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RESEARCH ARTICLE

Improved Particle Swarm Fuzzy PID Temperature Control for the Pellet Grills

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ABSTRACT To improve the stability and accuracy of temperature control in pellet grill, this article proposes a method that applies a Fuzzy PID controller optimized with Improved Particle Swarm Optimization (IPSO). Techniques such as Circle mapping are introduced to enhance the convergence speed and efficacy of the particle swarm algorithm (PSO). The optimized particle swarm algorithm is used for the identification of the transfer function of the pellet grill, as well as for the optimization of the quantification factor and the proportional factor within the Fuzzy PID controller. The IPSO optimized Fuzzy PID control strategy was then experimentally applied to a prototype pellet grill. The results show that the control system limits the overshoot to 1.6% and temperature fluctuations to within 1.83°F, demonstrating good stability and anti-interference capability, and significantly improving the effectiveness of temperature control. Therefore, the research findings provide a feasible solution for the temperature regulation of pellet grill.

INDEX TERMS Fuzzy systems, PID control, pellet grill, particle swarm optimization, temperature control.

I. INTRODUCTION

Nowadays, outdoor barbecuing is gaining popularity among consumers [1]. Traditional outdoor barbecues typically use coal, electricity, or propane gas as fuel for grilling food. However, with advances in renewable energy, biomass pellets are increasingly being utilized in this regard. Pellet grills that use biomass pellets as fuel are becoming more and more popular. Biomass pellets are made from renewable resources such as plant-based materials and waste materials. They have lower carbon emissions and are environmentally friendly [2]. They are also easy to store and transport [3] and can ignite quickly and burn completely [4]. Additionally, when food is cooked on a pellet grill, the Maillard reaction occurs [5], which enhances the flavor of the food. The smoke produced by fruit wood pellets imparts a fruity aroma to the meat [6], satisfying people's high expectations for the taste and quality of their food. Therefore, pellet grills are very popular for outdoor grilling.

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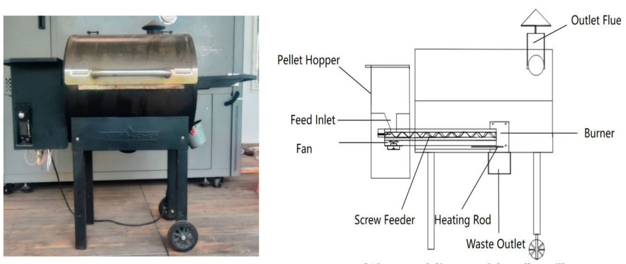
Food baking is closely related to the temperature. In temperature control studies, PID controllers are favored because of their simple structure, easy operation, convenient implementation and adjustment [7]. V.G. Ryckaert et al. [8] applied the PID control algorithm to the temperature control of oven. However, when faced with complex control objects, PID often cannot meet the requirements, and an adaptive PID control algorithm is needed. Bu combined fuzzy control with PID to solve these problems of temperature variation, nonlinearity, and time delay in the biomass microwave pyrolysis process [9]. However, traditionally determining the PID values requires operators' experience and a large number of experiments [10]. Xi utilized particle swarm optimization method to optimize the PID parameters in the control process, which enhanced the control performance and adaptive capabilities of the PID controller [11]. Tang et al. [12] combined Particle Swarm Optimization (PSO) with fuzzy PID to solve the significant nonlinear and large time delay problems in steam temperature control, demonstrating the control performance of the particle swarm fuzzy PID approach. However, the particle swarm algorithm is prone to getting trapped in local optima, making it difficult to achieve timely optimization goals and guarantee the best performance of the PID model [13].

Pellet grills heat food by burning biomass pellets, and their temperature control presents challenges, such as nonlinearity, poor stability, and significant time delays. Large temperature fluctuations significantly affect the appearance and flavor of food, making it difficult for some consumers to meet their expectations. Therefore, this study focuses on the temperature control issues of pellet grills and proposed the design of a fuzzy PID controller. An IPSO algorithm was used to adjust the scaling factors and proportional factors in the fuzzy PID to achieve better control performance. Simulated in Simulink and prototype tests in real-world environments were conducted to verify the effectiveness of the proposed temperature control based on IPSO, fuzzy PID, and the traditional PID methods for pellet grills. This study provided a valuable reference for the temperature control of pellet grills.

II. PELLLET GRILL OPERATION AND STRUCTURE

The appearance and structure diagram of the pellet grill are shown in Fig.1 On the left side, there is a pellet hopper for loading biomass pellet fuel, a screw feeder below the hopper for fuel feeding, and a fan to provide the oxygen required for combustion. The main body structure is on the right side, with an outlet flue at the top.



(a)an Exterior view of the pellet grill (b)Structural diagram of the pellet grill

FIGURE 1. Structure diagram of the pellet grill.

