

# Intelligent Temperature Control Method of Instrument Based on Fuzzy PID Control Technology

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**Abstract**—The current instrumentation intelligent temperature control is generally realized based on PID control technology, whose efficiency and precision are low and cannot meet the actual production requirements. A fuzzy PID (FPID) control technique is suggested as a solution to this issue with the goal to increase the control precision by adjusting the PID parameters in real-time using a fuzzy algorithm. In addition, a multi-strategy-fused Improved Grey Wolf Optimization (MGWO) algorithm is used to obtain the optimal fuzzy rule parameters for the fuzzy controller to achieve the optimization of FPID. In addition to the aforementioned, the MGWO-FPID-based instrumentation intelligent temperature control model is created to enhance the instrumentation's ability to regulate temperature. The testing results demonstrated that the MGWO-FPID model outperformed the other two models with values for the objective function of  $5 \times 10^{-8}$ , adaptation degree of 13.1, control regulation time of 2.08 s, F1 value of 96.14%, MAE value of 8.53, Recall value of 95.37%, and AUC value of 0.995. The above results prove that the MGWO-FPID-based instrumentation intelligent temperature control model proposed in the study has high accuracy and efficiency, which can effectively realize the instrumentation intelligent temperature control in industrial production, and then improve the accuracy and efficiency of instrumentation temperature control, ensure the safe production of industry, and promote the industrial development to a certain extent. This model can monitor and regulate the temperature in the industrial production process in real time, avoiding safety accidents caused by temperature anomalies, and ensuring the safety of industrial production. And the application of this model can improve the efficiency and product quality of industrial production, help reduce production costs and improve economic benefits. This can not only promote the development of related industries, but also drive the economic development of the entire society.

**Keywords**—Fuzzy PID control; instrumentation; intelligent temperature control; differential negative feedback; grey wolf optimization algorithm

## I. INTRODUCTION

In industrial production, temperature is a key parameter, especially in thermal production processes. However, due to the continuous changes in production conditions, temperature parameters may drift, leading to data distortion [1]. Distorted data not only affects product quality, but may also cause damage to production equipment. Therefore, accurate control of temperature parameters is a problem that must be solved in industrial production [2]. The full name of PID controller is proportional integral derivative controller, which is the most classic and widely used controller in the design of automatic control systems. In fact, it is an algorithm. The traditional

instrumentation intelligent temperature control method is generally based on the PID control algorithm to achieve, but the method's need for frequent adjustment of PID parameters, resulting in reduced accuracy and efficiency, cannot meet the actual needs of industrial production [3-5]. Therefore, the core issue is how to improve the reliability of temperature parameters through effective control strategies, thereby ensuring the authenticity of data and the normal operation of the instrument. Although traditional PID control methods are widely used, their high frequency of parameter adjustment in complex production environments and frequent parameter changes leads to a decrease in control accuracy. This study aims to develop an intelligent temperature control method for instruments based on fuzzy PID (FPID) control technology. This method combines the advantages of fuzzy logic and PID control, and adjusts the parameters of the fuzzy controller through optimization algorithms to achieve more accurate temperature control. By improving the temperature control method, this study not only helps to improve the production efficiency of the heat treatment industry, but also provides new solutions for other similar parameter control problems in industrial production. More importantly, this method is expected to provide technical support for the demand for intelligence and automation in modern industrial production. There are two main innovations in the study. The first one is to propose a fuzzy PID control technology-based instrumentation intelligent temperature control method, thus improving the accuracy of instrumentation temperature control; The second is to boost the performance of fuzzy PID by optimising the fuzzy rule of the fuzzy controller using the Multi-strategy-Grey Wolf Optimisation (MGWO) algorithm using multi-strategy fusion parameters. The research content is divided into four main sections: the first section elaborates and summarises the most recent research findings that are pertinent; the second section suggests an MGWO optimised fuzzy PID control algorithm model (MGWO-FPID) to achieve intelligent and precise temperature control of the instrument; and the third section offers a conclusion; the third part is the performance verification of the MGWO-FPID model; and the last part is the summary of the whole research content.

## II. RELATED WORKS

PID controller has a simple structure, high stability, high reliability and easy to adjust, so it is widely used in industrial control. However, when a PID controller is applied in hopes of maintaining the control accuracy, the PID parameters need to be adjusted frequently, resulting in its control efficiency and control accuracy are not ideal. The fuzzy PID algorithm, which uses fuzzy logic to optimize the PID parameters in real

time based on certain rules, overcomes the defects existing in traditional PID and therefore has received wide attention. In order to develop a fuzzy PID control system and enhance the PID's control effectiveness, Phu N. D. et al. used a fuzzy algorithm to optimise the PID parameters in real time [6]. To improve the control impact of a fuzzy PID controller, which is crucial for increasing the efficiency of industrialised production, Shi J. Z. presented a fractional order generalised type-2 fuzzy PID controller [7]. Shi L et al. designed an amphibious spherical robot in order to better perform coastal environmental monitoring and autonomous search and rescue tasks at sea. A fuzzy PID control method was proposed to address the drawback that this robot is difficult to control its motion autonomously underwater. In accordance with experimental findings, the fuzzy PID control method outperformed the classic PID control method in terms of robustness and dynamic performance [8]. Ghamari S. M. et al. created a buck converter fractional-order fuzzy PID controller to increase the buck converter's control accuracy and used the Antlion optimisation algorithm (AOA) to optimise the fuzzy PID control algorithm for its flaws [9]. Shi Q and colleagues built an adaptive neural network fuzzy PID controller to address the shortcomings of linear PID controllers and suggested a double-delay depth determination method gradient technique to optimise it. The outcomes demonstrate improved robustness and generality of the adaptive neural network fuzzy PID controller [10]. Given that the speed control system of levitated permanent magnet maglev trains is more complex, the parameters vary more, and the control accuracy of the classic control method is not great, Liu Y et al. suggested a weighted predictive fuzzy PID control algorithm. The findings demonstrate that the weighted predictive fuzzy PID control algorithm may more effectively minimise train energy consumption and stopping error while also providing higher levels of train tracking accuracy and comfort [11]. Kumar Khadanga R designed a type-2 fuzzy PID controller, thus achieving high accuracy control of the frequency of a hybrid distributed power system, thus improving the safety of the power system [12]. Sain D et al. designed a nonlinear fuzzy PID controller and modeled, simulated and tested the nonlinear fuzzy PID controller based on simulation software, thus proving the performance of the controller [13].

