



Adaptive Proportional–Integral–Derivative (PID) Temperature Control for Industrial Heating Systems under Setpoint Variations and Thermal Disturbances

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ABSTRACT: This study proposes an adaptive proportional–integral–derivative (PID) controller for an industrial heating system to improve temperature-tracking performance under varying setpoints and thermal load disturbances. Unlike a conventional PID controller with fixed gains, the proposed method updates the proportional, integral, and derivative gains (K_p , K_i , and K_d) online based on the temperature error and its rate of change. The system was simulated for 6,000 s using multiple temperature setpoints ranging from 50 to 100 °C and three thermal load disturbance intervals, with a conventional PID controller used as the benchmark. Control performance was evaluated using the mean absolute error (MAE), root mean square error (RMSE), integral absolute error (IAE), integral squared error (ISE), overshoot, settling time, and steady-state error. The results showed that the adaptive PID controller reduced MAE by 34.90%, RMSE by 23.86%, IAE by 34.90%, and ISE by 42.03% compared with the conventional PID controller. The average steady-state error decreased from 6.251 to 3.081 °C, corresponding to a 50.72% improvement. The adaptive controller also maintained the temperature closer to the setpoint and demonstrated better recovery from thermal load disturbances. However, improvements in overshoot and settling time were not consistent across all setpoint changes because of thermal inertia and heating-power limitations. Overall, the results demonstrate that a simple error-based gain adaptation strategy can enhance temperature-control performance while retaining the practical and straightforward structure of conventional PID control.

KEYWORDS: Adaptive PID; temperature control; heating system; thermal load disturbance; online parameter tuning; conventional PID.

1. Introduction

Temperature control is a critical task in various industrial processes, including heating, drying, heat treatment, material production, and thermal energy storage. Large thermal inertia, time delays, nonlinear characteristics, and variations in thermal loads make maintaining a stable temperature at the desired setpoint challenging, particularly when the system operates over a wide temperature range or is subjected to external disturbances [1–3]. Thermal processes characterized by large inertia and significant time delays also impose simultaneous

requirements for accurate setpoint tracking, robustness, and effective disturbance rejection [4, 5]. Therefore, the performance of a temperature control system depends not only on its ability to track the desired setpoint but also on its capability to maintain stable performance under variations in operating conditions and process parameters [5].

The proportional–integral–derivative (PID) controller remains widely used in industrial control systems because of its simple structure, ease of implementation, and low computational requirements [6, 7]. However, PID performance depends strongly on the selection of the three controller gains, K_p , K_i , and K_d . In conventional PID control, these parameters are typically tuned for a specific operating condition and remain fixed during operation. When process dynamics, setpoints, or thermal loads change, a fixed set of gains may no longer provide satisfactory performance, resulting in increased tracking error, longer settling time, or degraded disturbance rejection [6, 8, 9]. This limitation is particularly relevant to nonlinear thermal systems affected by measurement noise and control delays, where the effectiveness of PID tuning methods can vary considerably with process dynamics [9]. Moreover, setpoint tracking and disturbance rejection represent different control objectives that may require different tuning strategies; consequently, optimizing one objective does not necessarily ensure satisfactory performance for the other [10]. PID design studies therefore emphasize the simultaneous consideration of setpoint tracking, disturbance rejection, and robustness against model uncertainty and parameter variations when selecting controller parameters [5, 11]. These considerations provide a strong basis for investigating PID tuning and adaptive parameter-adjustment methods capable of maintaining control performance across varying operating points and thermal conditions.

Various approaches have been investigated to improve the temperature-control performance of PID controllers. Optimization algorithms such as Particle Swarm Optimization (PSO) have been employed to determine PID parameters and improve transient response characteristics. For an air-heating system, Jaen-Sungthong et al. (2016) demonstrated that PSO-based PID tuning improved the integral squared error (ISE), settling time, and overshoot compared with conventional tuning methods [12]. Hybrid PSO–PID approaches have also been applied to heat-transfer systems and heat-pump temperature control [13, 14]. However, offline optimization generally produces a set of controller parameters optimized for the operating conditions considered during the optimization process and does not necessarily provide sufficient adaptability when operating conditions subsequently change.