The system structure of the pellet grill is illustrated in Fig.2. The grill is powered by 110V, and the hardware mainly consists of the GD32F130 microcontroller as the main control unit. Temperature sensing is performed using a PT1000 thermistor, and the analog signal from the sensor is transferred through a 12-bit A/D converter using DMA configuration. Temperature control is facilitated through a digital display screen for user interaction, allowing the setting of the desired operating temperature and mode. The control signals are then transmitted to the feed motor and heating element to increase the temperature. The PT1000 thermistor continuously measures the temperature inside the pellet grill in real-time. The collected temperature data are fed back to the microcontroller for analysis and calculation. Based on this information, the microcontroller adjusts the feeding time to control the temperature effectively.

The pellet grill uses apple wood pellets to bake food, and its operating process involves loading wooden pellets into the pellet hopper, placing the food on the grilling tray inside the grill, setting the temperature and baking mode through the controller, and feeding the pellet fuel into the combustion chamber via the fuel inlet at the bottom of the hopper. The screw feeder, controlled by a motor, transfers the pellets to the combustion chamber by rotating the screw rod. The heating element ignites the pellet fuel in the combustion chamber while a fan at the bottom provides the necessary oxygen for combustion. The temperature control of the pellet grill is determined by the duration of the rotation of the screw feeder motor. A temperature sensor installed inside the grill detects the temperature and provides feedback to the digital controller. Based on the relationship between the actual temperature inside the grill and the set temperature, the digital controller calculates and controls the number of pellets fed by the screw feeder motor to achieve temperature control. However, since it takes time for pellets to ignite and burn, there is no real-time and accurate temperature feedback, resulting in inaccurate temperature control and affecting the texture of the food. To meet the requirements of food preparation, an intelligent control method is needed to precisely control the temperature.

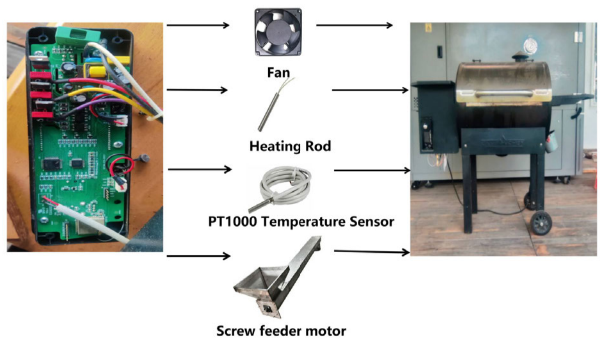


FIGURE 2. Pellet grill system diagram.

III. PELLET GRILL CONTROLLER DESIGN

The pellet grills in this instance employed a fuzzy PID control strategy. PID control is one of the most widely used regulators in engineering practice, and fuzzy PID can resolve issues such as lag, oscillation, and time-variability that are difficult to address with traditional PID control [14]. In the design of fuzzy control systems, quantization factors and scaling factors are crucial parameters, they have a decisive impact on system performance. However, traditional methods rely on tedious manual tuning and experience-based adjustments, which are not only time-consuming but also inefficient. Therefore, this paper adopts a fuzzy PID controller design based on an IPSO offline optimization algorithm. By using simulation models and offline optimization techniques, the quantization and scaling factors of the fuzzy PID are tuned, and the optimized control parameters are applied to the actual system, thereby effectively improving the temperature control performance of the pellet grills.

A. IMPROVEMENTS TO PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization is an advanced intelligent algorithm [14]. At the initial stage, each particle is assigned an initial position and velocity. In each iteration, particles update their state by tracking two extreme values. The first is the personal best solution (pbest), which is the best solution found by the particle itself. The second is the global best solution (gbest), which is the best solution found by the swarm as a whole. The formula for updating velocity and position are shown below.

Equation (1) is the formula for updating particle swarm velocity:

$$v(k+1) = \omega v(k) + c_1 r_1(\text{pbest}(k) - \text{present}(k) + c_2 r_2(\text{gbest}(k) - \text{present}(k)) \quad (1)$$

Equation (2) represents the position and the new formula:

$$\text{present}(k+1) = \text{present}(k) + v(k+1) \quad (2)$$

The basic Particle Swarm Optimization algorithm has the problem of slow convergence and a tendency to get trapped in local optima. To address them, the following improvement measures are proposed in this paper:

(1) In the basic Particle Swarm Optimization algorithm, particle initialization is set randomly, and particle distribution is also randomized. This paper uses the Circle mapping method for population initialization, which generates a more uniform and diverse initial population, which helps to improve the convergence speed and accuracy of the algorithm [16]. The expression for generating chaotic sequences using Circle mapping is as shown in (3), where x_i represents the i-th chaotic sequence number, and mod(a, b) represents the modulo operation of a with respect to b.