In comparison to conventional optimisation methods, the grey wolf optimisation algorithm is a novel intelligent population optimisation algorithm with low complexity, high convergence, robustness, and improved efficiency and accuracy, so it has received the attention of many scholars and its application has been thoroughly studied. Zamfirache I A et al. combined the neural network by strategy iteration and GWO algorithm, thus training to propose a reinforcement learning based control method. The outcomes demonstrated that the control approach suggested in this study had superior stability and precision [14]. Liu J et al. optimized the GWO using the Lion Swarm Optimization (LSO) algorithm and dynamic weighting strategy to improve the accuracy and

convergence of the GWO in response to the defects of poor convergence and weak global search ability of the GWO. To enhance the path planning effect, the path planning optimisation was built based on the modified GWO algorithm [15]. In order to improve the performance of this cell, Hao P suggested employing the chaos method to improve the GWO algorithm and using the improved GWO to the prediction and estimate of new fuel cell parameters [16]. Otair M et al. mixed GWO with particle swarm algorithm (Particle Swarm Optimization (PSO) and Support Vector Machine (SVM) to construct a network intrusion detection model to enhance the security of wireless sensor networks [17]. The effectiveness of the state feedback control in the drive control system of a bearingless permanent magnet synchronous motor is addressed by Sun X et al. The deficiency of poor control is optimized by using GWO algorithm to improve its control effect [18]. To boost the effectiveness of managing urban traffic and ensure its smooth flow, Rajamoorthy R et al. suggested a charging scheduling approach for electric car intelligent transportation systems based on GWO algorithm optimisation. Experimental results showed that the application of this method can effectively alleviate urban traffic pressure [19]. In order to prevent the GWO algorithm from succumbing to the local search flaw during iteration and enhance the GWO algorithm's performance, Xu Z et al. adopted a chaotic local search approach to optimise the GWO algorithm [20]. The GWO algorithm's structure and update technique were enhanced by Ahmadi B et al. to improve optimisation performance. Additionally, to optimise voltage distribution and lower energy losses and emission costs, the upgraded GWO was used in smart grid planning [21].

The current fuzzy PID control technique is widely utilised, as can be seen from the explanation above, however there are still certain flaws, necessitating its optimisation. Few studies currently apply GWO to the optimization of fuzzy PID, and there are few research results related to the instrumentation temperature control in industrial production. To achieve this, a fuzzy PID control approach is presented and used to the field of instrumentation intelligent temperature control in order to increase the accuracy of instrumentation parameters and boost industrial production efficiency.

### III. MGWO-FPID-BASED INSTRUMENTATION INTELLIGENT TEMPERATURE CONTROL MODEL CONSTRUCTION

#### A. FPID-based Instrumentation Intelligent Temperature Control Method

In the current thermal processing industry, the temperature parameter control of the instrument is very important, which is related to the safety and productivity of industrial production. The traditional instrumentation intelligent temperature control method is based on PID to achieve; PID is divided into two kinds, respectively, hardware PID and software PID, its general structure is shown in Fig. 1.

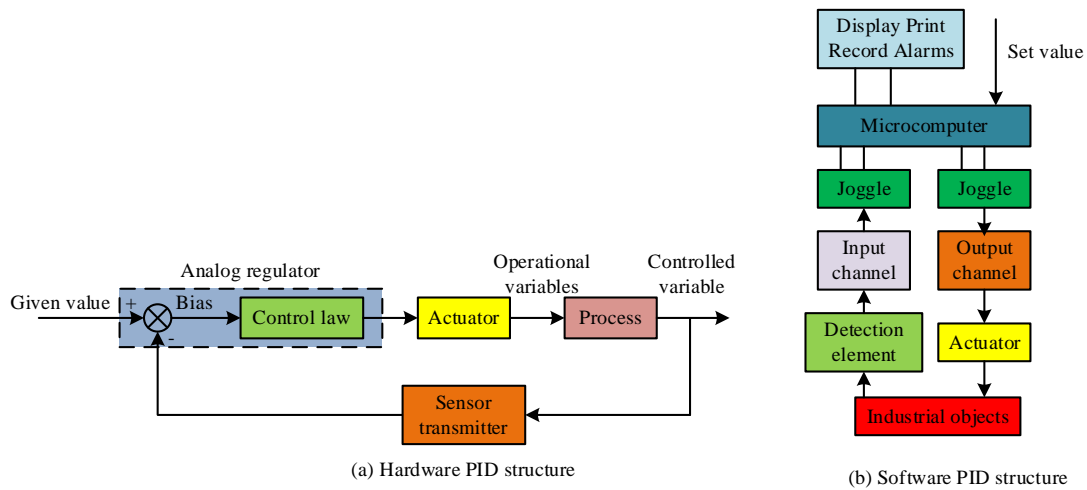


Fig. 1. Structure of hardware PID and software PID.

