

Article

Research on Temperature Field Control in a Thermostatic Chamber with Static Baffle-Mediated Natural Convection

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Abstract

Temperature uniformity in thermostatic chambers is critical for material testing, biological incubation, and precision measurements, as even minor thermal gradients can compromise reliability. However, in chambers designed to avoid airflow disturbances, such as those used in semiconductor fabrication and optical experiments, forced convection and mechanical stirring are often impractical. Consequently, natural convection becomes the dominant heat transfer mechanism, introducing significant nonlinearity, large thermal inertia, and multivariable coupling among multiple heat sources. To address these issues, this study develops a multi-input–multi-output (MIMO) temperature control strategy for a rectangular chamber equipped with eight heating elements (grouped into four channels) and adjustable-angle baffles. The proposed method combines a multi-PID controller array with genetic algorithm (GA)-based parameter tuning using a transfer-function matrix model. Experiments demonstrate that baffle angles below 90° improve spatial uniformity, and the relative grouping of heaters outperforms adjacent grouping in both thermal inertia and correlation. Using GA-optimized PID parameters, the controller maintains steady-state error within ± 0.5 °C and reduces settling time by approximately 140 s compared to conventional Ziegler–Nichols tuning. Validated through simulations and experiments, the proposed approach provides a reliable and cost-effective alternative to forced convection for airflow-sensitive applications, achieving superior uniformity and steady-state accuracy.

Keywords: multi-input–multi-output; thermostatic chamber; natural convection; temperature field control

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1. Introduction

Natural convection is the dominant heat transfer mechanism in thermostatic chambers for precision measurements, semiconductor processing, and biological incubation. In these applications, forced ventilation is deliberately avoided to prevent airflow disturbances that could compromise sensitive operations. However, conventional on/off or single-loop PID control strategies inherently struggle to achieve global temperature uniformity in such enclosed spaces due to their strong nonlinearity, large thermal inertia, and significant multivariable coupling. Therefore, developing advanced control strategies that exploit natural convection while actively compensating for these inherent limitations is of substantial engineering significance.

Natural convection in enclosures heated from side walls, where the temperature gradient is perpendicular to gravity, has been extensively studied as the canonical configuration relevant to chamber applications [1]. Davis [2] and Fusegi et al. [3] established benchmark solutions for square and cubic cavities, revealing that flow symmetry and thermal boundary layer formation are strongly dependent on the Rayleigh number. Subsequent work extended these baselines to non-uniform heating configurations [4,5], demonstrating that the positions of heated and cooled regions govern flow patterns and secondary vortex structures. Collectively, however, these benchmark studies are confined to idealized boundary conditions such as uniformly heated walls or perfectly insulated surfaces. These conditions differ substantially from those in practical chambers containing multiple discrete heat sources. Moreover, they focus on open-loop flow and heat transfer characterization rather than control-oriented system modeling. Consequently, the dynamic input-output relationships among multiple heaters and points remain largely unaddressed.

The presence of internal objects significantly alters flow topology and temperature distribution in enclosed cavities, as systematically reviewed by Pandey et al. [6]. For square internal bodies, studies on heated conductors [7,8] have shown that thermal conductivity and temperature difference ratios critically influence flow stability and wall heat transfer. Specifically, high Rayleigh numbers can induce transitions from steady to unsteady states [9]. For circular objects, the position of a cylinder governs flow symmetry and the onset of unsteadiness. Furthermore, horizontal or diagonal displacements can further modify vortex structures [10,11]. For multiple cylinders, arrangements of two or four cylinders reveal that the lower cylinder contributes more to heat transfer, while the Rayleigh number and inter-cylinder spacing jointly determine the transition to unsteady flow [12,13]. Despite the extensive parameter space explored in these studies, most have treated internal objects as passive heat sources or fixed obstacles, failing to consider them as actively controllable elements. Moreover, the majority of findings are derived from two-dimensional simulations or simplified geometries. This leaves the quantitative relationship between object arrangement and temperature uniformity at specific working zones insufficiently characterized from a control perspective.

Introducing structures such as baffles or fins within enclosed spaces is a common passive method to control natural convection. Parametric studies have shown that increasing baffle height or length can enhance convective heat transfer by up to 40% [14]. Additionally, the Nusselt number is strongly influenced by inclination angle, typically reaching minimum values near 90° and decreasing with greater baffle length [15,16]. These findings collectively confirm that even a rigid, stationary baffle can significantly alter flow topology and heat transfer, which provides a basis for the active control strategy adopted in the present work. However, the studies cited above have largely examined fixed angles or constant motion modes, with limited attention to integrating baffle angle adjustment with real-time temperature feedback. Furthermore, they focus on heat transfer performance metrics such as the Nusselt number rather than on control-oriented models that quantify the dynamic relationship between baffle configuration and spatial temperature uniformity. The present work begins to address this gap by systematically characterizing the effects of several fixed angles, serving as a first step toward future closed-loop angle control.

Further research has demonstrated that actively regulating natural convection within enclosed cavities can be achieved by parameterizing the position or angle of internal structures. Displacement of heat sources or cylinders within cavities has been shown to significantly alter thermal gradient distributions and induce transitions from steady to unsteady flow states [17–18]. Similarly, the inclination angle of internal structures has also been confirmed as a critical parameter influencing convective heat transfer [19,20].

However, existing research on movable components predominantly focuses on flow and heat transfer characteristics under static or constant motion modes, with little attention to real-time adjustment of structural parameters based on temperature feedback. Although this is the ultimate direction of our research, the present work does not yet incorporate such real-time angle control. Instead, it focuses on systematically characterizing the flow and heat transfer under several fixed baffle angles (45°, 60°, and 90°). This provides the necessary physical insights for the future development of a closed-loop control system with dynamic baffle actuation.

At the control strategy level, current thermal chamber temperature control predominantly employs a Single-Input–Single-Output (SISO) framework based on on/off or Proportional–Integral–Differential (PID) control. In this approach, each heater independently adjusts its output power based on feedback from a single temperature measurement point. While this decentralized control structure is simple and easy to implement, significant thermal interactions occur among heaters in enclosed environments with multiple heat sources and points. Power variations in a single heating element can influence temperature responses at other points through natural convection and radiation. This makes independent single-loop control inadequate for achieving global temperature uniformity and consistent dynamic response. In other multivariable engineering systems, model predictive control (MPC) has been successfully applied to coordinate multiple actuators and achieve high-performance regulation. For instance, in electrical drives [19] and autonomous vehicle lateral control [20], MPC has proven effective in handling nonlinearities and multivariable coupling. In thermal systems, adaptive MPC combined with subspace identification has been applied to building heating control, achieving substantial energy savings compared to conventional PID [21]. Similarly, genetic algorithm-based optimization and fuzzy self-tuning particle swarm optimization have been employed to tune PID parameters in air handling units, significantly improving control quality [22]. Multi-objective optimization algorithms, such as the imperialist competitive algorithm, have also been extended to fractional-order PID tuning for complex thermal regulation systems [23]. The multi-input–multi-output (MIMO) control strategy treats the system as a unified entity. It leverages coupling relationships between input–output channels to establish a system model and achieve simultaneous temperature regulation across multiple points through multivariable coordinated control. Compared to independent SISO controllers, the MIMO framework more effectively addresses channel thermal coupling and demonstrates superior performance in temperature uniformity, steady-state accuracy, and disturbance rejection capability. Recent advances have further integrated neural network prediction models with MPC frameworks, incorporating low-rank Jacobian updates and adaptive error compensation to achieve offset-free tracking on embedded hardware platforms [24]. In parallel, artificial neural networks have been combined with co-simulation environments to enable real-time multi-variable set-point optimization for HVAC systems [25]. Therefore, applying MIMO control theory to thermal chamber temperature control under natural convection conditions (by developing a system model and control strategy tailored for multiple heat sources and points) holds clear theoretical value and practical engineering significance.

In summary, existing research still has shortcomings in the following aspects: First, although previous studies have addressed natural convection in enclosed cavities containing multiple internal objects, research from a control perspective, i.e., modeling multi-source, multi-measure point systems as MIMO temperature control systems and designing multivariable controllers, is still limited. Most work remains at the level of flow and heat transfer characteristic analysis. Second, collaborative research on adjustable-angle baffles and active control strategies is insufficient, lacking a systematic analysis of the quantitative effects of baffle angle on flow patterns and temperature fields. Third, while

various optimization techniques and modern control strategies have been successfully applied in other engineering domains [19–25], their systematic integration for temperature field regulation in thermostatic chambers under natural convection remains an open challenge.

To address these gaps, the present work makes the following contributions. First, a transfer function matrix model is established to capture the dynamic input-output relationships among four independent heating channels and four control points in a rectangular chamber under natural convection. Second, a multi-PID controller array is designed to achieve approximate decoupling via spatial layout, with all 12 PID parameters globally optimized using a genetic algorithm that balances stability, accuracy, and uniformity. Third, the quantitative effects of heater grouping configurations (opposite vs. adjacent) and fixed baffle angles (45° , 60° , and 90°) on thermal inertia, heating rate, and spatial temperature uniformity are systematically characterized through response experiments. Fourth, a three-dimensional CFD model is developed in COMSOL Multiphysics, driven by actual experimental heating signals, to reveal the physical mechanism by which the baffle redirects natural convection flows. This integrated experimental, modeling, and optimization framework provides a reliable control strategy for temperature-critical applications requiring high uniformity and minimal flow interference, and lays a foundation for future hybrid control systems incorporating real-time baffle actuation.

2. Structure and Control Strategy of the Thermostatic Chamber

2.1. The Structure of the Chamber and the Mathematical Model

For practical implementation, this study developed a constant temperature chamber model equipped with eight heating modules. As shown in Figure 1a, the chamber measures $0.5\text{ m} \times 0.5\text{ m} \times 0.4\text{ m}$ internally. The walls are constructed from aluminum plates, secured to an aluminum frame using damping shafts and spring clips. Each wall is insulated with 20 mm thick high-density rubber-plastic insulation cotton of low thermal conductivity, with aluminum foil applied to one side to minimize radiation interference on the chamber's temperature field. Figure 1b illustrates two Polyimide film heating elements (24 V, 100 W) mounted on each side wall, at the upper left and lower right, totaling eight heating elements. A flow baffle is positioned 20 mm above the lower heating elements to prevent air from flowing solely upward along the walls during operation, thereby improving temperature distribution in the central region. As shown in Figure 2, the baffle consists of a servo motor and a rigid nylon plate (2 mm thick), mounted on the servo motor via connectors and partially embedded in the side wall's cutout. The seal between the baffle and wall ensures complete air isolation. Driven by a Pulse Width Modulation signal, the baffle rotates at an angle of 45° to 110° relative to the vertical line (all angles mentioned later are measured from this reference).

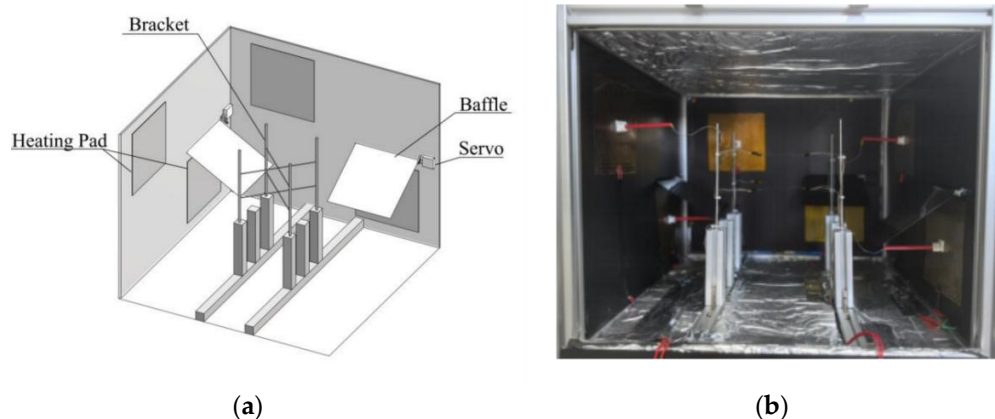


Figure 1. (a) Structural schematic diagram and (b) physical image.

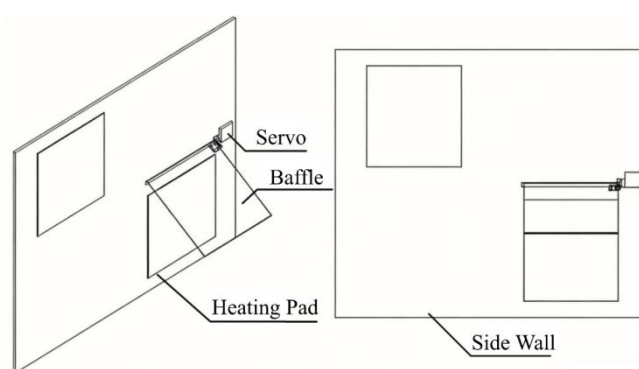


Figure 2. Schematic diagram of the baffle structure.

Temperature measurements were conducted using K-type thermocouples (diameter 0.127 mm), which had been previously calibrated to an absolute accuracy of ± 0.1 °C. The chamber contains eight operational points and eight control points. As shown in Figure 3, the operational points (T9–T16) are designated as the primary temperature working zone. A two-tiered cross-shaped beam is installed on the temperature measurement bracket at the chamber's center, with adjustable vertical positioning; the operational points are arranged along this beam, with four points per tier, forming a cubic configuration. The points can be moved along the beam. Due to the significant distance between the central points and the heating elements, which results in considerable delay time, the control points (T1–T8) were designated as the primary control targets. These control points are located 100 mm anterior to the center of each heating element, monitoring their operational status, and their data are used to establish the control model.