$$x_{i+1} = \text{mod}(\, x_i + 0.2 - \frac{0.5}{2\pi} \times \sin(\, 2\pi \times x_i), 1) \quad (3)$$

(2) In the Particle Swarm Optimization algorithm, the inertia weight and learning factor are important parameters that control particle movement [17]. A higher inertia weight can increase the particles global search capability, enabling them to escape from local optima. Conversely, a lower inertia weight can enhance the particles' local search ability [18] allowing them to fine-tune their positions near local optima for higher precision [19]. Therefore, in this study, a non-linearly decreasing inertia weight value, as shown in (4). is adopted. In the early stages of the algorithm, a larger inertia weight helps particles to conduct global search efficiently and explore the solution space extensively. As the algorithm progresses, gradually reducing the inertia weight allows particles to focus on local search near the local optima, thus improving convergence performance.

$$w(j) = w_{\max} - (w_{\max} - w_{\min}) \times (\frac{j}{T_{\max}})^2 \quad (4)$$

where $w(j)$ is the jth iteration, $w_{\max}$ is the maximum value of the set inertia weight, $w_{\min}$ is the minimum value of the set inertia weight, and $T_{\max}$ is the total number of iterations.

The learning factor is divided into individual learning factor and social learning factor. The individual learning factor controls the particle's local search capability in the solution space, while the social learning factor controls the particle's global search capability. A larger learning factor can accelerate the search process, while a smaller learning factor improves the accuracy of the search [20] In this study, the learning factor variation strategy given by (5) is adopted.

$$\begin{cases} c_1(j) = c_{1\max} - (c_{1\max} - c_{1\min}) \times \dfrac{j}{\text{sizepop}} \\ c_2(j) = c_{2\max} - (c_{2\max} - c_{2\min}) \times \dfrac{j}{\text{sizepop}} \end{cases} \quad (5)$$

Among them, sizepop is the size of the particle swarm, $c_{1\max}$ and $c_{2\max}$ are the maximum and minimum values of the set individual learning factor, and $c_{1\min}$ and $c_{2\min}$ are the maximum and minimum values of the social learning factor.

(3) During the update iterations of the algorithm, it is quite possible that the global optimal solution is not updated even after multiple iterations, indicating that the algorithm may fall into a local optimum. Therefore, in this paper, a scheme is established for the population to escape from the local optimum: if the fitness value of the optimal particle in the population does not change during K iterations, it is determined that the algorithm has fallen into a local optimum. At this point, the position information of a certain proportion of the particles within the population is reset.

During the optimization process, it is necessary to evaluate the performance of the control system, the Time Integral of Absolute Error J_{ITAE} function is used for this purpose [21] in (6), $e\,(t)$ represents the error value and t represents the sampling time of the system. By evaluating this function, the fitness value of the particle can be calculated, and a smaller fitness value is better.

$$J_{\text{ITAE}} = \int_0^{t_s} t\,|e(t)|\,dt \quad (6)$$

Based on the improved particle swarm optimization algorithm, the complete parameter adjustment steps of the PID controller can be summarized as follows:

Step 1. Initialize the particle swarm, define particle dimensions, learning factors, inertia weights.

Step 2. Calculate the fitness value for each particle.

Step 3. Based on the values calculated for each particle, select the individual best value pbest and global best value gbest. If the fitness value improves compared to the respective pbest or gbest, update the particle's velocity and position using (1) and (2).

Step 4. Check if the global best value has reached the termination condition K. If it has, return to Step 1.

Step 5. Update the inertia weight and learning factors using (4) and (5).

Step 6. Repeat Steps 2 to 5. If the maximum number of iterations is reached, stop the computation.

B. PARTICLE GRILL TRANSFER FUNCTION IDENTIFICATION

This paper simulated the temperature control of a pellet grill in MATLAB's Simulink, where the temperature model of the system was represented by a transfer function. The self-balancing system transfer function was expressed as shown in Equation (7).

$$G(s) = \frac{Ke^{-\tau s}}{(T_1 s+1)(T_2 s+1)\cdots(T_n s+1)} \tag{7}$$

In control processes, designs of high-order models involve numerous parameters, complex computations, lengthy optimization times, and precision is often challenging to ensure. Generally, complex systems are reduced to low-order transfer functions. [22] This paper focuses on the temperature control system of a pellet grill as the object of control, which possesses self-balancing capabilities and time-delay characteristics under step input conditions. It can be described by a second-order transfer function, as presented in Equation (8).

$$G(s) = \frac{Ke^{-\tau s}}{(T_1 s+1)(T_2 s+1)} \tag{8}$$

The rotational duration of the screw feeder was used as a step input to obtain the temperature data of the pellet grill. The screw feeder was set to a rotation cycle of 35%, and the ambient temperature of 83°F was set as the zero-starting point. Only the data during the temperature rise was recorded, and the recording stopped after the temperature stabilized at an increase of approximately 120°F. The temperature change data are shown in Table 1.