However, the PID-based instrumentation intelligent temperature control method is less effective and takes longer time, so the study proposes a FPID control method to achieve high precision and high efficiency intelligent temperature control of the instrumentation. To realize the intelligent temperature control of the instrument, the temperature parameter information data needs to be collected first, so the temperature data transfer model  $P(X)$  is constructed first, as shown in Eq. (1).

$$P(X) = \sum_d \frac{(r+y)}{Q_1(s)+Q_2(s)} \quad (1)$$

In Eq. (1),  $r$  is the input data;  $y$  is the output data;  $d$  represents the disturbance information in the production environment; and  $Q_1(s), Q_2(s)$  are the error scalar coefficients, whose main function is to control the temperature parameters and improve the output accuracy of the data by self-correction for error compensation and steady-state eigendecomposition. The feedback correction model enables to reduce the deviation of temperature control. Using the input of the differential negative feedback control  $P(X)$ , the closed-loop system expression of the controller  $x(t)$  can be obtained, based on which the eigen decomposition of  $x(t)$  can be performed to obtain the transfer function of the controller in the negative feedback process  $H(s)$ , as shown in Eq. (2).

$$H(s) = P(s)x(t) \quad (2)$$

In Eq. (2),  $P(s)$  is the transfer function in the temperature data transmission process. Based on Eq. (2), the feedback correction model of the temperature sensor  $H(X)$  is obtained, as shown in Eq. (3).

$$H(X) = \frac{H(s)EI(a_i)p(i)}{T} \quad (3)$$

In Eq. (3),  $E$  is the amplitude and frequency function;  $I(a_i)$  is the mutual information quantity of the temperature parameter characteristics;  $p(i)$  is the probability function of the disturbance parameter. In combination with the above, the feedback correction of the instrument temperature is performed. The intelligent control of the instrument temperature is the self-tuning control of the PID parameters based on the above contents. the essence of FPID is to construct the corresponding fuzzy rules by the temperature control situation of the instrument, and then use the controller to regulate the temperature and control the instrument temperature to maintain at a suitable value. The principle of FPID is shown in Fig. 2.

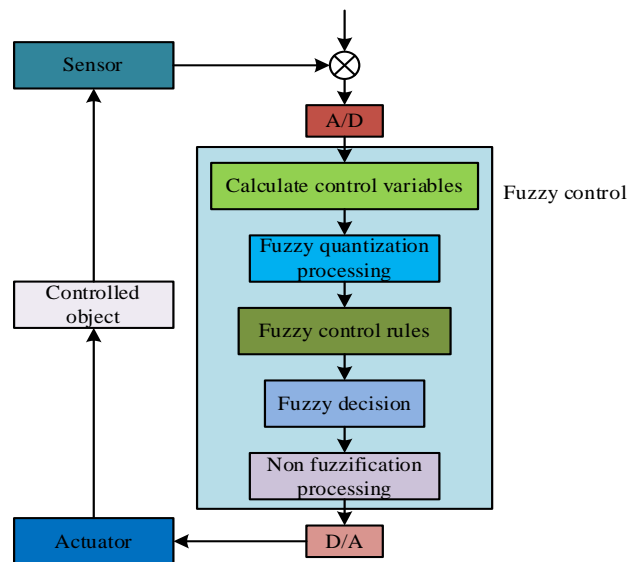


Fig. 2. Principle of FPID.

In Fig. 2, the control deviation signal can be obtained by comparing the control result of the instrument temperature with the expected result by using the corresponding fuzzy rules. After the controller performs the operations of fuzzification, fuzzy inference and anti-fuzzification, three

correction quantities can be obtained, which are noted as  $K_p, K_i, K_d$ . Based on the temperature data transfer model to obtain the corresponding data, the temperature deviation  $E$  and the rate of change of  $E$  can be obtained  $EC$ . Using the physical domain of the trigonometric affiliation function, we can represent  $E$  and  $EC$ . At this time, the temperature deviation is taken from -3 to 3; the rate of change of temperature deviation is taken from -0.2 to 0.2. In the physical domain of [-3,3], the affiliation function is chosen to present the triangular affiliation function with the affiliation degree of [0,1]; if the physical domain does not use the triangular affiliation function, when the physical domain is positive, the corresponding representation is PB, and when the physical domain is positive, the corresponding representation is NB. If the physical domain does not use the triangular affiliation function, when the physical domain is positive, it is denoted as PB, and when the physical domain is positive, it is denoted as NB. The fuzzy set affiliation function is shown in Fig. 3.

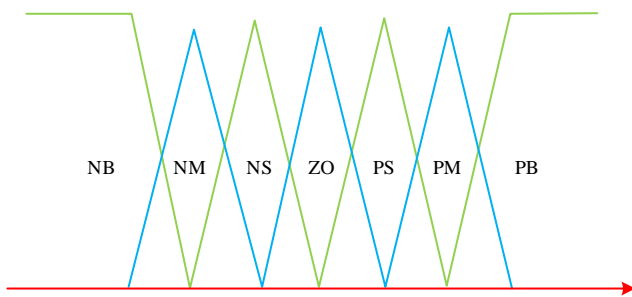


Fig. 3. Fuzzy set membership function.

The languages corresponding to the seven chosen fuzzy sets are indicated in Fig. 3 by the letters NS, NB, PS, NM, PB, PM, and ZO, respectively. By modifying the PID settings, it is possible to influence both the dynamic and static performance of the control system. The study uses the step case of the PID parameters to realize the fuzzy rule table. In accordance to the deviation and its rate of change, the three correction values of the controller are modified. When the deviation value  $E$  is larger than the set threshold and the system has good trackability and response speed, then  $K_p$  should be adjusted up and  $K_d$  should be adjusted down to make  $K_i = 0$ , and the integral action should be limited by the above operation. When  $E = EC$ , if the overshoot of the system is small and the response speed is moderate, then turn down  $K_p$  and take moderate values of  $K_d$  and  $K_i$ . When the value of the deviation rate of change  $EC$  is large and the system stability is good,  $K_p$  and  $K_i$  should be adjusted upwards and  $K_d$  should be taken moderately so as to avoid oscillations. Based on the input temperature variables  $E$  and  $EC$  and the output value  $U$ , the fuzzy inference relation matrix  $R$  can be obtained as shown in Eq. (4).

$$R = U_{i,j} (E_j \cdot EC_j \cdot U_{ij}) \quad (4)$$

In Eq. (4),  $E_j, EC_j, U_{ij}$  denotes the temperature deviation, the rate of change of temperature deviation, and the fuzzy state of the output, respectively, and the values of  $i, j$  are [1,5]. The fuzzy relations corresponding to the fuzzy inference relation matrix are obtained by Eq. (4). On the basis of obtaining the fuzzy state of the system input  $(NB_E \cdot PS_{EC})$ , a random element of  $E$  and  $EC$  in the domain is used as input, and the adjustment value of the PID parameters  $U(k)$  is obtained after fuzzy inference operation, as shown in Eq. (5).