An alternative approach is to adjust PID parameters online according to the system state. Self-tuning, gain-scheduling, and continuous adaptation techniques have been developed to maintain PID performance under varying process characteristics [15]. In temperature-control applications, fuzzy adaptive PID controllers that use the control error and its rate of change to update controller parameters have demonstrated improved adaptability and disturbance rejection [16]. More recently, Huang et al. developed a fuzzy adaptive PID controller for a metal-wire heat-treatment furnace in which the PID parameters were automatically adjusted according to the temperature response; implementation results showed a substantial reduction in temperature fluctuations [2]. Hybrid approaches combining fuzzy PID control with optimization techniques have also been investigated for composite induction-heating systems to improve adaptability and response speed [3].

Although intelligent control and optimization methods can improve control performance, their increased algorithmic complexity may impose additional requirements on controller

design, parameter tuning, computational resources, and practical implementation. A relatively simple adaptive PID strategy, in which the controller gains are updated directly using error information already available within the control loop, therefore remains attractive for thermal systems requiring straightforward implementation. Nevertheless, the performance of such an approach should be evaluated under multiple operating conditions rather than at a single setpoint. In particular, setpoint tracking, thermal load disturbance rejection, and heating-power constraints should be considered simultaneously to provide a more representative assessment of controller performance.

Accordingly, this study develops an adaptive PID controller for a heating system in which K_p , K_i , and K_d are updated online based on the temperature error $e(k)$ and the error variation $\Delta e(k)$. The system is investigated under multiple temperature setpoints and thermal load disturbance intervals to represent changes in operating conditions. A conventional PID controller is used as the benchmark under identical simulation conditions. The performance of the two control strategies is evaluated in terms of temperature tracking response, control error, power input, disturbance rejection, and quantitative performance indices, including mean absolute error (MAE), root mean square error (RMSE), integral absolute error (IAE), integral squared error (ISE), overshoot, settling time, and steady-state error. Through this comparison, the study aims to assess whether a relatively simple adaptation law can improve temperature control performance while retaining the practical structure and ease of implementation of conventional PID control.

2. Materials and Methods

2.1. Industrial Heating System.

In this study, an industrial heating system was developed in a simulation environment to evaluate the performance of the adaptive PID controller under different operating conditions. The system consists of an adaptive PID controller, a heating unit, a thermal process, a temperature sensor, and a feedback loop. In addition, factors such as ambient temperature, thermal load variations, external disturbances, and measurement noise were incorporated into the model to represent fluctuations commonly encountered under practical operating conditions. At each time instant, the temperature setpoint $T_{sp}(t)$ is compared with the measured temperature $T_m(t)$ to determine the control error:

$$e(t) = T_{sp}(t) - T_m(t) \quad (1)$$

This error is fed into the adaptive PID controller to determine the control signal $u(t)$. The controller output is constrained within the range of 0–100%, corresponding to the available heating power.

The system dynamics are described based on the following energy balance equation:

$$C \frac{dT(t)}{dt} = P_h(t) - K[T(t) - T_a(t)] - Q_d(t) \quad (2)$$

where $T(t)$ and $T_a(t)$ denote the system and ambient temperatures, respectively; C is the equivalent thermal capacitance; K is the heat-loss coefficient; $P_h(t)$ represents the heating power; and $Q_d(t)$ represents the external thermal load or disturbance.

The simulation was performed with a sampling interval of 1 s over 6,000 data points. The temperature setpoint was varied between 50 and 100 °C to evaluate setpoint tracking performance. In addition, three thermal load disturbance periods were introduced into the model to assess the disturbance rejection and recovery capability of the controller. The ambient temperature was maintained at approximately 25 °C with small fluctuations, while random noise was added to the measured temperature signal to simulate sensor measurement errors.