This paper employed the IPSO algorithm for parameter identification [23], [24], [25], focusing on the transfer function of the pellet grill, as defined in Equation (8). To import the temperature data into MATLAB, the population size was set to 100 and the number of iterations to 400. The algorithm then optimized the unknown variables in the transfer function, namely k, τ, T_1, and T_2, yielding the following results: k =120, τ =10.1, T_1=110.4, and T_2=691.7. The resulting transfer function for the pellet grill is presented in Equation (8), and the fitting effect is illustrated in Fig.3.

$$G(s) = \frac{120e^{-10.1s}}{(110.1s+1)(691.7s+1)} \tag{9}$$

C. IMPROVED PARTICLE SWARM OPTIMIZATION BASED FUZZY PID DESIGN

The improved particle swarm fuzzy PID temperature control is built upon the foundation of fuzzy PID control. First,

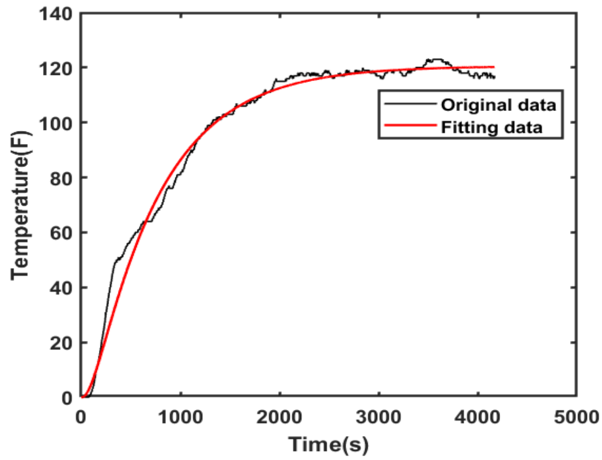


FIGURE 3. Temperature fitting diagram for open loop testing.

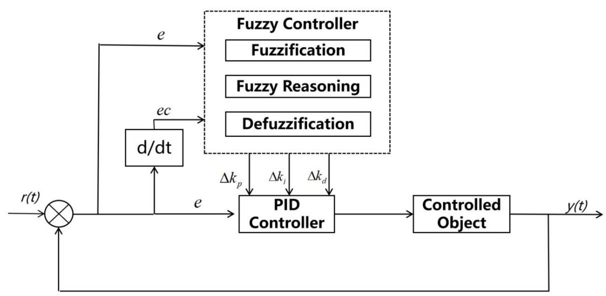


FIGURE 4. Principle of fuzzy PID control.

a fuzzy PID controller needs to be constructed. Fuzzy PID can dynamically change the three parameters of PID in real-time during the process, making the control more accurate and stable. In the pellet grill, a PT1000 thermistor is used to measure the temperature inside the grill and compare it with the set temperature to obtain the error e and the change rate of error ec. These values serve as inputs to the fuzzy PID controller. Fuzzy rules are formulated based on fuzzy inference in the fuzzy system. The three output parameters are then defuzzied to obtain values Δk_p, Δk_i, and Δk_d. Finally, these values are fed into the PID controller of the pellet grill. The detailed process is shown in Fig.4.

Given k_p=0.49, k_i=0.00026, k_d=16, the fuzzy set-in which NB represents negative large, NM represents negative medium, NS represents negative small, ZO represents zero, PS represents positive small, PM represents positive medium, and PB represents positive large. Based on the characteristics of the pellet grill, temperature control requirements, and expert experience, the domain of error e is set as $\{-6, 6\}$, and the domain of change rate of error ec is set as $\{-6, 6\}$. Gaussian membership functions are used for e, while triangular membership functions are used for k_p, k_i, and k_d with domains $\{-1, 1\}$, $\{-3, 3\}$, and $\{-5, 5\}$ respectively. Triangular membership functions are used for other variables. Mamdani fuzzy inference algorithm is used

TABLE 1. Measurement data of temperature variation of pellet grill over time.

Time(s)	0	100	200	300	400	500	600	700
Temperature (°F)	0	2	18	42	51	57	62	64
Time(s)	800	900	1000	1100	1200	1300	1400	1500
Temperature (°F)	69	76	81	89	95	99	102	103
Time(s)	1600	1700	1800	1900	2000	2100	2200	2300
Temperature (°F)	106	107	109	111	115	116	118	118
Time(s)	2400	2500	2600	2700	2800	2900	3000	3100
Temperature (°F)	117	118	117	118	118	119	117	119
Time(s)	3200	3300	3400	3500	3600	3700	3800	3900
Temperature (°F)	119	119	120	123	123	122	120	118
Time(s)	4000	4100	4174					
Temperature (°F)	117	117	117					