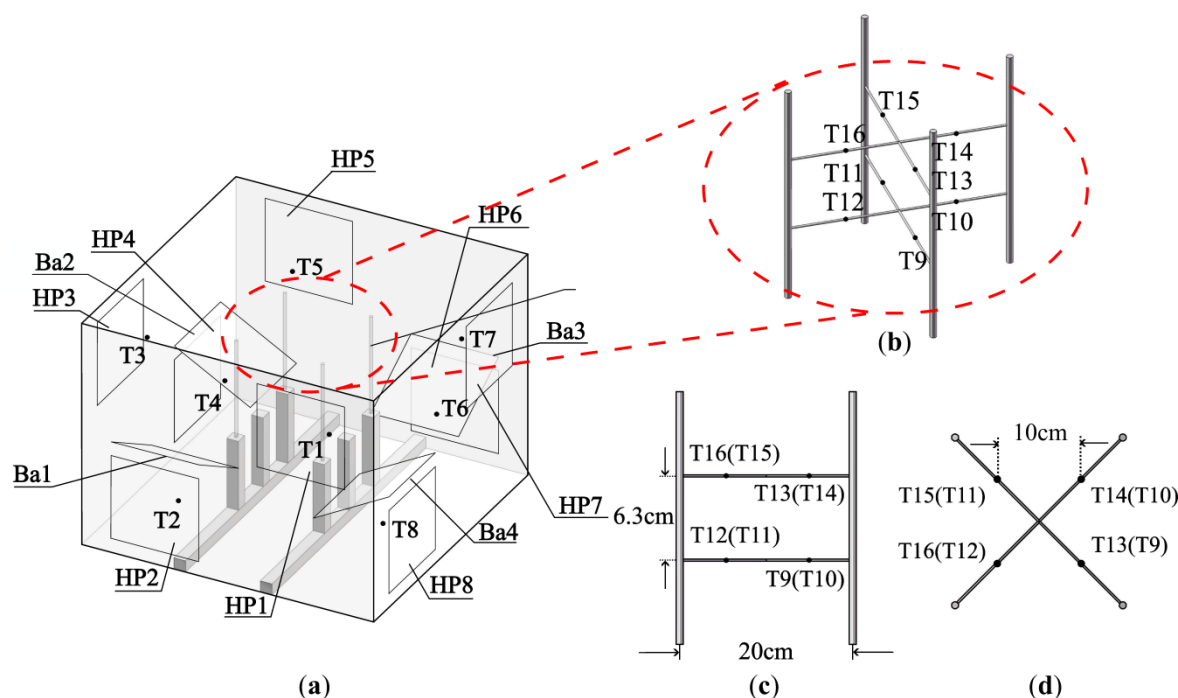


Figure 3. (a) Schematic diagram of control points. (b) Schematic diagram of work points. (c) Front view of the support. (d) Top view of the support.

In control systems, temperature variations exhibit nonlinear characteristics, high inertia, and long lag times. The controlled variables in typical temperature control systems can generally be modeled as first-order plus dead time (FOPDT) processes, as expressed in Equation (1):

$$H_{ij}(s) = \frac{K_{ij}e^{-\tau s}}{T_{ij}s+1}, (i,j=1,2,3,4) \quad (1)$$

In the formula, K_{ij} denotes the static gain, T_{ij} is the time constant, and τ represents the pure lag time. The transfer function H matrix of this system was determined experimentally using the orthogonal basis vector method. When only one heater group is activated, for example, the system input column vector $(1, 0, 0, 0)^T$ yields the first column of matrix H as its output, as shown in Equation (2):

$$H(1,0,0,0)^T = (H_{11}, H_{21}, H_{31}, H_{41})^T \quad (2)$$

Therefore, in the experiment, the values of the entire transfer function matrix H can be determined by sequentially activating four groups of heaters individually with the same thermal power. The power of each heating element group was set to 50 W, and the experiment was conducted under conditions of an initial system temperature of 25 °C and a set temperature of 30 °C. The identification was performed at a fixed power level of 50 W, and the resulting FOPDT model represents a local linearization of the system at this operating point. This modeling choice is consistent with the use of linear PID controllers, which inherently rely on local linear approximations of the plant dynamics. At power levels significantly deviating from 50 W, such as 25 W or 75 W, the model parameters would require re-identification, as the natural convection intensity and hence the heat transfer characteristics would differ. The results demonstrate how the dynamic relationship between the heating elements and the system response is quantified and reflected in the H matrix, as presented in Equation (3)

$$H = \begin{pmatrix} \frac{0.1128e^{-15.67s}}{176.78s+1} & \frac{0.0881e^{-30.675s}}{384.13s+1} & \frac{0.0675e^{-36.896s}}{383.73s+1} & \frac{0.0996e^{-18.233s}}{372.06s+1} \\ \frac{0.0682e^{-18.233s}}{339.89s+1} & \frac{0.1569e^{-17.661s}}{185.30s+1} & \frac{0.0715e^{-51.220s}}{345.10s+1} & \frac{0.1008e^{-42.186s}}{328.98s+1} \\ \frac{0.0219e^{-20.621s}}{349.21s+1} & \frac{0.0357e^{-47.635s}}{346.51s+1} & \frac{0.01654e^{-22.725s}}{194.25s+1} & \frac{0.0300e^{-19.783s}}{320.82s+1} \\ \frac{0.0336e^{-17.771s}}{347.35s+1} & \frac{0.0271e^{-34.514s}}{377.21s+1} & \frac{0.0329e^{-16.486s}}{331.84s+1} & \frac{0.1268e^{-25.400s}}{151.02s+1} \end{pmatrix} \quad (3)$$

After the transfer function matrix H was experimentally determined, the study further evaluated it using a partial-load startup operating scenario. It should be noted that the identified FOPDT model is valid within the 25–30 °C temperature range used for identification; deviations from this range are expected to introduce progressively larger modeling errors, as the system exhibits inherent nonlinearity due to the dependence of natural convection intensity on temperature.

It is worth emphasizing that the proposed modeling and controller design methodology is general and does not rely on the specific placement of the control points; relocating the sensors would only require re-identification of the transfer function matrix and re-optimization of the PID parameters within the same procedural framework. In this scenario, only a subset of heating elements was simultaneously activated to operate at full power (with the operating condition vector denoted as $(1, 0, 1, 1)^T$). The eight heating elements were pre-divided into four groups according to the opposite grouping method (see Section 3.1 for detailed grouping rules). The active heating groups were powered on for a set period and then switched off to allow natural equilibration. System experiments and simulations were conducted to compare the results, aiming to verify the accuracy and applicable scope of the derived transfer function model. The corresponding comparative analysis results are presented in Figure 4.

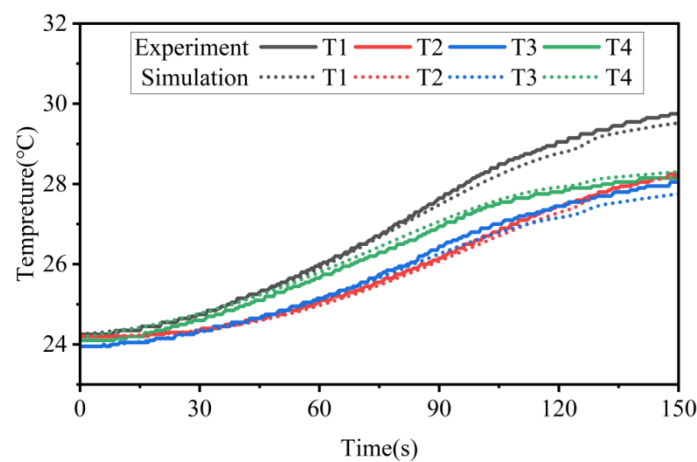


Figure 4. Verification temperature curve of the transfer function model under $(1, 0, 1, 1)$ operating conditions.

Analysis of the curves in the graph reveals that during the initial 150 s interval, the simulated temperature variation trajectories at the four points deviated from the measured data with an average absolute error of 0.17 °C and a maximum error of 0.30 °C, demonstrating good quantitative agreement between the model and the actual system. Given that the control actions are executed at a frequency exceeding 1 Hz, this finding further validates the appropriateness of employing a linearization approximation for the system, which is an approach that can be adopted without a significant accuracy compromise. These results not only confirm the effectiveness of the transfer function model but

also provide a theoretical foundation for subsequent system design and parameter optimization efforts.

2.2. Control Strategies and Parameter Optimization

The primary workflow of PID control is as follows: the difference between the set-point $r(t)$ and the actual output temperature t serves as the controller's input $e(t)$, and adjusting the output based on the control error feedback to bring the controlled variable close to the desired value. In a multi-PID controller array, each measurement point is individually controlled by a group of heating elements located in close proximity within the space. The controller is configured as a 4×4 diagonal matrix; Figure 5 shows the schematic diagram of this MIMO temperature control. This control method requires tuning 12 parameters across four PID controllers. Common PID tuning methods include empirical tuning, the Ziegler–Nichols method, the Cohen–Coon method, the IAE (Integral Absolute Error) method, and the frequency-domain approach.

In the PID parameter optimization process, both the ZN tuning method and the GA (genetic algorithm) were employed. Within the GA, two distinct evaluation metrics were utilized, yielding three sets of PID parameters in total.

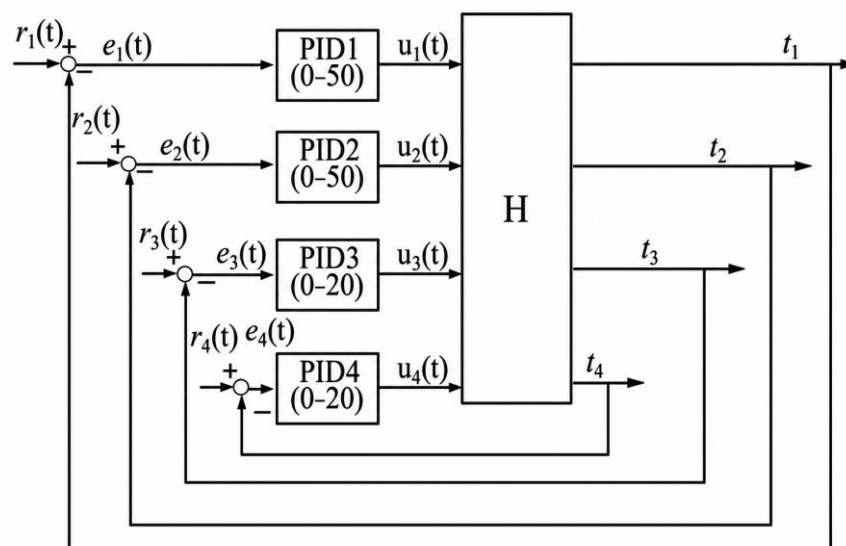


Figure 5. Multi-PID controller array principle.

During PID controller parameter tuning, the traditional approach utilizes the principle of the similar triangle to derive $a = K\tau/T$. This allows the determination of PID control parameters through ZN-based calibration using reference tables, as shown in Table 1.

Table 1. Ziegler–Nichols tuning formula.

Type	Response to a Step Function		
	K_p	K_i	K_d
P	$1/a$	0	0
PI	$0.9/a$	3τ	0
PID	$1.2/a$	2τ	$2/\tau$

The Ziegler–Nichols empirical formula provided preliminary parameter tuning results for the multi-PID controller array. Building upon this foundation, the MATLAB (2022a) PID-tuner toolbox was employed to achieve optimal control performance through manual fine-tuning. The Ziegler–Nichols values were used as the initial reference, and

then each channel was calibrated more precisely using MATLAB's built-in PID-tuner. After these two tuning steps, the resulting PID parameter matrix is denoted as P_{ZN} , and the corresponding control scheme is defined as Approach 1 in subsequent analyses. Element P_{ij} in matrix P_{ZN} represents the j -th parameter of the i -th control channel, where $j = 1, 2, 3$ corresponds to the proportional gain K_p , integral gain K_i , and derivative gain K_d , respectively. The final parameter matrix is presented in Equation (4).

$$P_{ZN} = \begin{pmatrix} K_{p1} & K_{i1} & K_{d1} \\ K_{p2} & K_{i2} & K_{d2} \\ K_{p3} & K_{i3} & K_{d3} \\ K_{p4} & K_{i4} & K_{d4} \end{pmatrix} = \begin{pmatrix} 120 & 31.34 & 7.835 \\ 80 & 35.32 & 8.83 \\ 63.16 & 45.45 & 11.36 \\ 57.14 & 50.8 & 12.70 \end{pmatrix} \quad (4)$$

A key challenge in tuning PID parameters is adjusting multiple parameters simultaneously, a procedure that is complex, time-consuming, and often relies on trial-and-error. To address this, we propose transforming the parameter tuning problem into a constrained global optimization solved by a genetic algorithm. The genetic algorithm is selected for three primary reasons. First, the objective functions are non-convex with multiple local optima due to system nonlinearity and thermal coupling, where gradient-based methods would risk converging to suboptimal solutions. GA performs a global search through its population-based evolution mechanism, significantly reducing this risk. Second, the 12 PID parameters constitute a high-dimensional search space with mixed discrete–continuous variables, which GA handles naturally without requiring differentiability or convexity assumptions. Third, GA has been widely validated for PID tuning in complex thermal systems, demonstrating consistent effectiveness. While alternative metaheuristics such as particle swarm optimization could be applied, GA offers a well-established balance between global search capability, implementation simplicity, and computational efficiency for the present problem. This choice is further validated by the performance comparison against Ziegler–Nichols tuning in both simulation and experiment. In this study, the parameters of the PID controllers to be tuned are represented by an array of twelve elements, as shown in Equation (5):

$$P_{GA} = \begin{pmatrix} K_{p1} & K_{i1} & K_{d1} \\ K_{p2} & K_{i2} & K_{d2} \\ K_{p3} & K_{i3} & K_{d3} \\ K_{p4} & K_{i4} & K_{d4} \end{pmatrix} \quad (5)$$

In the formula, K_p , K_i , and K_d are the parameter values of the PID controller corresponding to group i .

The objective function J comprehensively evaluates the stability t_{stab} , accuracy t_{acc} , and uniformity t_{uni} of the four temperature time series $\{t_{ij}\}$ ($i = 1, 2, 3, 4; j > 0$), which are defined in Equation (6):

$$\begin{aligned} t_{stab} &= \max_i \left(\sqrt{\sum_{j>j_0} (t_{ij} - \bar{t})^2} \right), i=1,2,3,4, j_0=1200 \\ t_{acc} &= \max_{j>j_0} |t_{ij} - t_{SV}|, i=1,2,3,4, j_0=1200 \\ t_{uni} &= \frac{1}{N} \sum_{k=1}^N \sqrt{\frac{1}{4} \sum_{i=1}^4 (T_i(k) - \bar{T}(k))^2} \end{aligned} \quad (6)$$

Two distinct sets of PID parameters were obtained by applying two different objective functions, with the respective objective functions being, as defined in Equation (7):

$$J_1 = 0.6t_{\text{stab}} + 0.4t_{\text{acc}}$$

$$J_2 = 0.4t_{\text{stab}} + 0.3t_{\text{acc}} + 0.3t_{\text{uni}} \quad (7)$$

The parameters tuned using the genetic algorithm require achieving the minimum values for J_1 and J_2 .