$$U(k) = (E(k) \cdot EC(k))R = (NB_E \cdot PS_{EC}) \cdot R \quad (5)$$

A multimode steady-state PID controller must be used to track and correct for the steady-state error that occurs throughout the PID parameter adjustment process in purpose to increase parameter adjustment accuracy. The state function of tracking compensation can be expressed by Eq. (6).

$$y_a = \varphi_a + f_d + b_u \quad (6)$$

Eq. (6),  $y_a, \varphi_a, f_d, b_u$  are the control deviation, the instrument temperature drift value, the correction factor of the sensitivity of the measuring element and the interference signal during error compensation, respectively. Combined with the above, the temperature control transfer function  $T_B$  of the instrument in the industrial process can be obtained, as shown in Eq. (7).

$$T_B = K_d \cdot U_d y_a \quad (7)$$

Eq. (7),  $K_d$  is the conversion factor,  $U_d$  is the output of the PID controller. Combined with the above, the intelligent temperature control of the instrument can be achieved.

### B. FPID Optimization Based on Improved GWO

In the above, the study implements the intelligent temperature control of the instrument based on FPID. It is clear that the values of fuzzy parameters like  $K_p, K_d$  and  $K_i$  have a significant impact on the temperature control performance of the FPID-based instrument intelligent temperature control model. In order to further improve the temperature control accuracy of the instrumentation intelligent temperature control model, the GWO algorithm is used to obtain the optimal fuzzy parameter values to optimize the FPID model. In the population of GWO algorithm, there are four kinds of gray wolf individuals, namely  $\alpha$  wolf,  $\beta$  wolf,  $\delta$  wolf and  $\omega$  wolf, which represent the location of the best individual, the location of the second best individual, the location of the second best individual and the location of other gray wolf search individuals in the gray wolf population. The algorithm's search for superiority is mainly implemented by  $\omega$  wolves, and the other three wolves mainly guide the displacement direction of  $\omega$  wolves. The location update of gray wolf individuals in GWO is shown in Fig. 4.

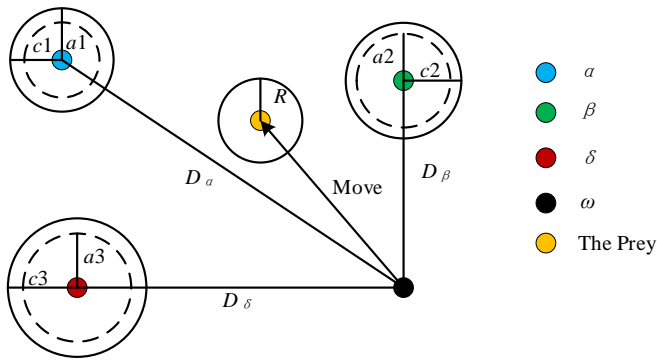


Fig. 4. Location update of grey wolf individuals in GWO.

The mathematical model of the prey seeking process, in which individual gray wolves search for and surround their prey in GWO, can be represented by Eq. (8).

$$\begin{cases} D = |CX_p(t) - X(t)| \\ X(t+1) = X_p(t) - AD \end{cases} \quad (8)$$

In Eq. (8),  $t$  is the number of iterations of the GWO algorithm;  $X_p(t)$ ,  $X(t)$  is the location of the prey and the location of the individual gray wolf after  $t$  iterations, respectively;  $A$ ,  $C$  represents the convergence factor and the swing factor, respectively. When searching for the optimal solution, the individual wolves at  $\omega$  will be guided by  $\alpha$  wolf,  $\beta$  wolf and  $\delta$  wolf to move closer to the direction of the prey, and its position updating strategy is shown in Eq. (9).

$$X(t+1) = (X_1 + X_2 + X_3) / 3 \quad (9)$$

In Eq. (9),  $X_1, X_2, X_3$  denotes the direction of movement of  $\omega$  in the next iteration guided by  $\alpha$  wolves,  $\beta$  wolves, and  $\delta$  wolves, respectively. The GWO algorithm has strong optimization performance and plays an important role in various fields, but it has certain shortcomings, such as less than ideal convergence and easy to fall into local optimality, so certain improvements are needed. First, a good point set initialization strategy is introduced to generate the gray wolf population. With this strategy, it is possible to uniformly distribute gray wolf individuals in the vicinity of all potential solutions in the search space, so it can effectively avoid the GWO population from falling into local extremes. To further enhance the GWO, Differential Evolution (DE) is implemented. firstly, Eq. (10) is used to implement variation operations on the gray wolf individuals in the GWO population, thus enhancing the population diversity and improving the search effect.

$$V_{i,g} = X_{a,g} + F_r (X_{b,g} - X_{c,g}) \quad (10)$$

In Eq. (10),  $X_{a,g}, X_{b,g}, X_{c,g}$  is the randomly selected gray wolf individual in the current population;  $V_{i,g}$  represents the new gray wolf individuals generated after the mutation operation;  $F_r$  represents the scaled difference vector. After the mutation operation, the grey wolf population is subjected to

two-by-two crossover operations using Eq. (11) in order to add new grey wolves, increase the population's variety, and boost the algorithm's capacity for merit-seeking.

$$U_{i,g+1} = \begin{cases} V_{i,g}^j & \text{if } (rand^j(0,1) \leq C_r) \text{ or } (j = j_{rand}) \\ X_{i,g}^j & \text{otherwise} \end{cases} \quad (11)$$

In Eq. (11),  $C_r$  is the crossover probability, which ranges from 0% to 100%;  $j_{rand}$  indicates the dimension of random selection;  $U_{i,g+1}$  indicates the new gray wolf individuals obtained after the crossover operation. Then, the greedy algorithm is used to optimize the GWO. by the selection operation in the greedy algorithm, the better individuals in the GWO population are selected and participate in the next iteration, thus ensuring that the GWO is continuously optimized during the iteration. The selection operation of the above content is shown in Eq. (12).