TABLE 2. Fuzzy rule table for Δk_p, Δk_i, and Δk_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/ZO/ZO
NS	PM/NB/ZO	PM/NM/NS	PM/NS/NM	PS/NS/NM	ZO/ZO/NS	NS/PS/NS	NS/PS/ZO
ZO	PM/NM/ZO	PM/NM/NS	PS/NS/NS	PB/ZO/NS	NS/PS/NS	NM/PM/NS	NM/PM/ZO
PS	PS/NM/ZO	PS/NS/ZO	NB/ZO/ZO	NS/PS/ZO	NS/PS/ZO	NM/PM/ZO	NM/PB/ZO
PM	PS/ZO/PB	ZO/ZO/NS	NS/PS/PS	NM/PS/PS	NM/PM/PS	NM/PB/PS	NB/PB/PB
PB	ZO/ZO/PB	ZO/ZO/PM	NM/PS/PM	NM/PM/PM	NM/PM/PS	NB/PB/PS	NB/PB/PB

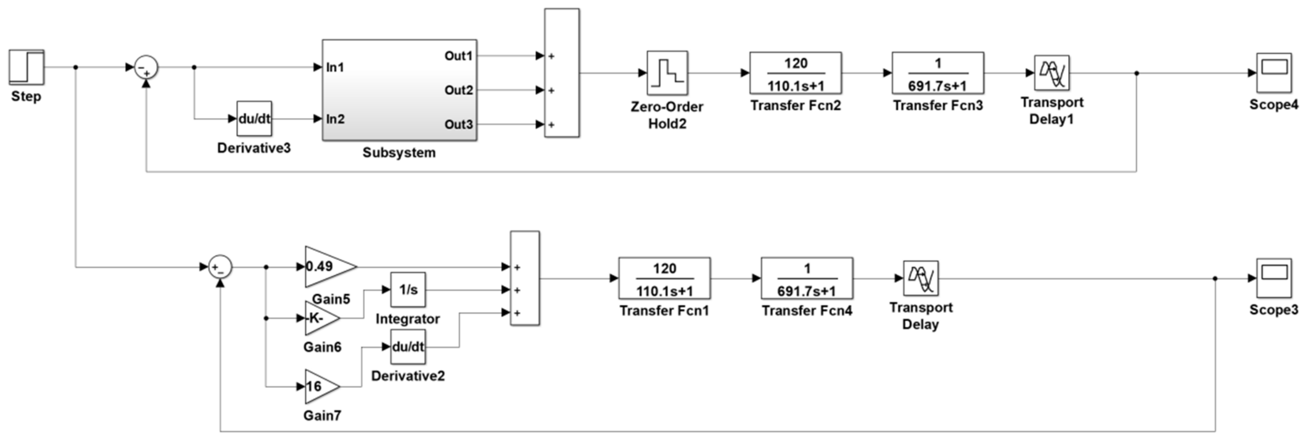


FIGURE 5. Simulation model of temperature control system using fuzzy PID controller and PID controller.

for reasoning [26], and the weighted average method is used for defuzzification. The fuzzy rules for membership Δk_p, Δk_i, and Δk_d can be found in Table 2. The simulation of the fuzzy PID and PID is shown in Fig.5.

When the IPSO algorithm was combined with the Fuzzy PID, the quantification factors k_e, k_{ec}, and the proportional factors k_p, k_i, k_d, were set as the parameters to be optimized. The simulation model is constructed as shown in Fig.6.

IV. SYSTEM TESTING AND VALIDATION

A. SIMULATION EXPERIMENT

The target temperature was set at 300°F, and the performance of three control strategies was assessed based on overshoot, rise time, and steady-state error. The particle swarm had a size of 100 with 50 iterations. The initial inertia weights were $w_{max} = 0.9$ and $w_{min} = 0.3$, while the learning factors were $c_{1min} = c_{2min} = 1$, and $c_{1max} = c_{2max} = 2$. Upon completion of the iterations, the calculated results yielded a proportional gain k_p=3, integral gain k_i=1.42, and derivative gain k_d=2.76, with the quantization factors k_e=0.93 and k_{ec}=0.2. The comparative simulation responses were illustrated in Fig.7., with specific performance metrics detailed in Table 3.