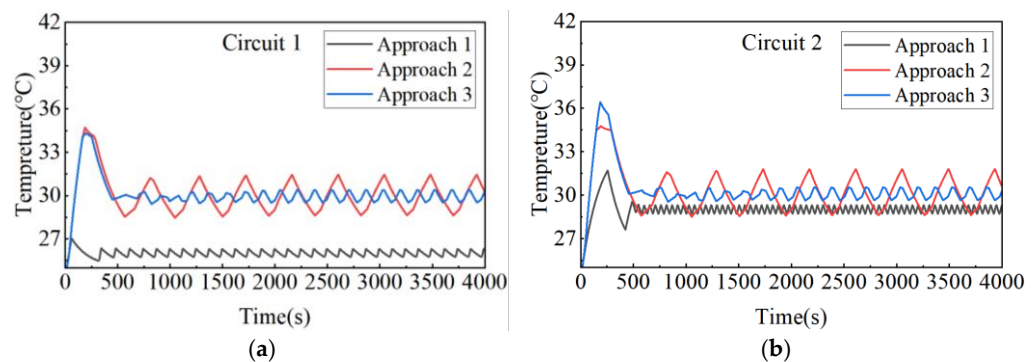
In the aforementioned expression, t_{stab} represents the maximum root mean square error of the four-channel temperature data, used to assess the stability of the temperature field over time; t_{acc} is defined as the maximum absolute temperature difference between the four-channel temperature data and the set point t_{sv} , indicating control accuracy; t_{uni} denotes the standard deviation of the four-channel temperature samples at a given instant, reflecting the spatial uniformity of the temperature distribution. The simulation duration is 4000 s, with the system considered to reach a steady state after 1200 s. Temperature data from this period are employed for optimizing performance metrics, and the sampling frequency is set at 1 Hz.

The parameter combination obtained through the GA optimization program is shown in Equation (8). Here, P_1 represents the optimization result for target parameter J_1 , while P_2 corresponds to the optimization result for target parameter J_2 .

$$P_1 = \begin{pmatrix} K_{p1} & K_{i1} & K_{d1} \\ K_{p2} & K_{i2} & K_{d2} \\ K_{p3} & K_{i3} & K_{d3} \\ K_{p4} & K_{i4} & K_{d4} \end{pmatrix} = \begin{pmatrix} 19.040 & 0.003 & 7.800 \\ 1.912 & 0.860 & 0.643 \\ 8.252 & 0.759 & 2.442 \\ 5.445 & 0.971 & 4.609 \end{pmatrix}$$

$$P_2 = \begin{pmatrix} K_{p1} & K_{i1} & K_{d1} \\ K_{p2} & K_{i2} & K_{d2} \\ K_{p3} & K_{i3} & K_{d3} \\ K_{p4} & K_{i4} & K_{d4} \end{pmatrix} = \begin{pmatrix} 19.562 & 2.804 & 6.520 \\ 4.760 & 0.367 & 0.986 \\ 0.358 & 0.121 & 0.440 \\ 2.950 & 1.509 & 1.344 \end{pmatrix} \quad (8)$$

To compare the differences in actual control performance among the three parameter tuning schemes mentioned above, this study conducted simulations under unified conditions. The initial simulation temperature was set at 24 °C, the target temperature at 30 °C, and the total simulation duration was 4000 s. The parameter scheme obtained using the ZN tuning method is designated as Approach 1, while the GA optimization schemes with target parameters J_1 and J_2 are sequentially labeled as Approach 2 and Approach 3. The comparative temperature response curves of the three schemes are shown in Figure 6.



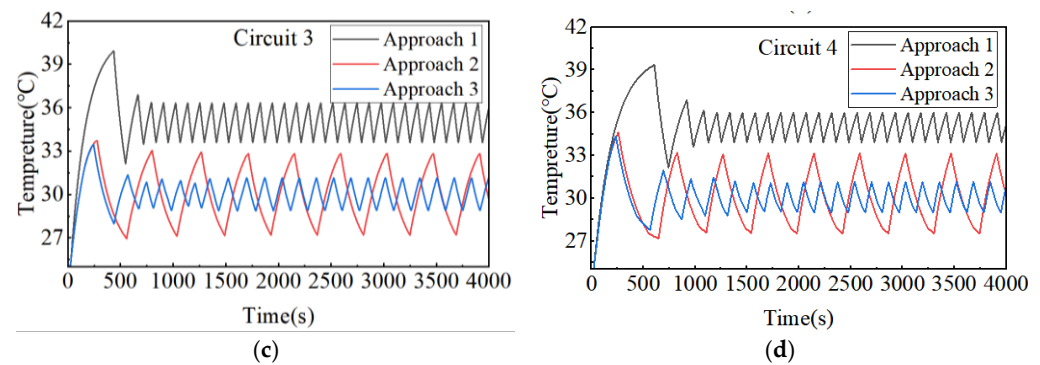


Figure 6. Simulated temperature responses of the multi-PID controller array under different parameter optimization schemes: (a) Circuit 1, (b) Circuit 2, (c) Circuit 3, and (d) Circuit 4. Each subfigure compares the performance of Approach 1 (ZN tuning), Approach 2 (GA optimization with objective function J_1), and Approach 3 (GA optimization with objective function J_2).

Approach 1 employs the ZN method for PID parameter tuning. Simulation curves reveal that under this approach, the four channels reach markedly different steady-state temperatures. Specifically, T4 reaches approximately 34.7 °C, while T1 stabilizes at about 26.4 °C; the other two channels settle at intermediate values. Consequently, the average steady-state temperature across the four channels is approximately 34.30 °C, yielding an average deviation of 4.3 °C from the setpoint of 30 °C. During the steady-state phase, the temperature curves continue to show persistent fluctuations within ± 1.82 °C, suggesting oscillatory behavior near the steady state. These figures indicate insufficient control accuracy and poor spatial uniformity. Overall, the ZN tuning scheme demonstrates suboptimal performance in stability, accuracy, and uniformity, with its limitations particularly pronounced in large-inertia, strongly coupled MIMO temperature control systems.

Approach 2 employs a genetic algorithm optimization strategy based on objective function J_1 to determine PID parameters. Compared to the first approach, this method demonstrates certain improvements in control performance. The average temperature of the four channels is 31.43 °C, which is closer to the setpoint of 30 °C than the average of Approach 1 (34.30 °C). During the period after 1200 s, each channel's temperature oscillates around its mean value with an amplitude of approximately ± 0.35 °C. Compared to Approach 1, the oscillation amplitude is larger. However, the key improvement is that the mean values of the channels are much closer to the setpoint, resulting in a smaller average deviation. The maximum absolute deviation from the setpoint among the four channels is 3.26 °C, observed at T3. The deviation at T4 is also substantial and close to that at T3. The temperature uniformity is quantified by the metric t_{uni} defined in Equation (6), i.e., the temporal average of the spatial standard deviation across the four channels during the period after 1200 s. The computed t_{uni} for this approach is 3.17 °C. However, the dynamic response reveals that the system does not reach a steady state within the simulation horizon. The channel temperatures continue to exhibit persistent oscillations, without settling into a stable band. This indicates that under objective function J_1 , the controller fails to achieve true steady-state behavior, and further optimization is needed to balance convergence and accuracy.

Approach 3 employs a genetic algorithm optimization strategy based on objective function J_2 to determine PID parameters. Compared to Approach 2, J_2 incorporates an additional temperature uniformity factor into its objective function formulation, aiming to further minimize temperature variations between channels. Simulation results show that the average temperature of the four channels under Approach 3 is 31.75 °C. During the period after 1200 s, each channel's temperature oscillates around its mean value with an

amplitude of approximately ± 0.39 °C. Both the mean temperature and the oscillation amplitude exhibit only minimal changes compared to Approach 2, without any significant order-of-magnitude shifts. The maximum absolute deviation from the setpoint among the four channels, i.e., the absolute error, is 1.79 °C, which represents a nearly 45% decrease from Approach 2 (3.26 °C). This indicates that the integration of uniformity constraints in the optimization objective leads to more balanced temperature control across the system channels and effectively alleviates excessive errors at individual points. The temperature uniformity metric t_{uni} , defined in Equation (6), reaches 2.11 °C for Approach 3, demonstrating substantial improvement over the other two solutions. From a dynamic response perspective, Approach 3 exhibits smoother regulation processes with reduced overshoot magnitudes compared to Approach 2.

The comparison above demonstrates that the parameter-tuning strategy based on genetic algorithms significantly outperforms the traditional ZN engineering tuning method across all performance metrics. The inferior performance of Approach 1 arises from the Ziegler–Nichols method’s inherent limitation: it is based on a DOPDT approximation for each channel and thus cannot adequately account for thermal coupling among the four channels. In contrast, the genetic algorithm optimizes all 12 PID parameters simultaneously, balancing stability, accuracy, and uniformity within a unified objective function, thereby achieving a more favorable trade-off for this strongly coupled MIMO system. Among the two GA optimization approaches, Approach 2 exhibits an advantage in convergence speed, while Approach 3 demonstrates superior performance in overall control quality, particularly in system stability and spatial temperature uniformity, due to its comprehensive consideration of the uniformity criterion in the objective function. The diagonal structure of the transfer function matrix represents a deliberate trade-off between modeling accuracy and controller tunability. Incorporating off-diagonal coupling terms would require a substantial increase in the number of PID parameters to be optimized, which would significantly expand the search space for the genetic algorithm and compromise the reliability and uniqueness of the optimization results. Instead, the diagonal structure relies on the spatial layout of the heating elements and points to minimize physical coupling, while the GA optimization implicitly compensates for the residual unmodeled coupling by coordinating the parameter sets of all four controllers within a unified objective function that balances stability, accuracy, and uniformity. Consequently, Approach 3 was selected as the PID parameter configuration scheme for the subsequent experiments of this study, as summarized in Table 2.

Table 2. Comparison of simulation performance indicators for three PID parameter tuning schemes.

Evaluating Indicator	Approach 1 (ZN)	Approach 2 (GA- J_1)	Approach 3 (GA- J_2)
Convergence Value (°C)	34.30	31.43	31.75
t_{stab} (°C)	± 1.82	± 0.35	± 0.39
t_{acc} (°C)	12.90	3.26	1.79
t_{uni} (°C)	16.47	3.17	2.11

Through the aforementioned simulation and comparative analysis, the following conclusion can be drawn: For a MIMO temperature control system with four inputs, four outputs, high inertia, and channel coupling, employing an effective optimization algorithm for global parameter tuning of the controller, compared to traditional setting methods reliant on empirical formulas, can more effectively balance multiple control objectives such as stability, accuracy, and uniformity, providing a more valuable parameter basis for the practical implementation of the system.

2.3. Experimental Equipment and Procedure

The temperature control system for the incubator developed in this study employs a four-input, four-output closed-loop feedback control architecture, as illustrated in Figure 7. In the temperature acquisition module, 16 K-type thermocouples are deployed: eight serve as control points positioned 100 mm in front of each heating element array to monitor the gas temperature near the heating zones, and the remaining eight function as working points fixed on a cubic crossbeam at the chamber center to assess temperature uniformity in target areas. All thermocouple signals are processed by temperature transmitters and transmitted to the host computer via the Modbus protocol over an RS485 bus. The host computer, acting as the control core, runs a multi-PID controller array program written in Python 3.8 that generates four independent control signals in real-time based on deviations between preset targets and actual temperatures. These signals are converted into PWM square waves with independently adjustable duty cycles by pulse output modules and distributed to two parallel execution channels. In the heating circuit, PWM signals are amplified to 24 V through solid-state relays, driving four sets of PI film heating elements to deliver continuously adjustable heat within the 0–100 W range. In the baffle angle control module, PWM signals simultaneously activate servos to precisely rotate nylon baffles at angles ranging from 45° to 110° relative to the vertical axis, thereby altering the natural convection airflow patterns inside the chamber.

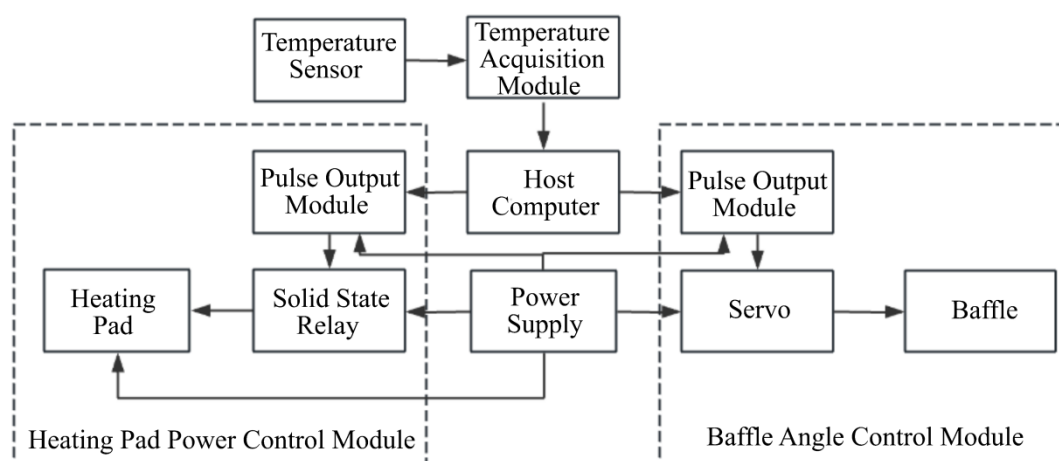


Figure 7. Schematic diagram of temperature control system for thermostat.