$$X_{i,g+1} = \begin{cases} U_{i,g+1} & \text{if } f(U_{i,g+1}) < f(X_{i,g}) \\ X_{i,g} & \text{otherwise} \end{cases} \quad (12)$$

In Eq. (12),  $X_{i,g+1}$  is the individual after selection. In GWO, the location update strategy of gray wolf individuals is closely related to the locations of  $\alpha$  wolf,  $\beta$  wolf and  $\delta$  wolf, and the convergence and search ability of the algorithm are directly related to the control factor  $a$ . In the general GWO algorithm, the value of  $a$  decreases linearly with the increase of iterations, which leads to the weak search ability of the algorithm in the early stage and the weak convergence in the later stage? For this reason, the study proposes a nonlinear control factor adjustment strategy, as shown in Eq. (13).

$$a = 2\sqrt{1 - (t/t_{max})^2} \quad (13)$$

In Eq. (13), the maximum number of iterations is denoted by  $t_{max}$ . The research proposed strategy and the traditional strategy are shown in Fig. 5.

It can be seen that under the strategy proposed in the study, the  $a$  value changes slowly at the beginning of the iteration and the search performance of GWO is strong; at the later part of the iteration the  $a$  value changes faster, which makes GWO have good convergence. As the GWO algorithm has the disadvantage of maturing and convergent too early, resulting in poor search accuracy, the study proposes a segmentation step strategy that adjusts the update mechanism according to the  $A$  value. When  $|A| \leq 1$  is used, the update mechanism shown in Eq. (7) is adopted. When  $|A| > 1$ , three individuals are randomly selected  $r_1, r_2, r_3$  to determine the search range of search individuals  $R'$ . With this tactic, it is possible to provide some of the members of the badly located grey wolves an opportunity to take part in the algorithm's location update choice, successfully increasing population diversity and preventing the early GWO algorithm occurrence. The above can be represented as Fig. 6.

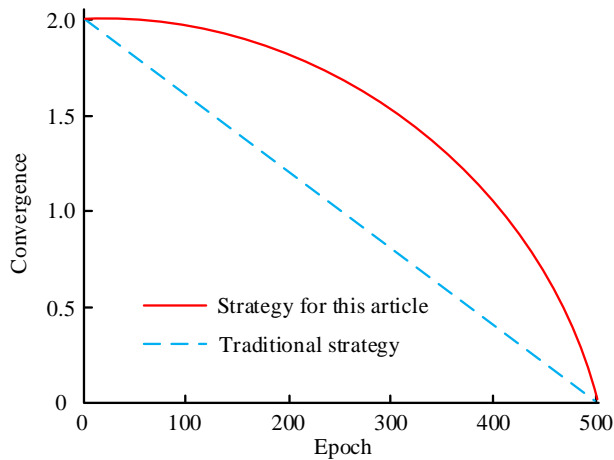


Fig. 5. Control factor adjustment strategy.

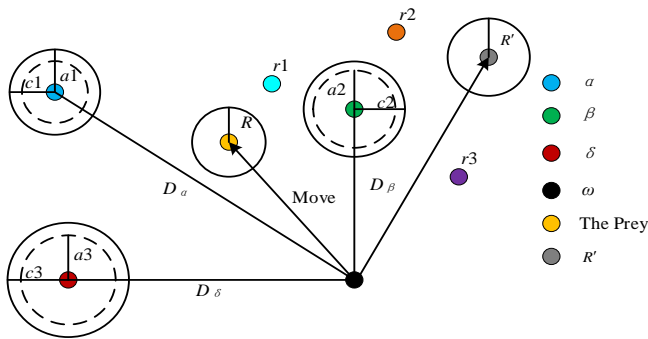


Fig. 6. Segmental update strategy of GWO algorithm.

Comprehensive above, build MGWO, use MGWO to find the best parameters of FPID, optimize it, build MGWO-FPID model, realize the high precision intelligent temperature control of the instrument, improve the temperature control effect, and then improve the industrial production efficiency, which has positive significance to the safety guarantee of industrial production.

#### IV. PERFORMANCE ANALYSIS OF MGWO-FPID INSTRUMENTATION INTELLIGENT TEMPERATURE CONTROL MODEL

To validate the capability of the MGWO-FPID instrumentation intelligent temperature control model proposed in this study, the study selects an instrumentation used for thermal power metering for the experiment and uses the software Matlab for the simulation experiment. The experimental parameters are as follows, the voltage is 10V, the network signal state temperature, the program state is offline, the operation model is selected as the IoT operation model, and the analysis method uses platform computing analysis. The current state-of-the-art PID control algorithms are particle swarm optimization FPID (PSO-FPID) model and FPID (ISOA-FPID) model optimized based on improved seeker optimization algorithm (ISOA). It collected a large amount of historical temperature data, including temperature changes under different working conditions. Use platform computing

