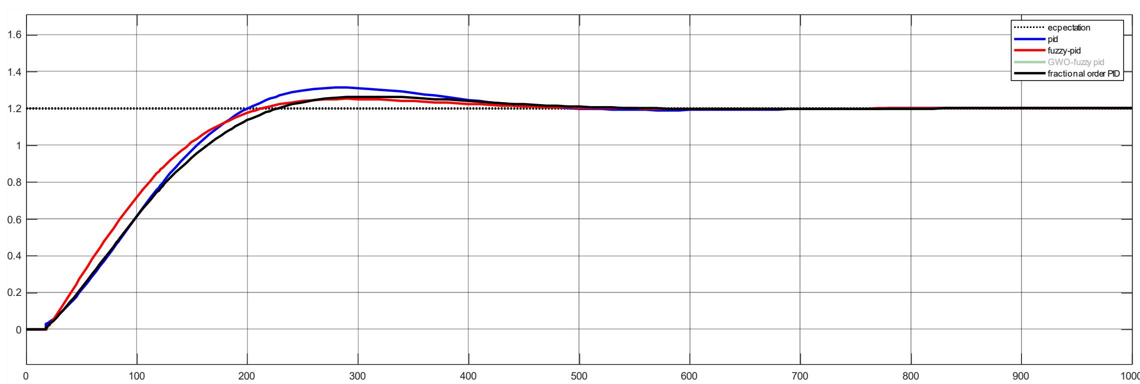


Figure 5. Comparison of simulation curves.

Temperature control in greenhouses is essential for plant growth. However, in practical applications, the greenhouse environment is often disturbed by external factors, such as climate change, sunshine intensity, etc., which could influence the functioning of the greenhouse temperature control system. This paper aims to examine the effects of interference on the performance of different control modes and to explore the advantages and experimental results after adding interference. Figure 6 shows the simulation curves of the greenhouse temperature control system in the three modes of PID, fuzzy PID and fractional PID after adding disturbance.

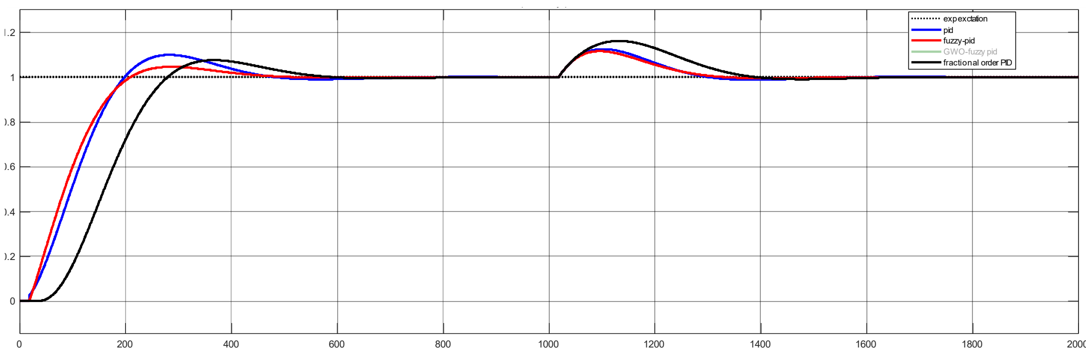


Figure 6. Interference simulation curve comparison.

### 5.2 Comparative experimental simulation analysis

To verify the advantages of various algorithms in optimizing the parameters of the fuzzy PID controller, the population size is set to 20, the maximum number of iterations is 20, and the problem dimension is 5. Other parameter settings are as shown in Table 4.

Table 4. Initial parameter settings of the algorithm.

| Algorithm | Parameter values |
|---|---|
| Bat algorithm | Decay factors $a$=0.9 the minimum weight is 0.3 and the maximum weight is 0.7 |
| Particle swarm optimization | Factor of inertia w=0.6, Constant of acceleration $c_1$=$c_2$=0.6 |
| Genetic algorithm | Cross distribution index *etac*=20, Variation distribution index *etam*=20, Probability of crossover $P_c$=0.8, Mutation probability $P_m$=0.2 |
| Grey wolf algorithm | a is the step size factor, it decreases from 2 to 0 as the number of iterations increases |

The transfer function was established by MATLAB/Identification, the corresponding system parameters were set, and the GWO algorithm was run to optimize the parameters. Figure 6 shows that the GWO algorithm performs parameter optimization when the number of iterations reaches 7. Parameters before optimization: all five parameters of the lower boundary are 0; The upper bounds are set to 1, 0.3, 0.3, 0.008, and 1, respectively. $K_{p0}$ =0.2, $K_{i0}$ =0.011, $K_{d0}$ =1.4.