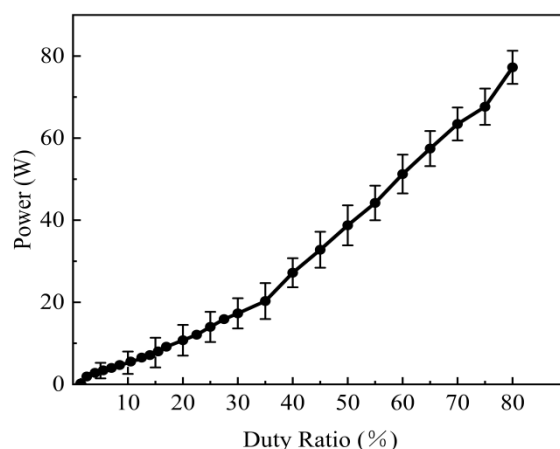
To establish a four-input, four-output MIMO control architecture, the eight heating elements inside the box must be grouped accordingly. The grouping principle requires that heating elements within the same control loop must be positioned simultaneously in either the upper or lower section of the box to ensure a symmetrical temperature field distribution. The first grouping method is relative grouping: pairs of heating elements located on opposite walls and in the same upper or lower section are grouped together (HP1 and HP5 form the first group, HP3 and HP7 the second group, HP2 and HP6 the third group, HP4 and HP8 the fourth group). The second grouping method is adjacent grouping: pairs of heating elements situated on adjacent walls and in the same upper or lower section are grouped (HP1 and HP3 the first group, HP5 and HP7 the second group, HP2 and HP4 the third group, HP6 and HP8 the fourth group). The correspondence between these two grouping methods is detailed in Table 3.

Table 3. Opposite group and adjacent group situations.

	Circuit 1	Circuit 2	Circuit 3	Circuit 4
Opposite group	HP1/HP5	HP3/HP7	HP2/HP6	HP4/HP8
Adjacent group	HP1/HP3	HP5/HP7	HP2/HP4	HP6/HP8

The baffle serves as the core component in this experiment for passive airflow guidance and intervention of natural convection paths. Three characteristic angles were selected for comparison. At 45°, the baffle forms a small angle with the vertical axis, exerting the strongest lateral obstruction on the rising hot air along the wall, forcing it to move upward primarily close to the wall. At 60°, the obstruction and guidance are intermediate between the two. At 90°, the baffle approaches perpendicular to the vertical axis, virtually eliminating lateral airflow obstruction and allowing the hot air to diffuse freely toward the central region of the chamber. These three angles cover the full range from strong obstruction to near-zero obstruction, providing a clear gradient for subsequent quantitative analysis of the baffle angle's impact on temperature uniformity.

Prior to the experiment, the actual output power of each heating element group under different PWM duty cycles was calibrated using a power meter; the calibration results are shown in Figure 8. This step aimed to minimize individual variations among the heating elements and the additional effects caused by the nonlinear characteristics of the drive circuit. The temperature acquisition system collects temperature signals from all thermocouples at 0.5 s intervals. After being processed by the temperature transmitter (accuracy of ± 0.1 °C), the signals are transmitted to the host computer via the RS485 bus using the Modbus protocol.

**Figure 8.** Relation between the heating element power and its duty ratio.

To evaluate the performance of different grouping configurations, response experiments were conducted under both adjacent and relative grouping conditions. In these experiments, the baffle angle was set at 45°. Once the temperature stabilized, four heating elements were activated sequentially at the same thermal power (50 W), while the remaining elements remained inactive; the heating duration ranged from 0 to 120 s, with temperature data recorded at control points. The experimental naming convention was as follows: when only Circuit 1 was activated, and the other heating elements were inactive, the experiment was designated as (1, 0, 0, 0).

Secondly, to investigate the temperature field distribution and airflow patterns within the chamber under varying baffle angles, as well as the influence of angle on the central measurement point, response experiments were conducted separately for baffle angles of 60° and 90° under relative grouping conditions. In each experiment, four heating

elements were activated individually at the same thermal power (50 W), while the remaining elements remained inactive; the heating duration ranged from 0 to 120 s, with temperature data from the control measurement point being recorded simultaneously.

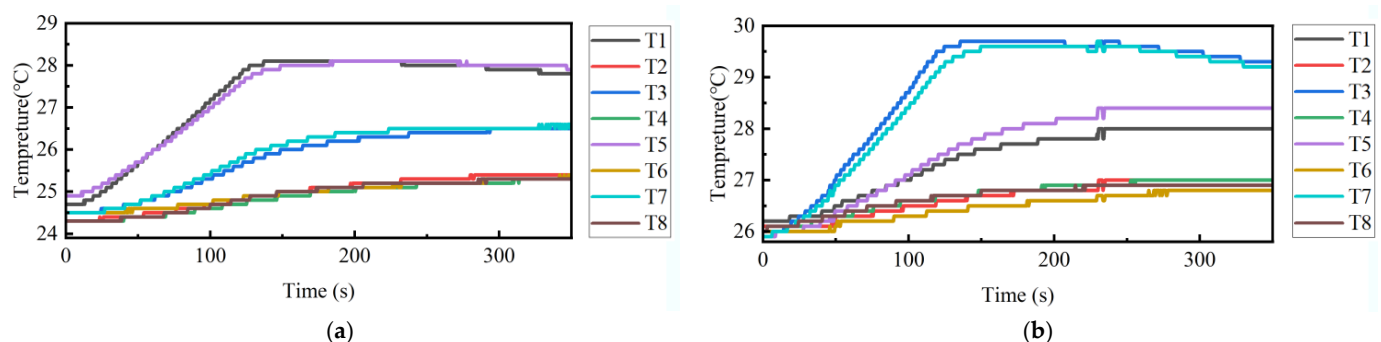
A control experiment was ultimately conducted. In the multi-PID controller array experiment, the parameters obtained through ZN tuning and GA optimization were applied to the actual control system to establish the control code. This code outputs the actual power and drives the heating element via PWM technology to enable the heating process. The experimental control conditions were set as follows: the target control temperature was set to 30 °C, the entire control process lasted 800 s, and the control cycle was 1 s.

To systematically investigate the effects of heating element grouping configurations and baffle angle on the temperature field, this chapter establishes a progressive experimental matrix. Under two grouping configurations, namely relative grouping and adjacent grouping, baffle angles of 45°, 60°, and 90° were employed, yielding six distinct operational combinations. Experiments were labeled using a four-element array (a_1, a_2, a_3, a_4), where a_1 to a_4 indicate the operational status of each heating element group, corresponding to Circuit 1 through Circuit 4 as defined in Table 3, respectively: 1 denotes activation, and 0 denotes deactivation. For each configuration, four sub-experiments were conducted sequentially: (1, 0, 0, 0), (0, 1, 0, 0), (0, 0, 1, 0), and (0, 0, 0, 1), with only one heating element group activated at a constant power output of 50 W while the remaining three remained inactive. This design yielded a total of 24 valid experimental datasets, consisting of two grouping methods, three baffle angles, and four heating conditions. All experiments were repeated three times under identical conditions. The results are reported as mean values.

3. Results and Discussions

3.1. The Impact of Heating Pad Grouping Methods

In the experiment on altering the grouping method, the baffle angle was fixed at 60°. Two grouping methods, adjacent grouping or opposite grouping, were employed. Four heating elements were activated sequentially at 50 W, while the remaining elements remained inactive. The heating duration was 120 s, after which the heating was turned off. Temperature data from the control points (T1–T8, defined in Section 2.1) were continuously recorded during the subsequent natural cooling phase. The experimental data for the opposite grouping are shown in Figure 9.



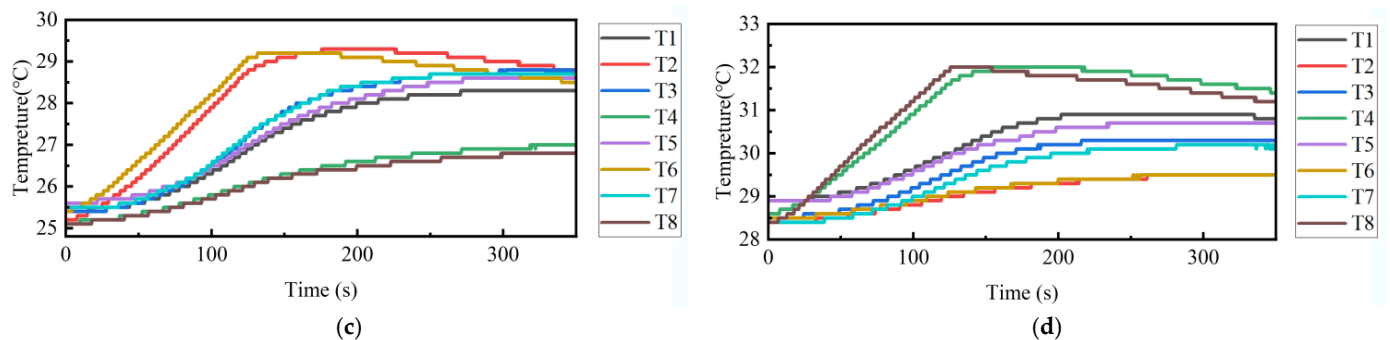


Figure 9. Temperature responses of the control points under opposite grouping configuration for different activated heating circuits: (a) Circuit 1 only (1, 0, 0, 0); (b) Circuit 2 only (0, 1, 0, 0); (c) Circuit 3 only (0, 0, 1, 0), and (d) Circuit 4 only (0, 0, 0, 1).

In the relative grouping where only the first heating group is activated (i.e., the (1, 0, 0, 0) experiment), heating elements No. 1 and No. 5 (upper part of the chamber) are activated, while the remaining heating elements remain off. At the start of heating, the temperatures of T1 and T5 rise rapidly. After a period of heating, the temperatures of the other upper points (T3 and T7) increase more quickly than those of the lower points (T2, T4, T6, and T8). This occurs because, upon activation of the upper heating elements, the air near them, being less dense than cold air, rises and moves upward and toward the left, resulting in a slower temperature increase at T3 and T7. Simultaneously, the presence of the baffle suppresses the downward airflow, leading to a slower temperature rise in the lower region. In other words, activating the upper heating elements also engages a secondary heating group, which consists of the same upper heating elements.

In the experiment where only the third heating group (i.e., 0010) was activated within the relative grouping, the temperature curve exhibited significant differences from the previous two groups. Notably, the temperatures of T1, T3, T5, and T7 rose markedly faster than those of the preceding groups, with T3 and T7 slightly higher than T1 and T5. This occurred because, when the bottom heating elements began operating, the surrounding air near them moved upward along the wall, was deflected by the baffle, and then flowed upward along both sides of the wall, thereby raising the air temperature near the upper heating elements. Since points T3 and T7 were closer to the heating elements HP2 and HP6 compared to T1 and T5, their temperature increases were more rapid. Additionally, when the lower heating elements were activated, two secondary heating groups emerged on the upper chamber surface. The secondary group opposite the main heating group exhibited slightly higher temperatures than the other. In the experiment where only the second and fourth heating groups (i.e., 0100 and 0001) were activated, the data closely resembled those obtained with the first and third heating elements (i.e., 1000 and 0010), due to the chamber's symmetry.

Figure 9 also shows that after heating is stopped at 120 s, temperatures at all points continue to rise slowly, exhibiting significant thermal inertia. This occurs because the temperature gradient allows heat to transfer from higher-temperature areas to lower-temperature areas; even after heating ceases, the delay in heat transfer causes the temperatures at points to continue rising. Additionally, due to thermal inertia, temperature changes lag behind adjustments in heating control. Furthermore, after heating stops, the heating pad's temperature does not decrease immediately but continues to emit heat as a heat source.

As shown in Figures 9 and 10, the temperature response curves of the opposite and adjacent grouping methods exhibit broadly similar trends. In both cases, the overall temperature rise follows a comparable pattern: the directly heated channels show a rapid initial increase, while the non-heated channels experience a delayed but gradual tempera-

ture rise due to thermal coupling through natural convection. Additionally, both grouping methods exhibit the secondary heating phenomenon, where the activation of heating elements in one location indirectly raises the temperature at other points. After heating ceases at 120 s, both configurations display significant thermal inertia, with temperatures continuing to rise for a period before gradually stabilizing. The primary differences between the two grouping methods lie in the specific values of the fitted parameters (initial temperature, heating rate, and delay time). To enable a more precise comparison between the two grouping methods, linear fitting with a delay component was applied to each dataset, using the following fitting formula, as expressed in Equation (9):

$$T(t) = T_0 + k(t - t_{\text{delay}}), t \geq t_{\text{delay}}$$

$$T(t) = T_0, t < t_{\text{delay}} \quad (9)$$

In the fitting formula, $T(t)$ denotes the instant temperature ($^{\circ}\text{C}$), T_0 is the initial temperature ($^{\circ}\text{C}$), t represents time (s), t_{delay} is the delay time (s), and k is the heating rate ($^{\circ}\text{C/s}$).

The data obtained from curve fitting are presented in Tables 4 and 5. To provide a more intuitive representation of the heating rate, the values listed are expressed as $k \times 100$.

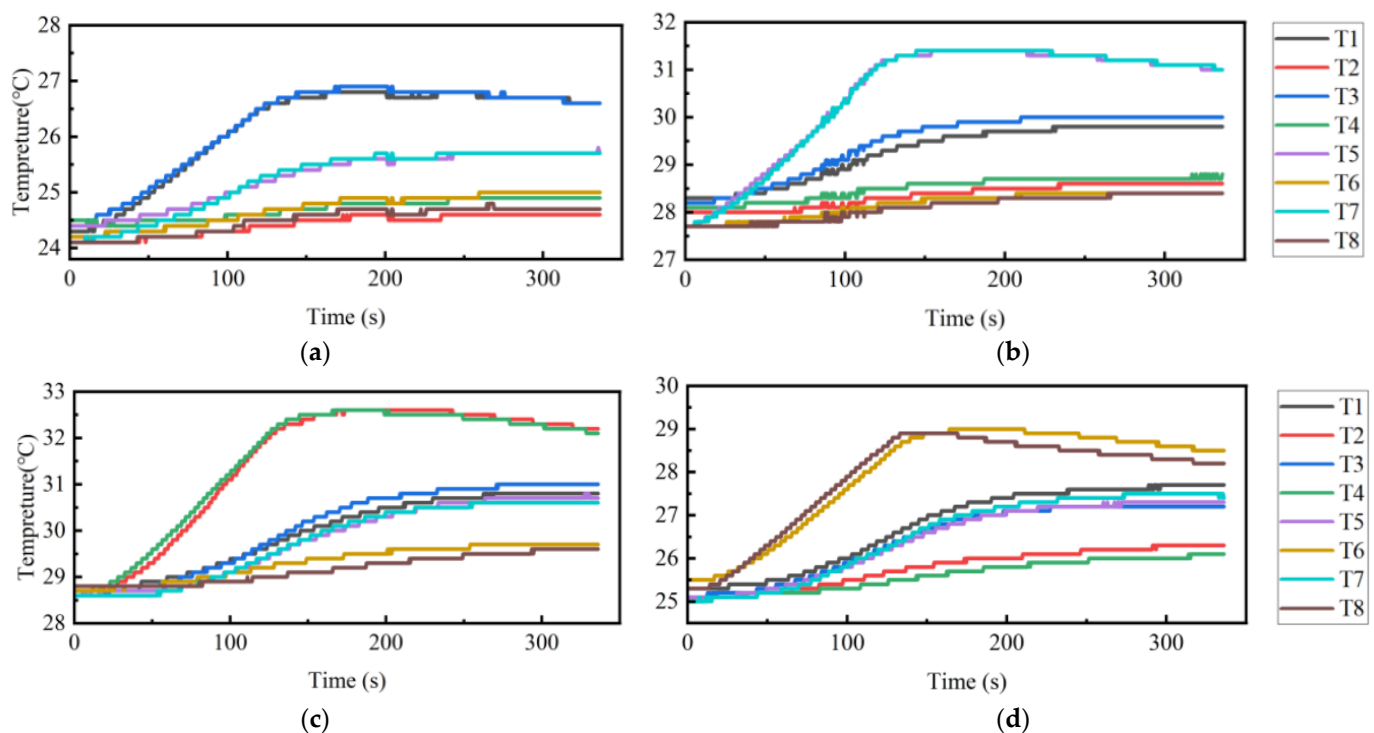


Figure 10. Temperature responses of the control points under adjacent grouping configuration for different activated heating circuits: (a) Circuit 1 only (1, 0, 0, 0), (b) Circuit 2 only (0, 1, 0, 0), (c) Circuit 3 only (0, 0, 1, 0), and (d) Circuit 4 only (0, 0, 0, 1).