analysis methods to preprocess, clean, and analyze data to extract key features and trends. In the comparison model, Particle Swarm Optimization FPID (PSO-FPID) model: based on particle swarm optimization algorithm, PID parameters are optimized to improve the response speed and stability of temperature control. FPID (ISOA-FPID) optimization model based on improved seeker optimization algorithm (ISOA): By improving the seeker optimization algorithm to adjust PID parameters, the robustness and adaptability of the control are improved. Under the same experimental conditions, run the MGWO-FPID model, PSO-FPID model, and ISOA-FPID model separately. Record the temperature control effects of each model under different working conditions, including control accuracy, response speed, and stability indicators. By comparing the experimental results, analyze the superiority and performance characteristics of the MGWO-FPID model compared to other models. In the experiment, MGWO-FPID was compared with PSO-FPID and ISOA-FPID models to conduct a comprehensive analysis in terms of objective function and fitness, temperature control regulation efficiency, control accuracy, model MAE, recall, and AUC. The temperature control performance of the above three intelligent temperature control models are compared respectively. The particle number of the PSO-FPID model is 45, the inertia weight is 0.8, and the acceleration constant is 1.51; The initial population of the ISOA-FPID model is 45, with a crossover probability of 0.5, a mutation probability of 0.51, and a learning factor of 0.3; The wolf pack size of the MGWO-FPID model, with an initial population of 45, a wolf pack level of 0.55, and contraction and expansion factors of 0.4 and 0.5, respectively. The maximum number of iterations for all models is 300. Firstly, the optimization effects of the above three models are compared. During the iterative process, the changes of the fitness values and the objective function values of MGWO-FPID model, ISOA-FPID model and PSO-FPID model are shown in Fig. 7. It is evident that the MGWO-FPID model's convergence is superior to that of the ISOA-FPID model and the PSO-FPID model because the objective function value of the MGWO-FPID model declines faster and the fitness value increases faster during the iterative process. Compared to the ISOA-FPID model and the PSO-FPID model, the MGWO-FPID model achieves an objective function value of  $5 \times 10^{-8}$  in Fig. 7(a). This value is four orders of magnitude lower. In Fig. 7(b), the fitness value of the MGWO-FPID model reaches 13.1, which is 2.8 and 3.3 higher than the ISOA-FPID model and the PSO-FPID model, respectively.

The data related to the instrumentation used for thermal power metering were input into the MGWO-FPID model, ISOA-FPID model and PSO-FPID model and simulated using Matlab software, and the simulation curves of several temperature control models are shown in Fig. 8. In Fig. 8, it can be seen that the MGWO-FPID model has no overshoot and completes the temperature control regulation of the instrument in a shorter time compared with the ISOA-FPID model and PSO-FPID model. The above results demonstrate that the MGWO-FPID model is more efficient in temperature control regulation.

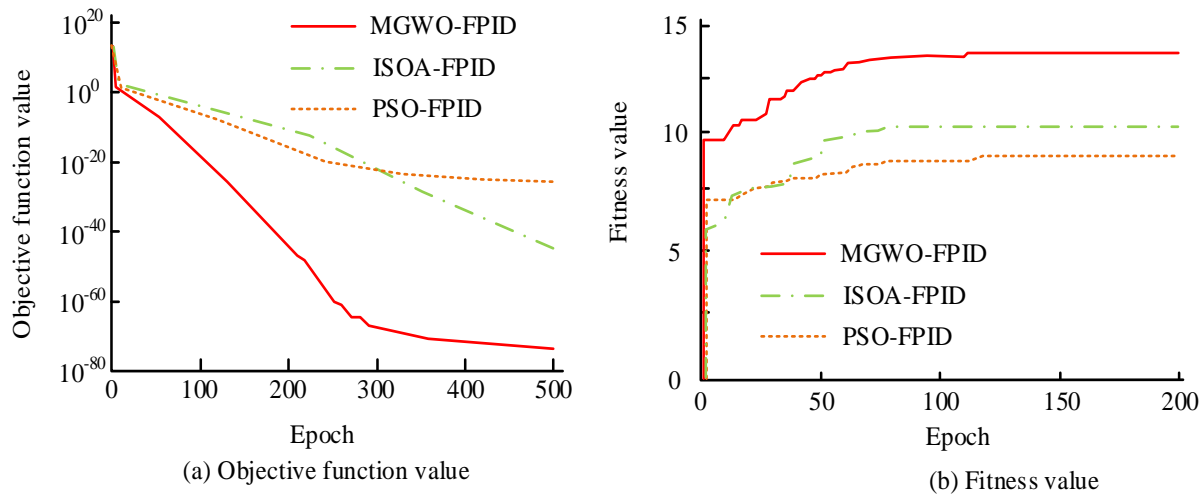


Fig. 7. Changes in fitness values and objective function values of the model.

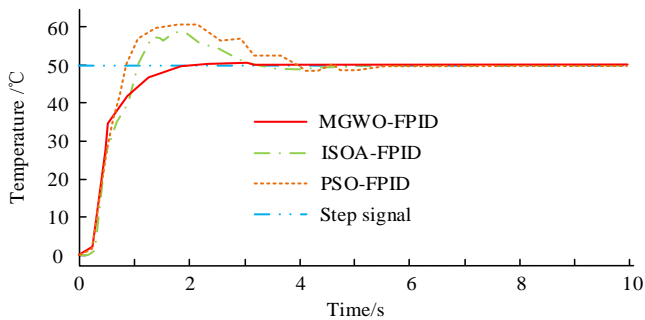


Fig. 8. Simulation curves of several temperature control models.

The control accuracies of MGWO-FPID model, ISOA-FPID model and PSO-FPID model in the intelligent control of instrument temperature are shown in Fig. 9. In Fig. 9, it can be seen that the MGWO-FPID model has higher accuracy and requires fewer iterations to reach the best accuracy. 68 iterations are required for the MGWO-FPID model to reach the best accuracy, which is 95 and 137, fewer than the ISOA-FPID model and the PSO-FPID model, respectively. The MGWO-FPID model's control accuracy is 99.52%, which is greater than the ISOA-FPID model's and the PSO-FPID model's, respectively, by 0.53% and 0.77%.

Mean Absolute Error (MAE), also known as Mean Absolute Error, is a commonly used goodness of fit evaluation criterion in regression analysis. It is the average absolute value of the difference between the predicted value and the actual value. Fig. 10 illustrates this comparison between the change in F1 value and the change in MAE during the course of an iteration of the MGWO-FPID model, ISOA-FPID model, and PSO-FPID model. Fig. 10 demonstrated that the F1 values of MGWO-FPID model, ISOA-FPID model and PSO-FPID model are rapidly increasing and the MAE values are rapidly decreasing at the beginning of the iteration, and after the F1 and MAE values reach a certain level, the F1 and MAE values

of MGWO-FPID model, ISOA-FPID model and PSO-FPID model no longer change significantly, indicating that the models have converged. It can be seen that the MGWO-FPID model converges faster. The F1 value of the MGWO-FPID model, which is 0.58% and 1.24% higher than the ISOA-FPID model and PSO-FPID model, respectively, reaches 96.14% as shown in Fig. 10(a). Fig. 10(b) illustrates that the MGWO-FPID model's MAE value is 8.53, which is 1.22 and 2.87 less than the MAE values for the ISOA-FPID model and PSO-FPID model, respectively. The above results can indicate that the MGWO-FPID model has better performance.