Under the condition of undisturbed experiments, it can be observed from Fig.7 that the traditional PID controller exhibits an overshoot of 13.6%, a temperature rise time of 932 seconds, and a steady-state error of 2.04°F upon reaching the set temperature. However, with the implementation of the fuzzy PID controller, the overshoot is reduced to

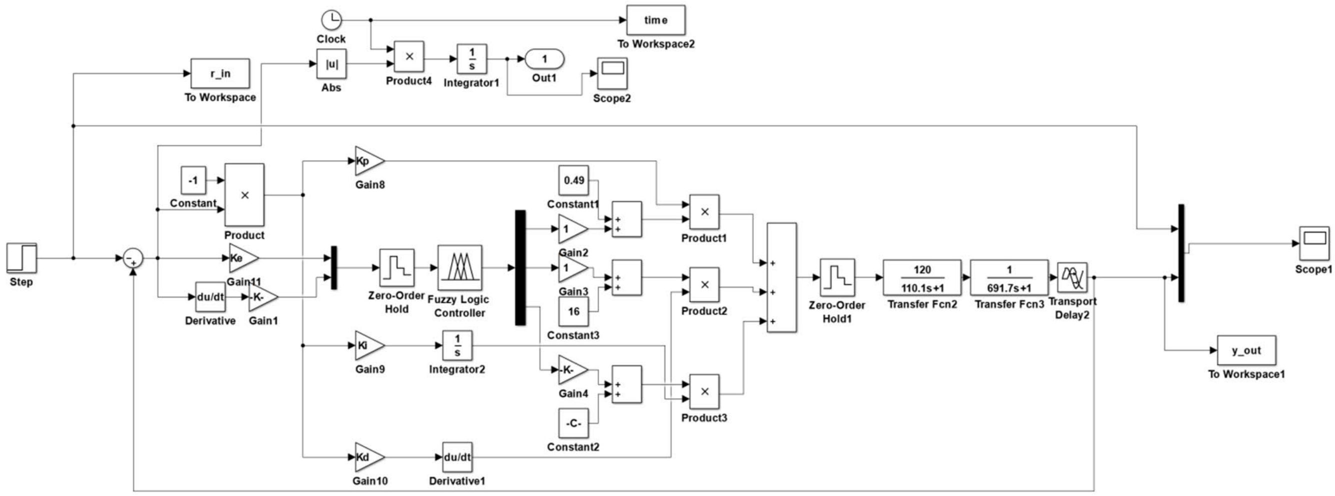


FIGURE 6. Improved particle swarm fuzzy PID Simulink model.

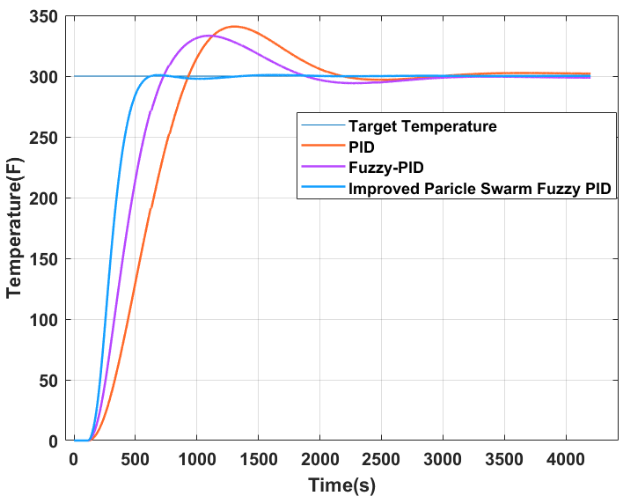


FIGURE 7. Response diagrams of three types of PID controllers.

TABLE 3. Three control performance indicators.

	Overshoot (%)	Heating up time(s)	Steady-State error (°F)
PID	13.6	932	2.04
Fuzzy-PID	11.3	730	1.19
IPSO	0.4	624	0.14

11.3%, the heating time is decreased to 730 seconds, and the steady-state error is lowered to 1.19°F. This indicates that the introduction of the fuzzy controller has significantly improved the performance of the control system. The fuzzy PID controller optimized with the IPSO demonstrates an overshoot of only 0.4%, a reduced temperature rise time to 624 seconds, and a substantial decrease in steady-state error to 0.14°F. The IPSO algorithm not only inherits the dynamic performance advantages of the fuzzy PID but also meets the requirements of temperature stability. The simulation results suggest that the IPSO optimized fuzzy PID achieves superior control effects compared to the previous two algorithms.

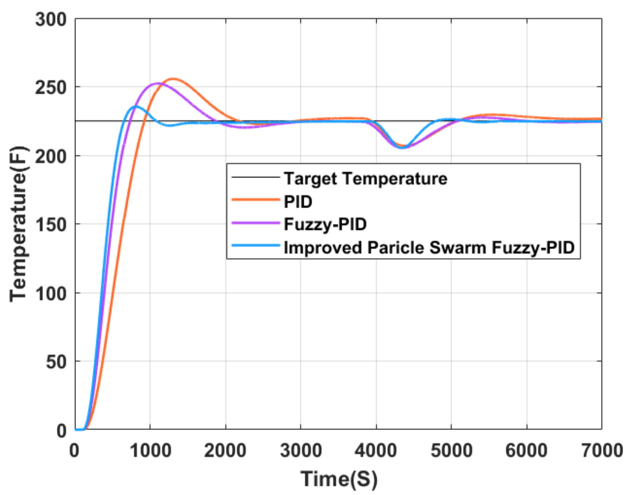


FIGURE 8. Disturbance response graph of the three PID controllers.