The overall structure of the control system is illustrated in Figure 1, in which the adaptive PID controller automatically adjusts the K_p , K_i , and K_d parameters based on the temperature error. The parameter adaptation mechanism and control algorithm are described in detail in the following sections.

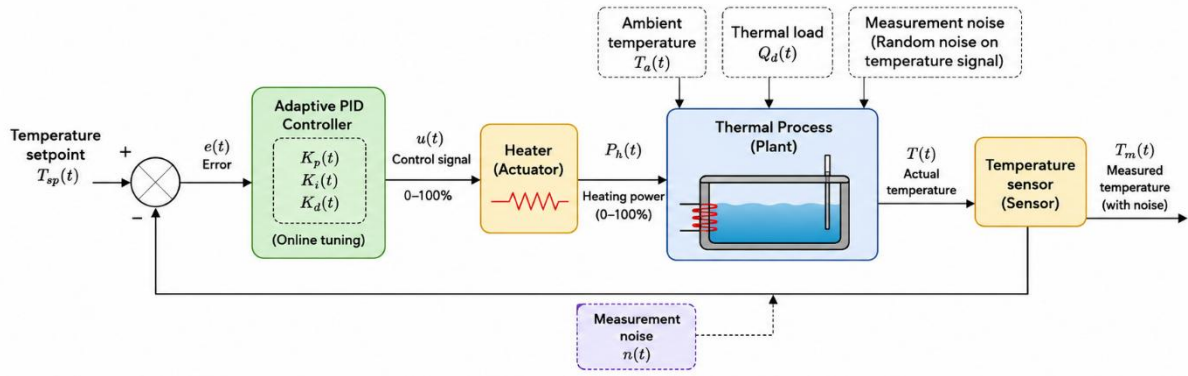


Figure 1. Schematic diagram of the temperature control system using an adaptive PID controller.

2.2. Conventional PID Controller.

The conventional PID controller was used as a benchmark to evaluate the performance of the adaptive PID controller. The temperature error at time step k is defined as:

$$e(k) = T_{sp}(k) - T_m(k) \quad (3)$$

The PID control signal in discrete form is calculated as:

$$u(k) = K_p e(k) + K_i I(k) + K_d \frac{e(k) - e(k-1)}{\Delta t} \quad (4)$$

where

$$I(k) = I(k-1) + e(k)\Delta t$$

and K_p , K_i , and K_d are the proportional, integral, and derivative gains, respectively. In this study, the conventional PID controller uses a fixed set of parameters:

$$K_p = 2.2, K_i = 0.05, K_d = 0.65$$

The control signal is constrained within the range of 0–100% to represent the power limitation of the heater. In addition, an anti-windup mechanism is applied by limiting the integral term to the range of –500 to 500.

The conventional PID and adaptive PID controllers are simulated using the same thermal process, temperature setpoint profile, ambient temperature, and thermal load disturbance conditions to ensure consistency and fairness in the performance comparison.

2.3. Proposed Adaptive PID Controller.

To improve the system response to variations in temperature setpoints and thermal loads, an adaptive PID controller is developed in which the K_p , K_i , and K_d gains are adjusted online based on the temperature error and its rate of change. At sampling instant k , the temperature error is defined as:

$$e(k) = T_{sp}(k) - T(k) \quad (5)$$

$$\Delta e(k) = \frac{e(k) - e(k-1)}{\Delta t} \quad (6)$$

These two variables are normalized as:

$$e_n(k) = \min\left(\frac{|e(k)|}{E_{\max}}, 1\right) \quad (7)$$

$$\Delta e_n(k) = \min\left(\frac{|\Delta e(k)|}{\Delta E_{\max}}, 1\right)$$

Where $E_{\max}=40$ °C and $\Delta E_{\max}=20$ °C/s are the normalization limits. The normalization limits and PID gain ranges were determined empirically through preliminary simulation trials rather than through a formal optimization procedure. The values $E_{\max}=40$ °C and $\Delta E_{\max}=20$ °C were selected to cover the representative magnitudes of the temperature error and its variation observed during the investigated setpoint transitions while limiting the normalized variables to the range [0,1]. The ranges of K_p , K_i , and K_d were established around the conventional PID settings ($K_p=2.2$, $K_i=0.05$, and $K_d=0.65$) and refined through preliminary simulations to achieve a practical compromise among response speed, steady-state error, oscillation suppression, and closed-loop stability. These values were therefore used as empirical design parameters rather than theoretically optimal gains.