Table 4. Opposite group fitting temperature data.

Heating Method	1000			0100			0010			0001		
Measure Point	T_0	$k \times 100$	t_{delay}	T_0	$k \times 100$	t_{delay}	T_0	$k \times 100$	t_{delay}	T_0	$k \times 100$	t_{delay}
Unit	$^{\circ}\text{C}$	$^{\circ}\text{C/s}$	s	$^{\circ}\text{C}$	$^{\circ}\text{C/s}$	s	$^{\circ}\text{C}$	$^{\circ}\text{C/s}$	s	$^{\circ}\text{C}$	$^{\circ}\text{C/s}$	s
T1	24.73	2.92	17.24	26.21	1.07	46.33	25.46	1.60	44.80	28.93	1.24	42.35
T2	24.30	0.47	19.10	26.00	0.58	54.72	25.29	3.23	19.83	28.40	0.56	27.27
T3	24.52	1.18	32.28	25.92	3.25	37.41	25.44	1.94	44.36	28.54	1.14	43.17

T4	24.30	0.46	33.13	25.90	0.64	14.00	25.17	0.90	32.27	28.65	2.69	16.66
T5	24.94	2.49	18.24	25.97	1.48	47.17	25.65	1.50	45.29	28.91	1.23	47.18
T6	24.50	0.36	32.76	26.00	0.46	52.92	25.49	3.17	14.28	28.50	0.53	27.72
T7	24.52	1.40	34.91	25.95	2.97	40.42	25.52	1.97	46.87	28.42	1.03	46.81
T8	24.30	0.54	34.72	26.00	0.59	19.04	25.14	0.84	30.28	28.43	3.10	9.79

Table 5. Adjacent group fitting temperature data.

Heating Method	1000			0100			0010			0001		
Measure Point	T_0	$k \times 100$	t_{delay}	T_0	$k \times 100$	t_{delay}	T_0	$k \times 100$	t_{delay}	T_0	$k \times 100$	t_{delay}
Unit	°C	°C/s	s	°C	°C/s	s	°C	°C/s	s	°C	°C/s	s
T1	24.33	2.12	19.67	28.32	1.08	41.33	28.80	0.99	44.37	25.34	1.29	46.23
T2	24.10	0.30	30.91	28.00	0.47	62.57	28.76	3.51	33.32	25.06	0.60	30.68
T3	24.53	1.98	22.82	28.24	1.33	29.79	28.64	1.11	36.77	25.16	1.24	41.31
T4	24.44	0.19	36.99	28.10	0.40	30.75	28.74	3.29	24.18	25.10	0.29	23.51
T5	24.43	0.77	30.36	27.77	3.04	14.71	28.70	0.97	56.75	25.12	1.18	41.38
T6	24.20	0.37	14.98	27.70	0.43	25.45	28.71	0.45	20.82	25.55	2.85	27.87
T7	24.15	1.09	27.38	27.80	3.18	19.82	28.60	1.16	55.41	25.09	1.50	49.78
T8	24.10	0.42	37.14	27.70	0.40	45.96	28.80	0.35	69.28	25.32	3.11	18.26

$$t_g = \frac{T_{\text{set}} - T_0}{2 \cdot k_{\text{heated}}}$$

$$\rho_t = \frac{1}{n} \sum k_i \quad (10)$$

The temperature inertia (t_g) and correlation coefficient (ρ_t) were employed to evaluate the two grouping methods. Temperature inertia is defined as the time required for the temperature to reach 50% of the total rise from the initial temperature T_0 to the setpoint T_{set} , calculated according to Equation (11). Here, k_{heated} is the average heating rate of the directly heated channels obtained from the linear fitting. A smaller t_g indicates a faster thermal response and thus better thermal inertia. The correlation coefficient ρ_t is defined as the average heating rate k_i of the unheated control points, as given in Equation (12), where k_i is obtained from the linear fitting. A higher ρ_t value indicates stronger thermal coupling between the heated and unheated channels, which leads to a higher average chamber temperature and improved uniformity at the central measurement point, suggesting superior correlation performance. The evaluation metrics for both grouping methods are detailed in Table 6, confirming that the relative grouping outperforms the adjacent grouping in both temperature inertia and correlation.

Table 6. Comparison of evaluation indicators between opposite and adjacent groups.

	Opposite Group	Adjacent Group
t_g (s)	136.2	232.5
ρ_t (°C/s)	0.01184	0.00905

The superior performance of the relative grouping method can be attributed to the symmetric flow structure it induces within the chamber. When heaters on opposite walls are activated simultaneously, the thermal plumes rise from both sides and converge toward the central region, establishing a symmetric circulation pattern. This symmetric configuration enables more efficient and uniform heat transport from the heated walls to the entire cavity, reducing the thermal resistance between the heat sources and the central

measurement zones. As a result, heat reaches the unheated regions more rapidly, which explains the shorter thermal inertia (t_g) observed for the relative grouping. In contrast, the adjacent grouping activates heaters on neighboring walls, producing an asymmetric flow pattern in which hot air rises along one side and travels a longer path across the chamber top before descending to the opposite side. This extended flow path creates stagnant zones where heat transfer is dominated by slow diffusion rather than convection, leading to larger thermal inertia. Concurrently, the asymmetric circulation provides stronger thermal coupling between the directly heated channels and the unheated points that lie along the primary flow path, but weaker coupling to those in the stagnant zones. The relative grouping, by establishing a more spatially distributed and symmetric flow, achieves a more balanced thermal coupling across all unheated channels, yielding a higher correlation coefficient (ρ_t). These flow-structure differences thus underpin the quantitative advantages of the relative grouping over the adjacent grouping in both thermal inertia and thermal correlation.

3.2. Robustness Assessment of GA-Optimized PID Parameters

While the preceding results demonstrated the superior performance of the GA-optimized PID parameters (Approach 3) under nominal operating conditions, the robustness of these parameters against long-term system variations warrants examination. In practical applications, several factors may gradually alter the system dynamics, including degradation of heating element resistance, aging of thermal insulation, and variations in ambient temperature. To quantitatively assess the robustness of the GA-optimized PID parameters, three representative perturbation scenarios were investigated based on the identified FOPDT model. The first scenario considers heating element degradation, where the static gain K is reduced by 10% to simulate the decrease in heating efficiency due to aging of the PI film heating elements. The second scenario addresses insulation degradation, where the time constant T is reduced by 10% to simulate accelerated heat loss caused by aging or moisture absorption of the rubber-plastic insulation. The third scenario represents lower ambient temperature conditions, where the pure delay τ is increased by 10% to simulate the prolonged initial heating period under reduced environmental temperatures.

The original FOPDT model was modified accordingly for each scenario and closed-loop simulations were performed using the GA-optimized PID parameters (Approach 3) under the same conditions (initial temperature 24 °C, setpoint 30 °C, duration 4000 s). The performance metrics for each scenario are summarized in Table 7.

Table 7. Performance of GA-optimized PID parameters under different perturbation scenarios.

Metric	Approach 3	Scenario A	Scenario B	Scenario C
Convergence value (°C)	31.75	31.49	31.93	32.09
Steady-state error (°C)	±0.39	±0.47	±0.50	±0.53
Absolute error (°C)	1.79	2.06	2.19	2.32
Uniformity (°C)	2.11	2.38	2.52	2.65

The results indicate that under $\pm 10\%$ parameter variations, the steady-state error remains within or near the ± 0.5 °C design target, with Scenario C (increased pure delay) exhibiting the most significant degradation. The absolute error and uniformity show moderate increases across all scenarios, suggesting that while the control quality degrades under parameter variations, the system maintains basic temperature regulation functionality. The degradation sequence follows the order: Scenario C > Scenario B > Scenario A, which is consistent with control theory expectations, as pure delay is the most detrimental factor for PID control performance, followed by time constant reduction due to increased

disturbance susceptibility, while moderate gain reduction has a comparatively milder effect.

The robustness of the GA-optimized PID parameters can be further understood from a control-theoretic perspective. PID control is fundamentally an error-based feedback mechanism that does not rely on an accurate plant model for basic functionality, provided that the closed-loop system remains stable. This inherent characteristic of PID controllers contributes to their tolerance of moderate model mismatches. Moreover, GA optimization seeks a globally optimal parameter set across the entire search space rather than a locally optimal solution, which tends to result in wider stability margins compared to parameters obtained through single-channel approximation methods such as Ziegler–Nichols tuning. The negative feedback loop itself provides a natural mechanism for compensating disturbances and model uncertainties, as any deviation from the setpoint generates a corrective action regardless of its source. This explains why the system maintains basic temperature regulation even when the model parameters deviate from their nominal values.

3.3. Effect of the Baffle on the Temperature Field

To investigate the effect of the baffle on the flow field and temperature distribution, CFD simulations were performed. The simulations were conducted using COMSOL Multiphysics (v6.2) with a time-dependent solver and a time step of 1 s, consistent with the experimental control cycle. The flow was assumed to be laminar based on the Rayleigh numbers in this configuration, which are of the order of 10^6 to 10^7 , and the Boussinesq approximation was adopted for buoyancy-driven flow. No-slip boundary conditions were applied to all solid walls. The heating elements were modeled as heat flux boundaries derived from the experimental PWM signals. The external walls were assigned convective heat transfer boundaries with an equivalent coefficient calculated from the experimental data based on the heat balance equation.

A mesh independence study was performed using three grids with approximately 0.47 million, 4.66 million, and 14.94 million elements. The 4.66-million-element grid was selected for all subsequent simulations, as it provided sufficient accuracy with substantially lower computational cost compared to the finest grid. The convergence criterion was set as a relative tolerance of 0.001. The model was validated against experimental measurements at the control points, showing good agreement in steady-state temperature trends. Table 8 presents the physical properties of the materials used in the simulations.

Table 8. Physical properties of materials involved in simulations.

Air (at 20 °C)	Value	Unit
Density	1.205	$\text{kg} \cdot \text{m}^{-3}$
Thermal capacity	1004	$\text{J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$
Viscosity	17.9×10^{-6}	$\text{Pa} \cdot \text{s}$
Thermal conductivity	0.0267	$\text{W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$
Coefficient of thermal expansion	3.67×10^{-3}	K^{-1}
Aluminum		
Density	2700	$\text{kg} \cdot \text{m}^{-3}$
Thermal capacity	900	$\text{J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$
Thermal conductivity	238	$\text{W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$
Rubber cotton		
Density	538.26	$\text{kg} \cdot \text{m}^{-3}$
Thermal capacity	950.16	$\text{J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$
Thermal conductivity	0.035	$\text{W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$

Figure 11 shows the velocity vector and temperature contour maps at three cross-sections ($y = -12.5$ cm, $y = -20$ cm, and $y = -24$ cm) at 600 s, with and without a baffle. The magnitude of the velocity vector is indicated by the arrow length.

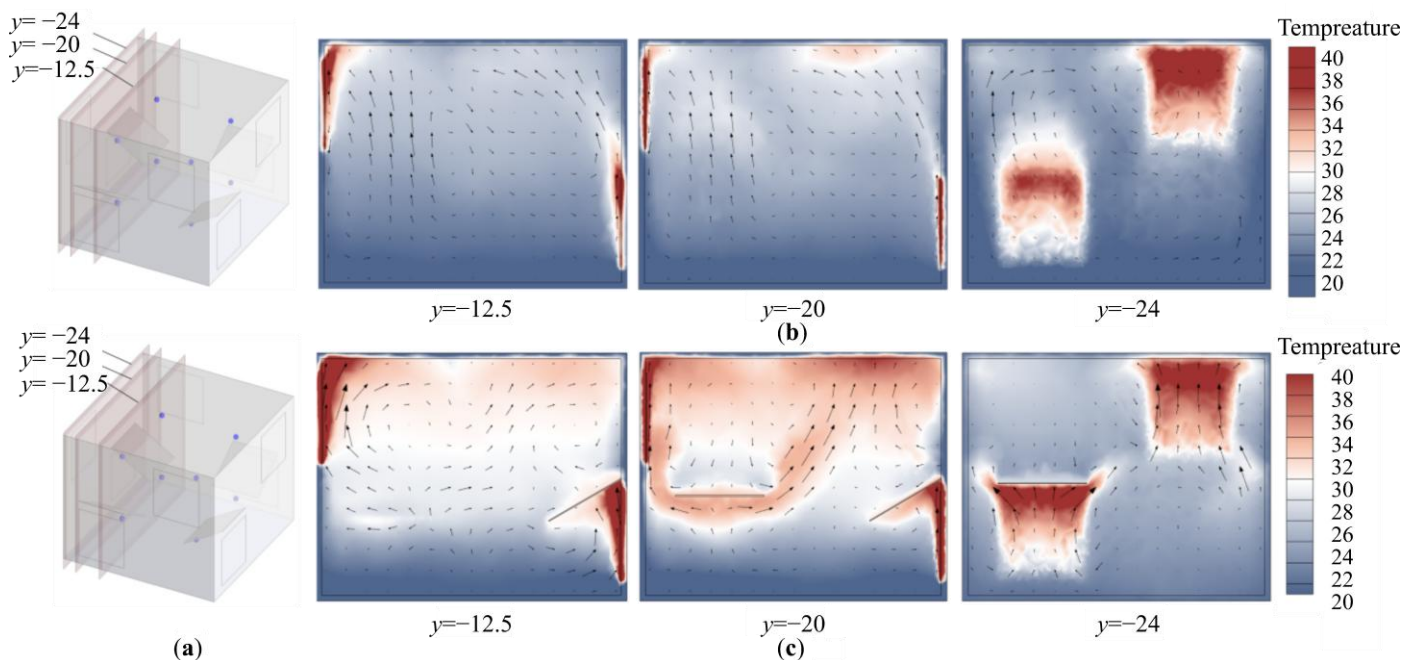


Figure 11. The temperature distribution cloud maps on three sections are shown in (a), which shows the relative positions of the three sections. (b,c) respectively represent the presence or absence of baffles.