TABLE 4. Three control performance indicators for interference test.

	Time to Warm-up Under Disturbance (s)	Magnitude of Disturbance Fluctuation (°F)
PID	695	4.49
Fuzzy-PID	673	2.47
IPSO	463	1.25

In the disturbance tests, the temperature was set to 225. The disturbance signal amplitude was set to 20. As shown in Fig.8, with specific performance metrics detailed in Table 4. among the three control modes under the influence of disturbances, the improved particle swarm algorithm optimized fuzzy PID

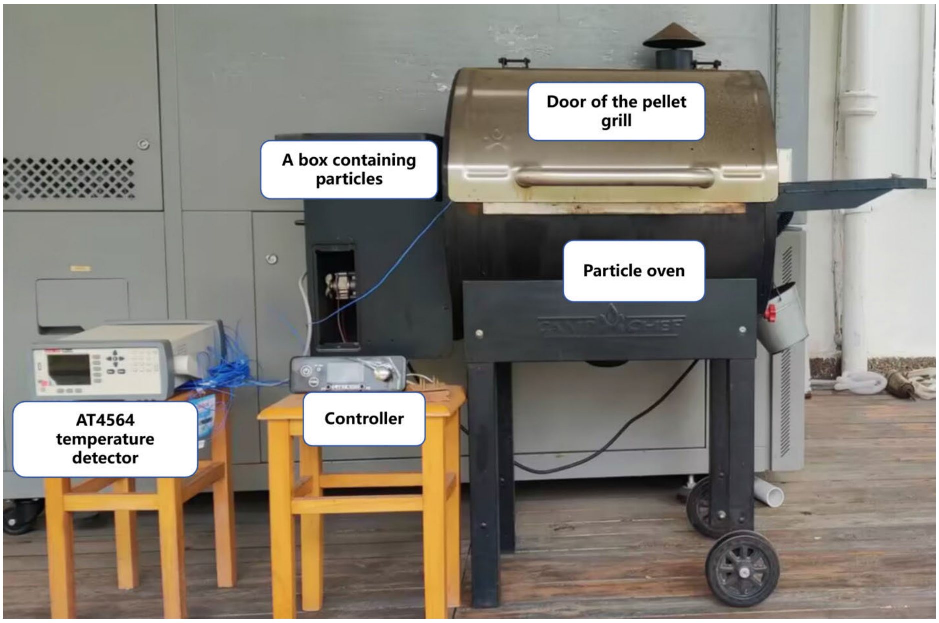


FIGURE 9. Pellet grill testing environment.

controller took 463s to reach the set temperature, which was the shortest time. The IPSO algorithm, when disturbed, is able to re-attain the set temperature with a deviation range within 1.25°F, which is the best performance among the three types of controllers tested. In comparison, the Fuzzy PID controller has a deviation of 2.47°F, while the conventional PID controller exhibits a deviation of 4.49°F. From this, it is evident that the IPSO algorithm significantly enhances the adjustment capability of the Fuzzy PID controller following a disturbance, demonstrating superior disturbance rejection performance. This aligns with the temperature control requirements of a pellet grill.

B. PROTOTYPE EXPERIMENT

Building on the foundation of simulation experiments, the optimized parameters were applied to a prototype pellet grill. Keil software was used to program and flash onto a control board based on GD32F130, aiming to conduct a performance comparison among PID, Fuzzy PID, and Fuzzy PID controllers optimized by IPSO. Ultimately, the temperature testing environment depicted in Fig.9. was established. The AT4564 multiplex temperature tester was utilized for temperature data detection and recording.

Simulation tests were conducted on different types of meat. In the first test, the scenario simulated was the long-term baking of steaks and beef ribs [27], [28], with the pellet grill set to a target temperature of 300°F. The curve illustrating the heating and temperature increase is shown in Fig 10. and the corresponding indicators are presented in Table 5.

After the initial ignition of the pellet grill, the temperature began to rise approximately 6 minutes later. In terms of reaching the set temperature, the IPSO Fuzzy PID mode took 18 minutes, the Fuzzy PID mode took 13 minutes, and the traditional PID mode required 24 minutes. Although the temperature rise time for the IPSO Fuzzy PID was not the shortest, its overshoot was mere 1.6%, which was significantly better than the 4% of traditional PID, and 7.7% of Fuzzy PID. Additionally, its average fluctuation was only 1.83°F, a reduction of 46.9% and 65.1% compared to the traditional PID's 3.45°F and Fuzzy PID's 5.25°F, respec-

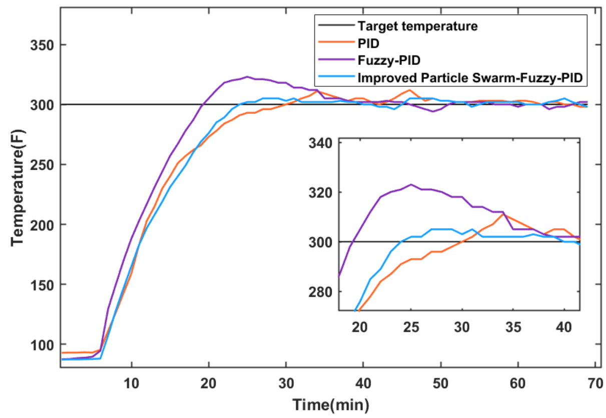


FIGURE 10. 300°F temperature rise curve.