The PID parameters are adjusted according to:

$$K_p(k) = 2 + 0.8e_n(k)$$

$$K_i(k) = 0.05 + 0.03[1 - e_n(k)] \quad (8)$$

$$K_d(k) = 0.55 + 0.3\Delta e_n(k)$$

In this study, the parameter ranges are defined as:

$$2.0 \leq K_p \leq 2.8$$

$$0.05 \leq K_i \leq 0.08$$

$$0.55 \leq K_d \leq 0.85$$

This adaptation mechanism is designed according to three principles. When the temperature error is large, K_p increases to accelerate the system response. As the temperature

approaches the setpoint, K_i increases to reduce the steady-state error. Meanwhile, K_d is adjusted according to the rate of change of the error to suppress oscillations and improve transient performance. The control signal is determined as:

$$u(k) = K_p(k)e(k) + K_i(k)I(k) + K_d(k)\Delta e(k) \quad (9)$$

subject to the constraint: $0 \leq u(k) \leq 100\%$

An *anti-windup* mechanism is also applied to limit the accumulation of the integral term when the control signal reaches its saturation limits.

2.4. Simulation Conditions and Data.

The simulation was conducted over 6,000 sampling intervals with a sampling time of $\Delta t = 1$ s. The initial system temperature was set to 25 °C, and the temperature setpoint was sequentially varied among 50, 80, 65, 100, 75, and 90 °C to evaluate the controller performance under different operating conditions (Table 1). Three thermal load disturbance periods were introduced at 1200–1450 s, 2850–3150 s, and 4300–4520 s. In addition, variations in ambient temperature and heater power constraints ranging from 0 to 100% were incorporated into the model.

Table 1. Simulation conditions used for the thermal control system.

Parameter	Symbol	Value/setting
Simulation duration	t	6000 s
Sampling interval	Δt	1 s
Initial temperature	T_0	25 °C
Temperature setpoints	T_{sp}	50, 80, 65, 100, 75, and 90 °C
Ambient temperature	T_a	Approximately 25 °C with small fluctuations
Thermal-load disturbance interval 1	—	1200–1450 s
Thermal-load disturbance interval 2	—	2850–3150 s
Thermal-load disturbance interval 3	—	4300–4520 s
Measurement noise	—	Random noise added to measured temperature
Heater power constraint	u	0–100%

The conventional PID and adaptive PID controllers were evaluated using the same thermal model and identical input conditions, ensuring that the observed differences in performance were primarily attributable to the control strategies.

2.5. Control Performance Evaluation Metrics.

The controller performance was evaluated based on the error between the temperature setpoint $T_{sp}(k)$ and the measured temperature $T_m(k)$. Four main error metrics were considered: MAE, RMSE, IAE, and ISE.

The mean absolute error (MAE) is defined as:

$$MAE = \frac{1}{N} \sum_{k=1}^N |e(k)| \quad (10)$$

The root mean square error (RMSE) is calculated as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^N e^2(k)} \quad (11)$$

The integral absolute error (IAE) and integral squared error (ISE) in discrete form are defined, respectively, as:

$$IAE = \sum_{k=1}^N |e(k)| \Delta t$$

$$ISE = \sum_{k=1}^N e^2(k) \Delta t$$
(12)

The improvement achieved by the adaptive PID controller relative to the conventional PID controller is calculated as:

$$Improvement(\%) = \frac{J_{PID} - J_{APID}}{J_{PID}} \times 100$$
(13)

where J_{PID} and J_{APID} denote the corresponding performance metric values obtained using the conventional PID and adaptive PID controllers, respectively. A positive value indicates that the adaptive PID controller provides better performance than the conventional PID controller.