In the absence of baffle, the air near the lower side of the chamber, heated by the heating elements, primarily flows upward along the wall with minimal lateral flow. Flow directed toward the center occurs only near the chamber top. Consequently, the overall temperature distribution exhibits higher temperatures at the wall and chamber top, while temperatures are lower in the central and lower sections of the chamber.

The cross-section at $y = -24$ cm was selected to investigate air motion near the wall and the effect of the baffle located in the y -plane on airflow there. The baffle acts as a solid obstacle that interrupts the upward boundary-layer flow along the wall. When the rising hot air impinges upon the baffle, its vertical momentum is redirected, forcing the flow to move laterally toward the chamber interior. Concurrently, the baffle itself is heated by the impinging hot air, which raises its surface temperature and creates an additional heated surface that enhances local thermal radiation and convection to the surrounding air. These two effects together transport more thermal energy from the wall-adjacent region into the central core of the chamber, thereby increasing the central temperature and improving spatial uniformity. Due to the baffle's influence, air flows laterally, altering the temperature distribution in the central and upper sections of the chamber, resulting in higher temperatures and a more uniform overall thermal distribution. The cross-section at $y = -12.5$ cm demonstrates how the baffle in the x -plane affects airflow in the y -plane: air near the lower heating element moves upward but stops in that direction upon encountering the baffle. The cross-section at $y = -20$ cm allows comparison of these two effects. The visualization at this depth shows that without the baffle, cold air flows downward. With the baffle, however, it suppresses this flow while promoting upward movement of hot air, significantly increasing the central temperature and enhancing thermal uniformity within the chamber's central region.

To investigate the temporal evolution of the flow, Figure 12 presents the velocity vectors and temperature cloud maps at the three cross-sections at $t = 200$ s, 400 s, and 600 s. At the cross-section at $y = -12.5$ cm, the airflow exhibits significant temporal variations from $t = 200$ s to $t = 400$ s. Initially, this cross-section is primarily influenced by the heating elements on the front and rear walls but not by the left wall element. The upper-left heating element induces upward airflow along the wall, while the lower-right heating element first promotes upward airflow and is then obstructed by the baffle plate. Consequently, the temperature near the right wall remains lower, causing the central airflow to begin moving toward the upper-right direction. The physical mechanism underlying this initial flow is the temperature asymmetry across the cross-section: the right wall region, being cooler, has higher air density and therefore higher local pressure, which drives the airflow toward that side. As heating progresses from $t = 200$ s to $t = 400$ s, the left wall heating element gradually raises the overall wall temperature, reducing the temperature difference between the left and right sides of the cross-section. This thermal equilibration diminishes the lateral pressure gradient that initially drove the rightward flow, thereby weakening the upward-right tendency and allowing a more symmetric circulation pattern to emerge. After a period of heating, the influence of the left wall heating element elevates the overall wall temperature, reducing the tendency for the central airflow to move upward to the right.

The airflow in the cross-sections at $y = -20$ cm and $y = -24$ cm shows no significant time-dependent variation, as these locations are closer to the left wall and are initially influenced by the heating elements on both the left and front sides.

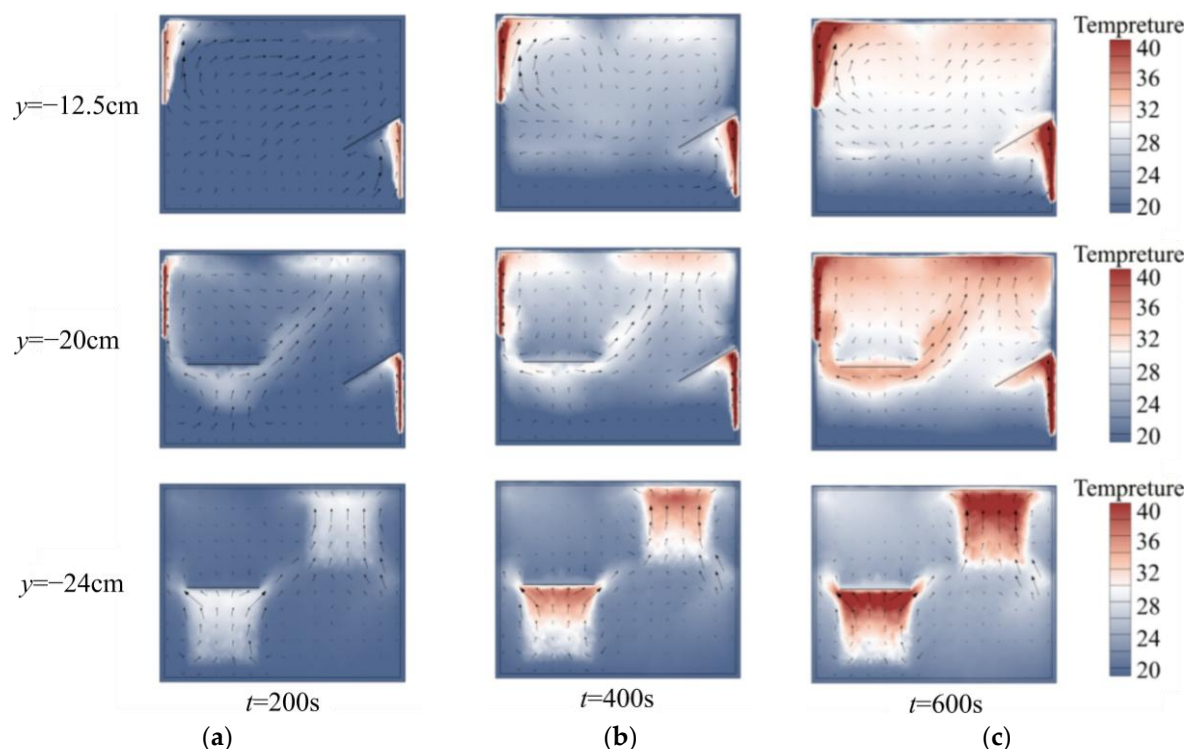


Figure 12. Velocity vectors and temperature distribution cloud maps at three cross-sections with baffles at different times: (a) $t = 200$ s, (b) $t = 400$ s, and (c) $t = 600$ s.

In the experiment on the baffle angle, the angle was set to 60° initially. The heating elements were arranged in relative groups, with four channels activated sequentially at the same thermal power (50 W), while the remaining elements remained inactive. The heating duration was 120 s. Temperature data were recorded simultaneously at both the control points and the working zone points. Subsequently, the baffle angle was adjusted

to 90° with all other parameters unchanged, and temperature data were recorded again at these same locations. The experimental results for the baffle angle at 60° are shown in Figure 13.

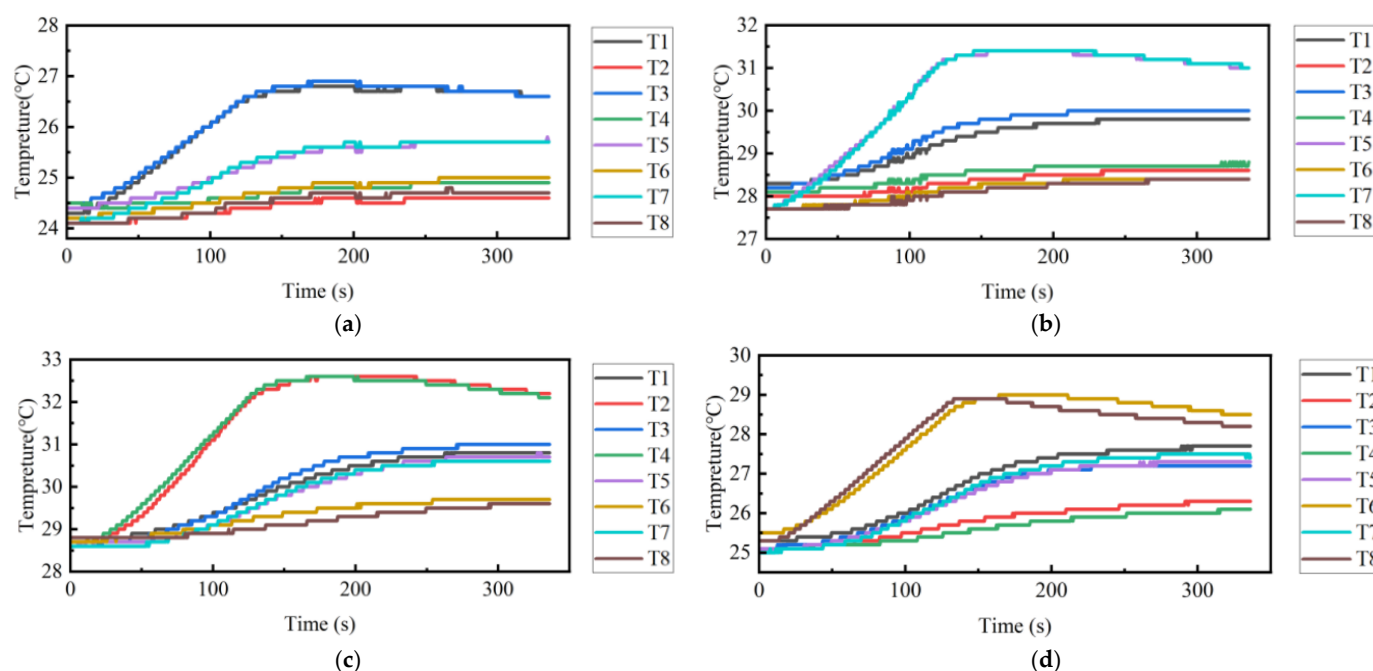
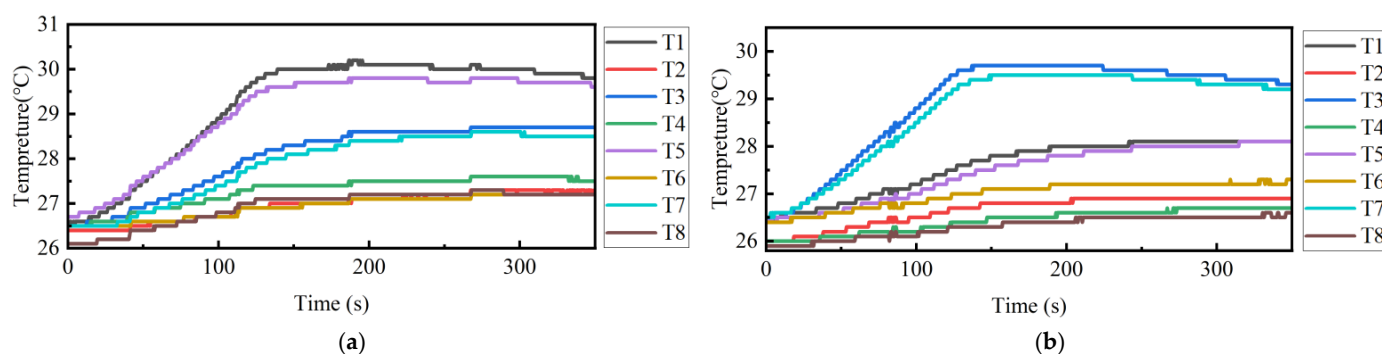


Figure 13. Temperature responses of the control points with a baffle angle of 60° under relative grouping configuration: (a) Circuit 1 only (1, 0, 0, 0), (b) Circuit 2 only (0, 1, 0, 0), (c) Circuit 3 only (0, 0, 1, 0), and (d) Circuit 4 only (0, 0, 0, 1).

To investigate the effect of baffle angle on temperature distribution, line graphs of control measurement point temperatures under various conditions with a 90° angle were plotted for each relative grouping, as shown in Figure 14. The temperature rise trend at 90° is similar to that at 60° : when heating the upper points, one set of points serves as secondary heating; when heating the lower points, two sets act as secondary heating. Unlike previous findings, in operating conditions 0010 and 0001, after a brief period of heating cessation, the temperature of the secondary heating group (located opposite to the activated heating elements) exceeded that of the primary heating group (Figure 13c,d). This occurs because a larger baffle angle reduces its resistance to rising hot air, resulting in faster temperature increase in the upper air region after heating termination.



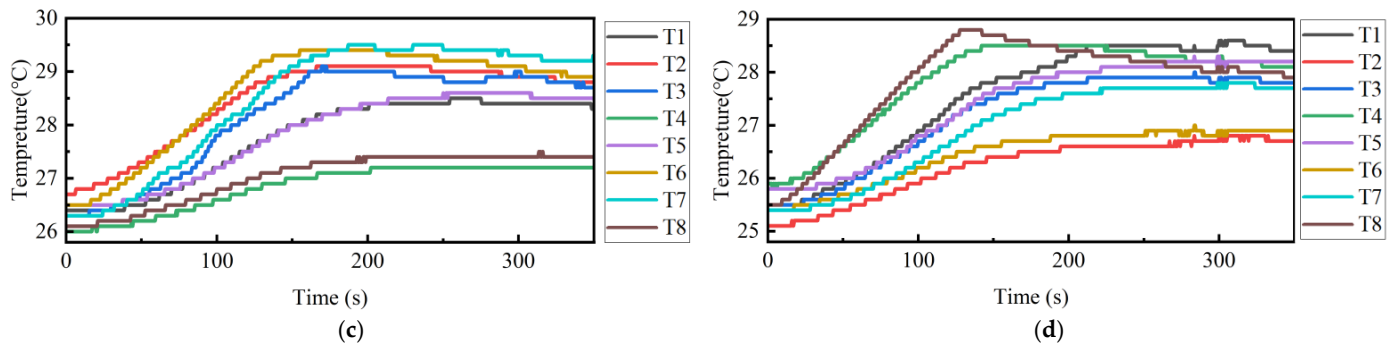


Figure 14. Temperature responses of the control points with a baffle angle of 90° under relative grouping configuration: (a) Circuit 1 only (1, 0, 0, 0); (b) Circuit 2 only (0, 1, 0, 0); (c) Circuit 3 only (0, 0, 1, 0); and (d) Circuit 4 only (0, 0, 0, 1).