Utilising the Recall value as shown in Fig. 11, the performance of the MGWO-FPID model, ISOA-FPID model, and PSO-FPID model is assessed. Fig. 11 illustrates how the MGWO-FPID model has a greater Recall value and better convergence. The Recall value of MGWO-FPID model is 95.37%, which is 0.62% and 1.33% higher than the ISOA-FPID model and PSO-FPID model, respectively.

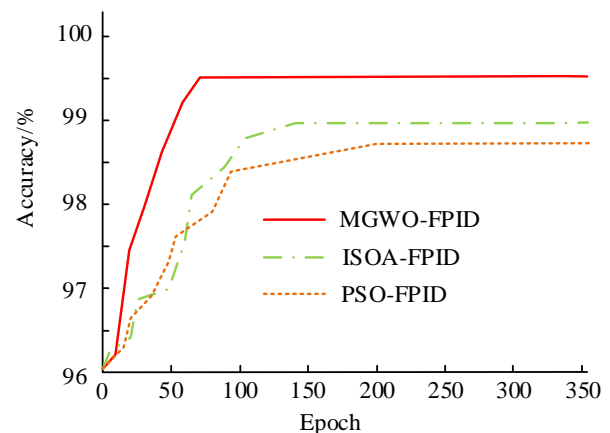


Fig. 9. Control accuracy of model in instrument temperature intelligent control.

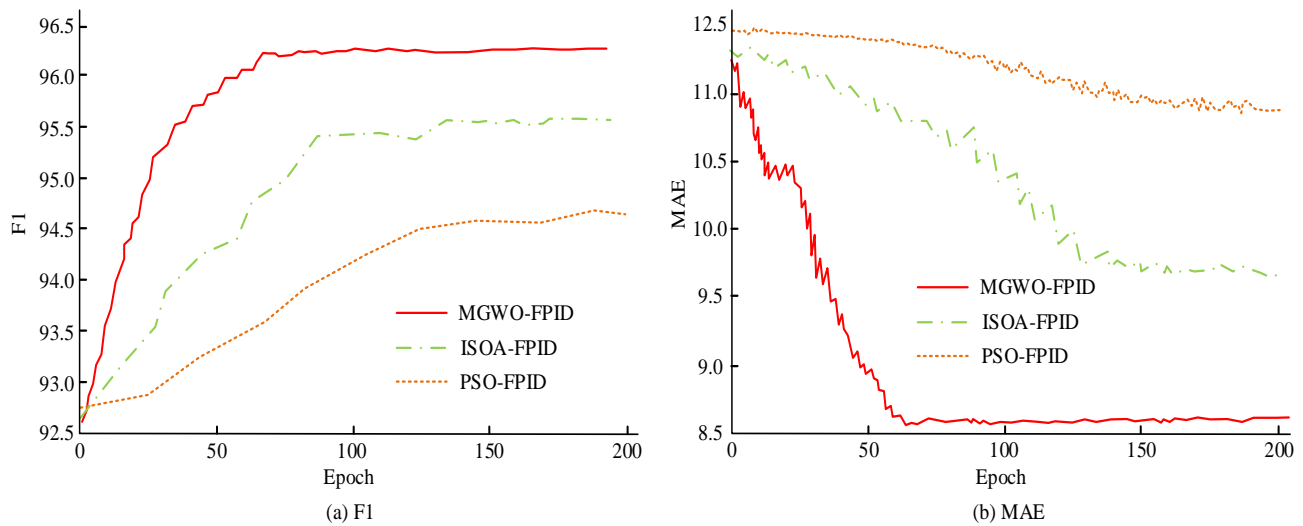


Fig. 10. Changes in F1 value and MAE during iteration of the model.

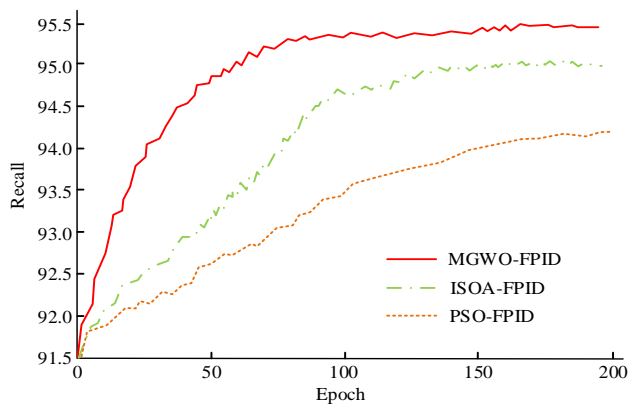


Fig. 11. Recall values for three models.

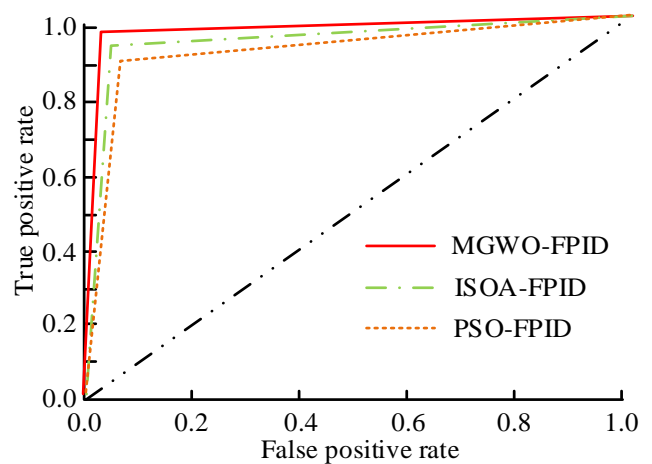


Fig. 12. ROC curve trends and AUC values for three models.