TABLE 5. Three control performance indicators.

	Overshoot (%)	Heating up time(min)	Steady-State error (°F)
PID	4	24	3.45
Fuzzy -PID	7.7	13	5.25
IPSO	1.6	18	1.83

tively, demonstrating the best control performance. These results clearly indicate that compared to traditional PID systems, the IPSO Fuzzy PID control strategy significantly improved the precision and stability of temperature control, fulfilling the temperature control requirements for the pellet grill.

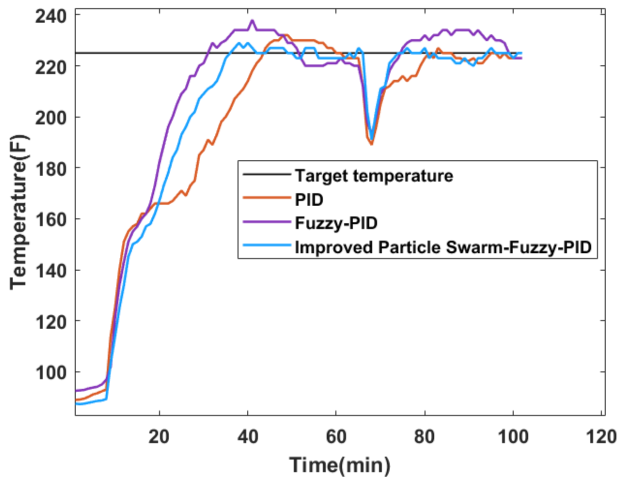


FIGURE 11. Temperature rise curve at 225°F.

TABLE 6. Three control performance indicators for interference test.

	Time to Warm-up Under Disturbance (s)	Magnitude of Disturbance Fluctuation (°F)
PID	795	2.18
Fuzzy-PID	360	5.65
IPSO	345	1.55

In the second test, a scenario of baking fish fillets and chicken legs [27], [28] was simulated. After the temperature had stabilized, the lid above the oven was opened to simulate actual cooking conditions where people would open the lid to observe or flip the food, thus affecting the temperature. The heating and temperature increase curve is shown in Fig. 11.

With the temperature set to 225°F, the experimental process included a disturbance test where, after temperature stabilization, the oven door was opened for 2 minutes and then closed. The temperature rise curve of the pellet grill is shown in Fig.11, and performance indicators are presented in Table 6. The Fuzzy PID controller optimized by the IPSO reached stable temperature at the set point in 345 seconds post-disturbance, compared to 360 seconds for Fuzzy PID and 795 seconds for traditional PID. After reaching the set temperature, the average fluctuation for the IPSO Fuzzy PID was only 1.55°F, whereas the Fuzzy PID had a much higher average fluctuation of 5.65°F. The results demonstrate that the Fuzzy PID controller improved through IPSO can respond quickly and adjust the pellet grill temperature in real-time.

V. CONCLUSION

This paper investigates the temperature control of a pellet grill and proposes a control strategy that integrates an IPSO algorithm with a Fuzzy PID controller. To address the issue of reliance on extensive experimental adjustments for the quantification and proportional factors in the Fuzzy PID controller, an IPSO algorithm is employed for optimization, aiming at achieving better temperature control performance. Initially, temperature data was collected, and parameter identification was conducted using the improved Particle Swarm Optimization to construct the transfer function of the pellet grill. Subsequently, a simulation platform was established to compare and analyze PID, Fuzzy PID, and IPSO-optimized Fuzzy PID controllers, demonstrating that the IPSO-optimized Fuzzy PID exhibited the least overshoot and the fastest convergence among the three controllers. Finally, the quantification and proportional factors optimized through simulation experiments were applied to the actual system for testing, and compared with PID and Fuzzy PID. The experimental results indicate that the Fuzzy PID controller optimized by the IPSO algorithm provides a pellet furnace with excellent dynamic performance, strong anti-interference capabilities, and achieves precise temperature control, offering insights and references for the intelligent temperature control of pellet grills.

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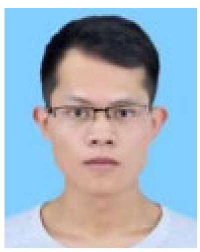

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