Special attention was paid to the impact of different baffle angles on the temperature at the central points (T9–T16). As shown in Figure 15, for different angles, the temperature trends in the upper and lower regions of the central measurement point are identical, with nearly identical temperatures. To clearly compare how angle variations affect the central measurement point temperature under different operating conditions, the average temperatures of the four points in the upper and lower regions of the central measurement point were used as the indicators.

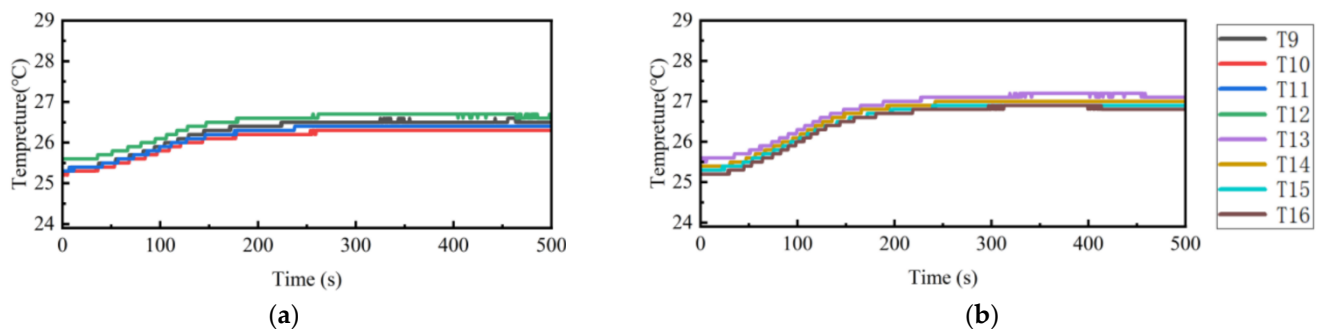
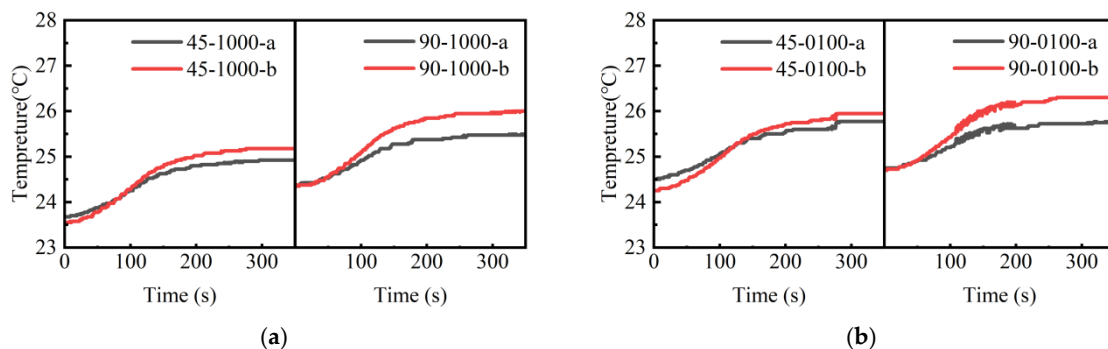


Figure 15. Comparison of average temperature data of the central points under different baffle angles: (a) 45° ; (b) 90° .

As shown in Figure 16, the average temperature data of the central points under different operating conditions at 45° and 90° are presented. In the legend, ‘a’ denotes the upper points (T9–T12) of the central points, while ‘b’ indicates the lower points (T13–T16).



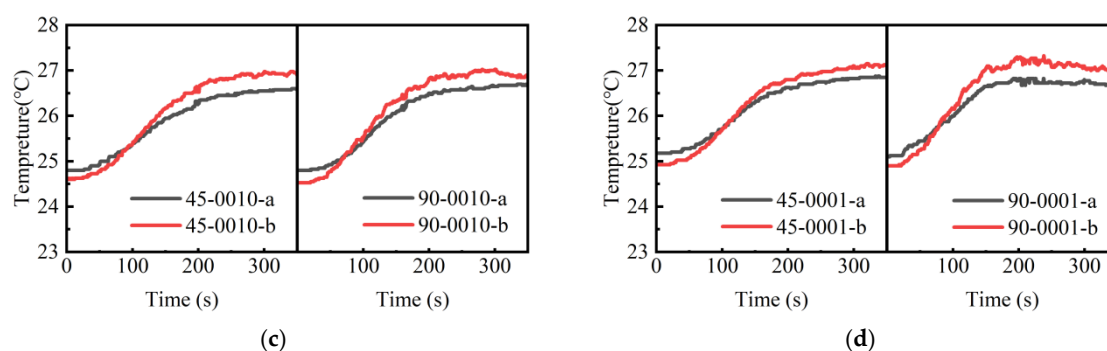


Figure 16. Average temperature data of the central measuring points (T9–T16) under different operating conditions with baffle angles of 45° and 90°. The markers “a” and “b” in the figure denote the upper and lower points, respectively. (a) Circuit 1 only (1, 0, 0, 0); (b) Circuit 2 only (0, 1, 0, 0); (c) Circuit 3 only (0, 0, 1, 0); (d) Circuit 4 only (0, 0, 0, 1).

When the upper heating pad is activated (corresponding to operating conditions (1, 0, 0, 0) and (0, 1, 0, 0)), as the baffle angle increases, the temperature difference at the central points significantly rises after the temperature stabilizes. At 45°, the temperature difference between the upper and lower sections is 0.2 ± 0.03 °C; at 90°, the temperature difference reaches 0.7 ± 0.05 °C, as summarized in Table 9. This increase is well above the experimental uncertainty, confirming the significant effect of baffle angle on temperature uniformity.

Table 9. Fitting results of the central measuring points.

	45°: $k \times 100$	90°: $k \times 100$
1000-a	0.553	0.643
1000-b	0.741	0.761
0100-a	0.455	0.475
0100-b	0.695	0.671
0010-a	0.640	0.877
0010-b	0.591	0.955
0001-a	0.378	0.922
0001-b	0.500	1.134

The table reveals that when the baffle angle remains fixed, the average temperature (b) in the lower section generally shows a higher heating rate than the (a) in the upper section. When only the upper heating elements are activated (1000/0100), the angle has minimal impact on the heating rates in the working zones. However, when the lower heating elements are activated (0010/0001), the heating rate increases significantly with a larger baffle angle.

To further elucidate the physical mechanism underlying the effect of baffle angle on temperature uniformity, CFD simulations were performed for baffle angles of 60° and 90° under otherwise identical conditions. Figure 17 presents the velocity vectors and temperature contours at different cross-sections for both angles. Figure 17a shows the cross-section at $y = -12.5$ cm with a baffle angle of 90°, while Figure 17b shows the same cross-section with a baffle angle of 60°. Figures 17c and 17d correspond to the cross-section at $x = -20$ cm at 90° and 60°, respectively. As shown in Figure 17b,d, when the baffle angle is 60°, the baffle effectively obstructs the lateral movement of hot air toward the chamber center. The heated air is forced to rise along the wall adjacent to the heating elements, while the baffle itself becomes heated, inducing air to flow upward along the baffle surface. After rising along the wall and cooling, the air descends in the central region of the cross-section, forming a localized recirculation zone. This flow pattern promotes heat

transfer from the wall to the central region, improving temperature uniformity. The recirculation zone plays a crucial role in suppressing thermal stratification: the descending cooler air from the upper region mixes with the upward heated air along the wall, enhancing convective exchange between the wall-adjacent hot layer and the central core. This mixing effect reduces the vertical thermal gradient across the working zone, resulting in a more uniform temperature distribution from the bottom to the top. In contrast, when the baffle angle is increased to 90° (Figure 17a,c), the obstruction effect is largely eliminated, allowing hot air to diffuse more freely toward the center, but without the enhanced mixing and recirculation observed at 60° . Consequently, thermal stratification persists under the 90° configuration, with warmer air accumulating near the top and cooler air remaining in the lower region, leading to a larger temperature difference between the upper and lower sections. These results confirm that a baffle angle below 90° is beneficial for redirecting natural convection and improving spatial temperature distribution, consistent with the quantitative findings presented in Table 9.

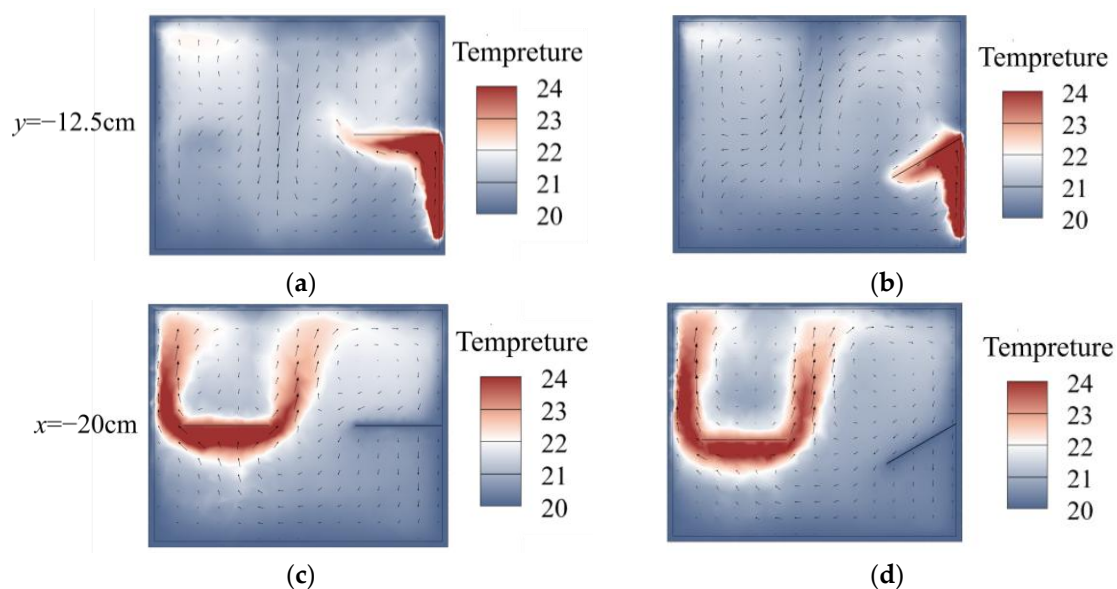


Figure 17. Velocity vectors and temperature contours for baffle angles of 60° and 90° at different cross-sections: (a) $y = -12.5$ cm, 90° ; (b) $y = -12.5$ cm, 60° ; (c) $x = -20$ cm, 90° ; (d) $x = -20$ cm, 60° .

3.4. Dynamic Temperature Field Under PID Control

While these experiments revealed the fundamental thermal behavior of the system, they did not incorporate closed-loop feedback control. In the multi-PID controller array experiment, the parameters obtained through ZN tuning and genetic algorithm optimization were implemented in the actual control system to develop the corresponding programming code. This code generates actual power output and drives the heating elements via pulse-width modulation (PWM) technology, enabling the heating process. The experimental parameters were set as follows: the target temperature was 24°C , the control duration was 800 s, and the control cycle was 1 s. The heating elements were grouped according to the opposite grouping method, and the baffle angle was set to 60° during the experiment. The control performance is demonstrated in Figure 18.

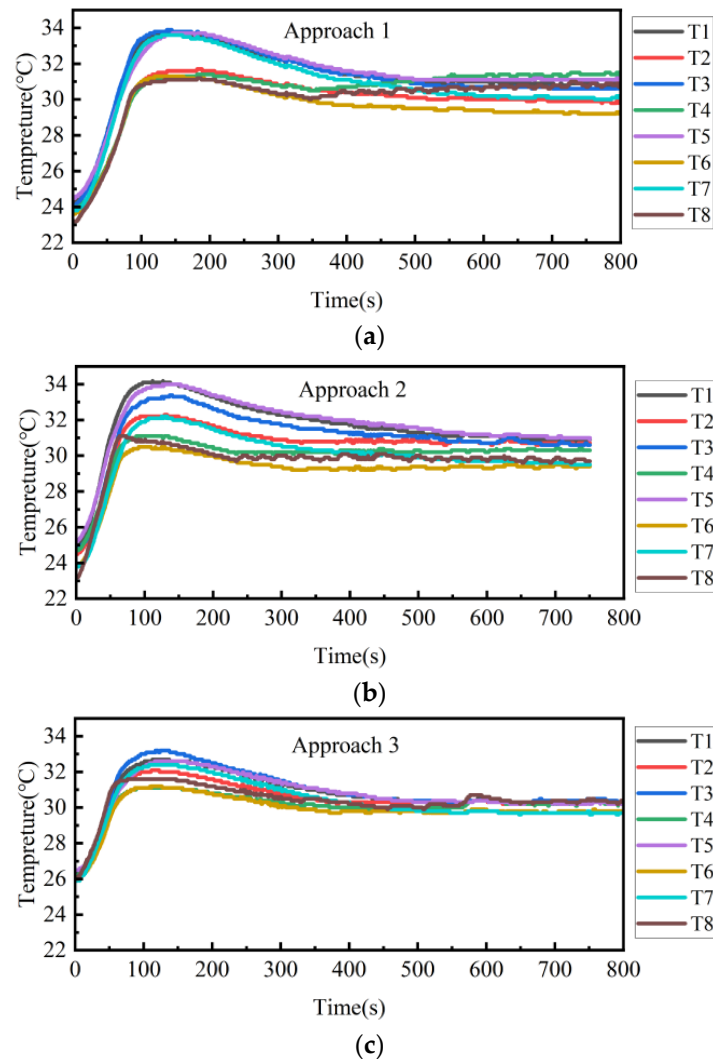


Figure 18. Experimental control results with different parameter optimization approaches: (a) ZN tuning; (b) GA optimization with objective function J_1 , and (c) GA optimization with objective function J_2 .