The comprehensive performance of MGWO-FPID model, ISOA-FPID model, and PSO-FPID model was evaluated by ROC curve trend with AUC value, as shown in Fig. 12. AUC (Area Under the Curve) is a commonly used metric to evaluate the performance of classification models, widely used in fields such as machine learning, data mining, and statistics. The range of AUC values is between 0 and 1, with values closer to 1 indicating better model performance, and values closer to 0.5 indicating relatively random model predictions. As can be noticed, the MGWO-FPID model's AUC value is 0.995, which is 0.011 and 0.024 higher than the AUC values for the ISOA-FPID model and the PSO-FPID model, respectively. The aforementioned results show that the MGWO-FPID instrumentation intelligent temperature control model suggested in the study performs more comprehensively than the other two models. In summary, the MGWO-FPID instrumentation intelligent temperature control model proposed in the study has high accuracy and efficiency, and effective comprehensive performance, which can effectively realize the high-precision intelligent temperature control of the instrumentation, enhance the temperature control effect, and then improve the industrial production efficiency, and has positive significance for the safety guarantee of industrial production.

In order to more intuitively demonstrate the performance of the three models, a composite table was formed based on the above experimental results, as shown in Table I.

TABLE I. SYNTHETIC TABLE OF PERFORMANCE RESULTS FOR THREE MODELS

/	MGWO-FPID	ISOA-FPID	PSO-FPID
Fitness value	13.1	10.3	9.8
Achieving optimal precision iteration times	68	163	205
Control accuracy	99.52%	98.99%	98.75%
F1 value	96.14%	95.56%	94.90%
MAE	8.53	9.75	11.4
Recall value	95.37%	94.75%	94.04%
AUC	0.995	0.984	0.971



## V. RESULTS AND DISCUSSION

The temperature control performance of intelligent temperature control models using three PID control algorithms, MGWO-FPID, PSO-FPID, and ISOA-FPID, was compared in the experiment. Firstly, the optimization effects of three models were compared. In terms of objective function and fitness, the fitness value of the MGWO-FPID model reached 13.1, which is 2.8 and 3.3 higher than the ISOA-FPID model and PSO-FPID model, respectively. In terms of temperature control efficiency, compared with the ISOA-FPID model and PSO-FPID model, the MGWO-FPID model has no overshoot and completes the temperature control adjustment of the instrument in a shorter time. In terms of control accuracy, the MGWO-FPID model requires 68 iterations to achieve optimal accuracy, which is 95 and 137 fewer than the ISOA-FPID model and PSO-FPID model, respectively. The control accuracy of the MGWO-FPID model is 99.52%, which is 0.53% and 0.77% higher than the ISOA-FPID model and PSO-FPID model, respectively. In terms of model MAE, the MGWO-FPID model has a MAE value of 8.53, which is 1.22 and 2.87 lower than the ISOA-FPID model and PSO-FPID model, respectively. In terms of recall rate, the MGWO-FPID model has a recall rate of 95.37%, which is 0.62% and 1.33% higher than the ISOA-FPID model and PSO-FPID model, respectively. In terms of AUC, the MGWO-FPID model has an AUC value of 0.995, which is 0.011 and 0.024 higher than the ISOA-FPID model and PSO-FPID model, respectively. In summary, through experimental comparison, we can conclude that the MGWO-FPID model exhibits better performance in intelligent temperature control compared to the PSO-FPID and ISOA-FPID models. It has significant advantages in terms of objective function and fitness, temperature control regulation efficiency, control accuracy, model MAE, recall, and AUC. Therefore, in actual industrial production, using the MGWO-FPID model for intelligent temperature control will help improve production efficiency and product quality.

## VI. CONCLUSION

In industrial production, the temperature control of the instrument is related to the accuracy of the instrument detection data, which affects the safety and stability of industrial production. Therefore, MGWO-FPID instrumentation intelligent temperature control model is proposed for the current instrumentation intelligent temperature control methods with low accuracy and efficiency defects. Based to the experimental findings, the MGWO-FPID model's objective function value was 510-8, which was 4 orders of magnitude less than that of the ISOA-FPID model and 6 orders of magnitude less than that of the PSO-FPID model; the adaptation degree value reaches 13.1, which is 2.8 and 3.3 higher than ISOA-FPID model and PSO-FPID model respectively; the control regulation time is 2.08s, which is higher than ISOA-FPID model and PSO-FPID model. FPID model and PSO-FPID model, respectively; 68 iterations are required to achieve the best accuracy, which is 95 and 137 times less than the ISOA-FPID model and PSO-FPID model, respectively; the F1 value reaches 96.14%, which is 0.58% and 1.24% higher than the ISOA-FPID model and PSO-FPID model, respectively. The MAE value was 8.53, which was 1.22

and 2.87 lower than the ISOA-FPID model and PSO-FPID model, respectively; the Recall value was 95.37%, which was 0.62% and 1.33% higher than the ISOA-FPID model and PSO-FPID model, respectively; the AUC value reached 0.995, which was 0.01% higher than the ISOA-FPID model and PSO-FPID model, respectively. The above results can prove that the MGWO-FPID instrumentation intelligent temperature control model proposed in the study has high accuracy and efficiency, and effective comprehensive performance, which can effectively realize the high precision intelligent temperature control of the instrumentation, improve the temperature control effect, and then enhance the industrial production efficiency, which is of positive significance to the safety guarantee of industrial production. In the experiment, due to limitations in data sources, there may indeed be discrepancies between the experimental results and the actual situation. In order to improve the accuracy and reliability of research, it is indeed necessary to broaden the scope of research to eliminate accidental errors. In order to make the research results more representative, it is necessary to obtain data from a wider range of thermoelectric metering devices to cover a wider range of device performance and possible sources of error; Compare with intelligent temperature control models in other fields to understand their respective advantages and limitations, and further improve the performance of instrument intelligent temperature control models based on MGWO FPID; Factors such as the operator's experience, skills, and psychological factors under environmental conditions can be considered to improve the comprehensiveness of the study.

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