Figure 7 provides a comparative study of the convergence curves of the 4 algorithms in Table 5. From the convergence rate, BA and PSO converge at about the third iteration, which is faster. The convergence of GA is relatively slow and does not start until the sixth iteration. GWO converges at the second iteration. In terms of the top fitness outcome, GA has the best fitness value of 15.784038, BA has the best fitness value of 16.8159, and PSO has the best fitness value of 21.5258. The optimal fitness value of GWO is 16.939. In terms of the perspective of algorithm iteration time, the iteration time of GA algorithm is 1114.4415s, which is the most time-consuming among the four algorithms. The iteration time of GWO algorithm was 121.4814s, which was the least time-consuming.

Table 5. Optimization results of parameter values.

| Optimization result/algorithm | BA | PSO | GA | GWO |
|---|---|---|---|---|
| $K_p$ | 9.0000 | 6.8680 | 2.0317 | **8.5853** |
| $K_i$ | 0.2000 | 0.1893 | 0.1301 | **0.1987** |
| $K_d$ | 0.1000 | 0.0939 | 0.0630 | **0.0803** |
| Iteration time/S | 384.248752 | 808.1041 | 1114.4415 | **121.4814** |

| **Optimization result/algorithm** | **BA** | **PSO** | **GA** | **GWO** |
|---|---|---|---|---|
| Optimal fitness value | 16.8159 | 21.5258 | 15.784038 | **16.939** |
| The iteration count for the best fitness score | 3 | 3 | 6 | **2** |

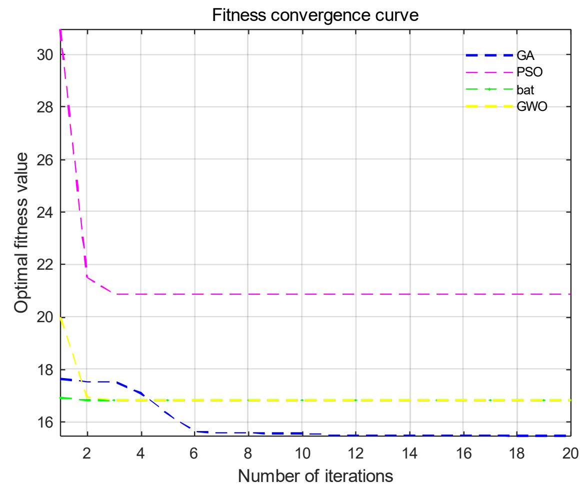


Figure 7. Comparison of convergence curves for four algorithms.

### 5.3 Discussion

Table 6 shows the performance indicators of the four algorithms for optimizing fuzzy PID parameters. Through comparative analysis, it is evident that the GWO optimizes the fuzzy PID controller parameters with the shortest rise time and the fastest convergence speed, and achieves a better fitness value under a very small number of iterations. The minimum steady-state error indicates that the solution has the highest quality and is closest to the ideal solution. The overshoot of all algorithms is similar, indicating that they have comparable stability during iterations.

Table 6. Algorithm evaluation metrics.

| **Algorithms/evaluation metrics** | **Rise time (Tr)** | **Overshoot (Mp)** | **Steady state error (Ess)** |
|---|---|---|---|
| BA | 15.99 | 5.22% | 16.8159 |
| PSO | 20.40061 | 5.52% | 21.5258 |
| GA | 14.99362 | 5.23% | 15.784038 |
| **GWO** | **16.08350** | **5.27%** | **16.939** |

## 6. CONCLUSION

In this study, a fuzzy PID parameter optimization method founded on GWO is proposed to find the optimal PID parameters through an intelligent search algorithm to optimize the efficiency of the control system. The simulation results show that after optimization is noted that the optimized fuzzy PID controller has a significant improvement in stability, rapidity and accuracy of solution. The Grey Wolf algorithm optimization enhances the adaptability and robustness of the fuzzy PID control system, so that it can quickly converge to the desired temperature set point. Future research can further explore the combination of GWO algorithm with other intelligent algorithms for application in more complex systems. Future research can focus on further optimizing the control parameters and exploring alternative optimization algorithms to improve the effect of greenhouse temperature regulation.

## ACKNOWLEDGMENTS

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