When evaluating the control performance across all experimental protocols, after 80 s, the system temperature approached the setpoint of 30 °C. Although the heating elements ceased operation thereafter, the temperature continued to rise gradually, demonstrating the characteristic high-temperature inertia observed in all protocols.

Regarding Approach 1, after the initial decline at each point and stabilization near the setpoint, the temperature difference gradually increases. At 600 s, the steady-state accuracy is approximately 1.7 °C. In contrast, neither Approach 2 nor Approach 3 exhibits this gradual temperature difference increase after reaching 400 s. Compared to ZN-tuned parameters, GA-optimized parameters significantly reduce both the peak value and the settling time, while maintaining steady-state accuracy within ± 0.5 °C at all points, enhancing system stability.

To further demonstrate the reliability of the experimental results and to validate the CFD model under closed-loop conditions, the simulated responses were compared with experimental measurements driven by the actual heating signals from Approach 3, as shown in Figure 19. The figure presents the comparison between the simulated and experimental temperature curves averaged over the two points within each circuit. The results show good agreement in both overall trend and steady-state values, with a mean absolute error of approximately 0.5 °C and a maximum deviation of 0.8 °C across all four

channels. A phase lag of approximately 30 s is observed between the simulation and experiment, attributed to the thermal inertia of the PI film heating elements simplified in the numerical model. The close agreement in steady-state temperature trends confirms the predictive capability of the CFD model for analyzing the temperature field distribution under closed-loop control conditions driven by real-time controller outputs.

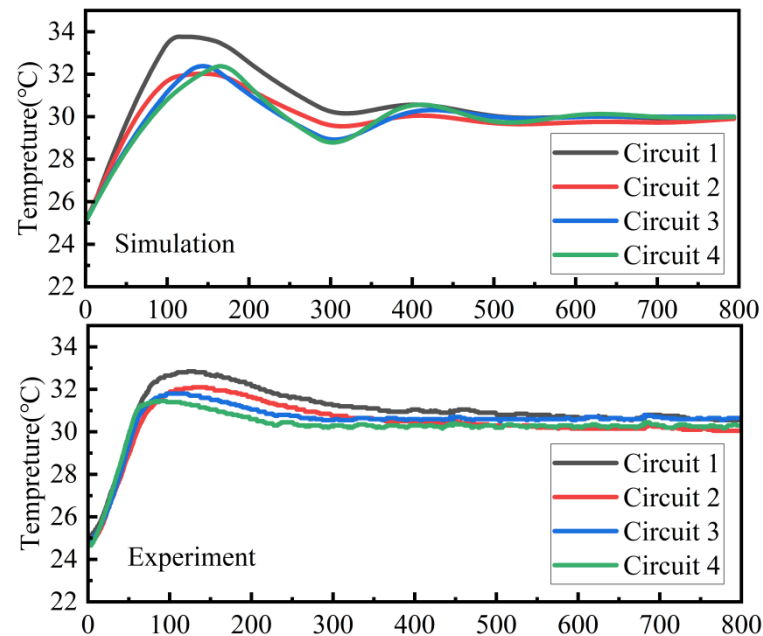


Figure 19. Comparison of simulated and experimental temperature responses driven by the actual heating signals from Approach 3.

As shown in Figure 20, to provide a more intuitive comparison between Approach 2 and Approach 3, the average temperatures from two points on the same channel were calculated and plotted as a temperature line graph. The graph clearly demonstrates that Approach 3 reduces the overshoot from 32.8 °C to 32.1 °C compared to Approach 2. In terms of time to reach steady-state temperature, with temperature fluctuations within ± 0.15 °C at all points, Approach 3 significantly outperforms Approach 2, with the required time reduced from approximately 630 s in Approach 2 to about 490 s in Approach 3. Regarding uniformity, Approach 3's performance improves by 0.2 °C compared to Approach 2. Additionally, Approach 3 exhibits a markedly smaller steady-state error: while Approach 2's average steady-state error is 0.93 °C, Approach 3's is only 0.37 °C.

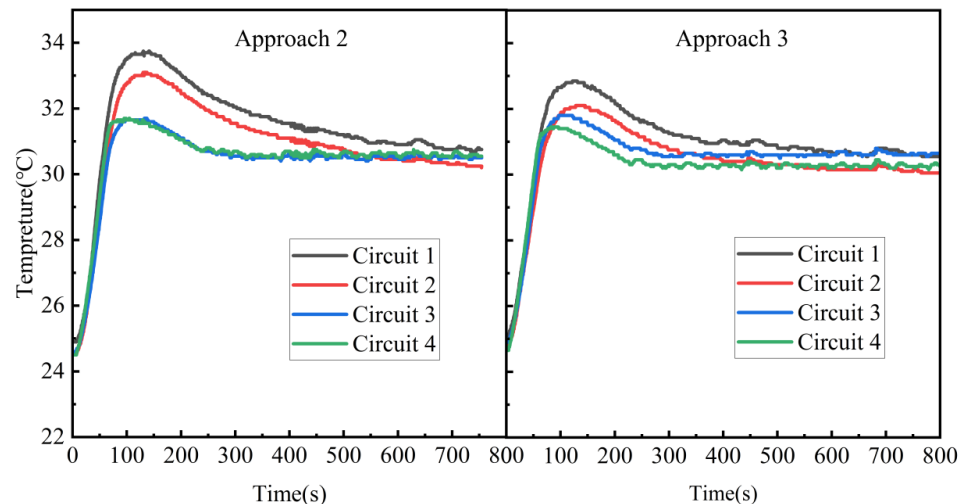


Figure 20. Comparison of average temperature points between Approach 2 and Approach 3. Each data point represents the average of two points within the same circuit (e.g., T1 and T5 for Circuit 1), as grouped in Table 3.

The preceding analysis focused on the control points (T1–T8), which are located near the heating elements. To evaluate whether the improved control performance is effectively transmitted to the working zone, the temperature responses of the central points (T9–T16) were further examined under the same closed-loop conditions.

Figure 21 presents the temperature responses of the central points (T9–T16) under Approach 2 and Approach 3. For Approach 2, the four channels exhibit clear stratification, with Circuit 1 being the most prominent and maintaining the highest temperature throughout the heating process, followed by the other three channels with noticeable offsets among them. This offset becomes more pronounced after 300 s as the thermal field gradually establishes. For Approach 3, the stratification among the four channels is significantly reduced, with all four curves converging toward a narrower temperature band, indicating improved spatial uniformity in the central working zone. Specifically, Approach 3 reduces the overshoot in the central region from 33.35 °C to 32.55 °C compared to Approach 2. In terms of the time required for the central temperatures to stabilize within a band of ± 0.15 °C around the setpoint of 30 °C, Approach 3 requires approximately 820 s, which is longer than the 730 s needed for Approach 2, indicating a trade-off between uniformity improvement and response speed. Regarding uniformity, the maximum temperature difference among the four central channels under Approach 2 is 0.95 °C, while under Approach 3 it is reduced to 0.50 °C, demonstrating improved spatial consistency in the working zone. Additionally, Approach 3 exhibits a markedly smaller steady-state deviation in the central region: while Approach 2's average deviation from the setpoint (30 °C) is 0.94 °C (above the setpoint), Approach 3's average deviation is only -0.24 °C (below the setpoint), indicating much higher steady-state accuracy. These results confirm that Approach 3 not only improves the control performance near the heating elements but also effectively enhances the temperature uniformity and steady-state accuracy in the central working zone, albeit with a longer settling time.

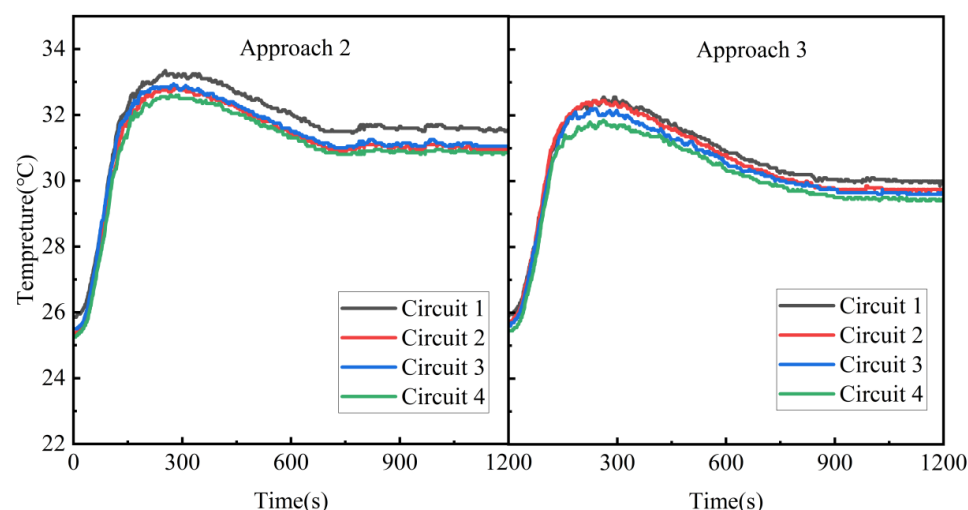


Figure 21. Comparison of average central measurement point temperatures between Approach 2 and Approach 3. Each data point represents the average of two points within the same circuit on the central bracket (e.g., T9 and T13 for Circuit 1), corresponding to the heating pad grouping defined in Table 3.

The experimental results presented above carry several practical implications. The achieved steady-state error within ± 0.5 °C and the 140 s reduction in settling time translate directly into improved thermal stability and faster recovery from disturbances in real-world operations. For applications such as precision optical measurements and semiconductor wafer inspection, where temperature drift directly affects measurement accuracy, this enhanced performance reduces the need for frequent recalibration and minimizes production downtime. In biological culture and pharmaceutical stability testing, the improved spatial uniformity (reduced from 0.95 °C to 0.50 °C in the working zone) ensures more consistent environmental conditions across sample arrays, enhancing experimental reproducibility and product quality control.

To contextualize the performance of the proposed control strategy, it is instructive to compare the achieved temperature uniformity improvement with results reported in the literature for similar thermal devices operating under natural convection. Smolka [26] conducted a genetic algorithm-based shape optimization of a natural air-circulation heating oven using an experimentally validated 3-D CFD model. In that study, the objective was to minimize the maximum temperature difference between the chamber center and the corners. Through optimization of heater positions and air distribution gaps, the temperature uniformity in the simplified model improved from 7.5 °C to 4.0 °C. In the full 3D model, the improvement was from 24.3 °C to 16.5 °C for heater optimization alone, and further to 8.2 °C when distribution gaps were optimized. The combined optimization achieved a final uniformity of 7.5 °C, representing a 69% reduction in the maximum temperature difference compared to the baseline [26]. In the present work, the proposed MIMO control strategy combined with GA-optimized PID parameters and static baffle redirection achieves a steady-state temperature uniformity of ± 0.5 °C in the working zone, with the spatial temperature difference among the four central channels reduced from 0.95 °C to 0.50 °C—a 47% improvement. While direct quantitative comparison is complicated by differences in chamber geometry, operating temperature range, and control objectives (hardware optimization versus active feedback control), the present results demonstrate that comparable or superior uniformity improvements can be achieved through control-oriented strategies without modifying the physical hardware. This finding highlights the potential of the proposed approach as a cost-effective alternative to

hardware redesign for improving temperature uniformity in existing thermostatic chambers. The improvements achieved by Approach 3 over Approach 2 and Approach 1 in steady-state error and settling time were all within the 95% confidence interval based on the repeated experiments.

For long-term industrial applications, it is advisable to periodically monitor the system dynamic characteristics through step-response tests at regular intervals (e.g., every 6 to 12 months). By tracking the evolution of the identified parameters K , T , and τ , the extent of system drift can be quantitatively assessed. When the variation in any key parameter exceeds a threshold of approximately 15–20% of its nominal value, re-identification of the model and re-optimization of the PID parameters are recommended to restore the optimal control performance.

4. Conclusions

This study addresses temperature control in thermostatic chambers under natural convection by establishing a transfer function matrix model and implementing multivariable coordinated control through a GA-optimized multi-PID controller array. Experiments reveal two key thermal phenomena: activation of upper heating elements generates one secondary heating zone, while lower heating elements generate two such zones; the system also exhibits significant thermal inertia, with temperatures continuing to rise after heating ceases. The relative grouping method outperforms the adjacent grouping method across both thermal inertia and correlation metrics.

The control system employs a spatially distributed multi-PID strategy with all 12 PID parameters globally optimized using a genetic algorithm. Simulations and experiments demonstrate that the GA-optimized scheme significantly outperforms conventional Ziegler–Nichols tuning, achieving steady-state error within ± 0.5 °C, reducing settling time by approximately 140 s, and improving temperature uniformity. Baffle angle experiments show that angles below 90° effectively suppress lateral diffusion of hot air; at 90°, the temperature difference between upper and lower central regions rises from 0.2 °C to 0.7 °C. CFD simulations reveal the physical mechanism: without the baffle, hot air rises along the wall, forming higher wall temperatures and lower central temperatures; with the baffle below 90°, local vortices near the wall suppress lateral diffusion and enhance central heating. Experimental results closely match CFD predictions, validating the proposed method.

From a practical standpoint, the strategy eliminates the need for active flow generators, reducing energy and maintenance costs. The achieved uniformity of ± 0.5 °C meets the requirements for most precision measurement, semiconductor inspection, and biological culture protocols (typically ± 1.0 °C). Limitations include the single-chamber geometry and heater layout tested, the linearization assumptions in the transfer function model, the laminar flow assumption in CFD, and the manually fixed baffle angle. These limitations point toward future work on multi-scale experiments, higher-fidelity modeling, and real-time baffle actuation.

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Abbreviations

The following abbreviations are used in this manuscript:

Ba	Baffle
CFD	Computational Fluid Dynamics
D	Derivative
FOPDT	First Order Plus Dead Time
GA	Genetic Algorithm
HP	Heating Pad
I	Integral
MIMO	Multiple-Input-Multiple-Output
P	Proportional
PI	Polyimide
PID	Proportional-Integral-Derivative
PWM	Pulse Width Modulation
Ra	Rayleigh Number
SISO	Single-Input-Single-Output
T	Temperature Measurement Point
ZN	Ziegler-Nichols

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