3. Results and Discussion

3.1. Temperature Tracking Response.

3.1. Temperature Tracking Response

Figure 2 compares the temperature-tracking responses of the conventional PID and adaptive PID controllers as the setpoint is sequentially varied between 50 and 100 °C. Overall, both controllers respond to the setpoint changes; however, the adaptive PID controller maintains the temperature closer to the setpoint during most of the simulation period. At each setpoint change, the temperature error increases rapidly because of the thermal inertia of the system. The adaptive PID controller adjusts K_p , K_i , and K_d online, enabling the temperature to approach the setpoint more rapidly and with a smaller tracking error than the conventional PID controller. This difference is particularly evident at the higher setpoints, especially at 100 and 90 °C, where the adaptive PID response remains closer to the desired temperature.

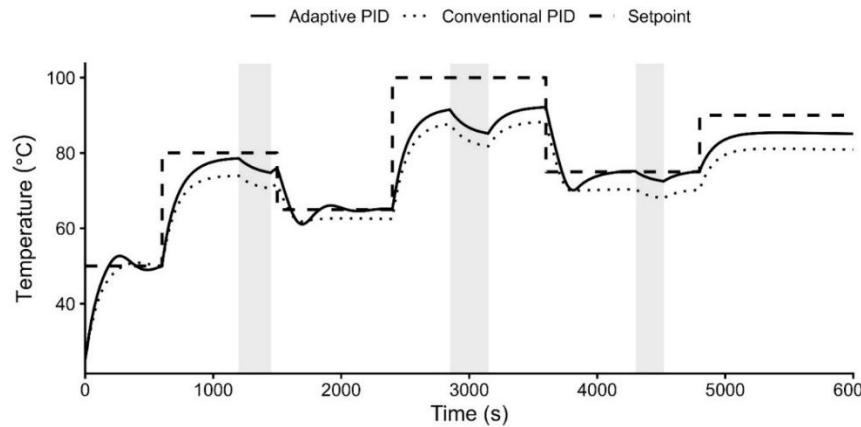


Figure 2. Comparison of the Temperature Setpoint Tracking Responses of the Conventional PID and Adaptive PID Controllers Under Setpoint Variations and Thermal Load Disturbances.

During the thermal load disturbance intervals, indicated by the shaded regions in Figure 2, the temperatures under both control strategies temporarily decrease. However, the adaptive PID controller generally maintains a higher temperature and exhibits better recovery after the disturbances. These results indicate that the online gain adaptation mechanism improves the controller's ability to respond to changes in operating conditions. Nevertheless, the temperature

does not fully reach the setpoint during some periods, particularly at higher setpoints. This behavior is primarily associated with the slow thermal dynamics and heating-power limitations of the system rather than solely with the controller parameters.

3.2. Temperature Error Response.

To further evaluate the tracking behavior observed in Figure 2, the corresponding temperature errors are compared in Figure 3. Large error peaks occur primarily immediately after setpoint changes, reflecting the thermal inertia and finite response capability of the heating system. Overall, the adaptive PID controller maintains the temperature error closer to 0 °C than the conventional PID controller during most of the simulation period. The difference is particularly evident following increases in the temperature setpoint, especially at higher setpoints, where the conventional PID controller exhibits larger and more persistent errors. This behavior indicates that the online adjustment of K_p , K_i , and K_d enables the adaptive PID controller to respond more effectively to changes in the operating state. When the temperature setpoint decreases, the error becomes negative because the actual temperature temporarily exceeds the new setpoint. After the transient period, the error under adaptive PID control approaches 0 °C. Nevertheless, several pronounced error peaks remain immediately after setpoint changes, indicating that the system response is still influenced by thermal inertia and actuator limitations.

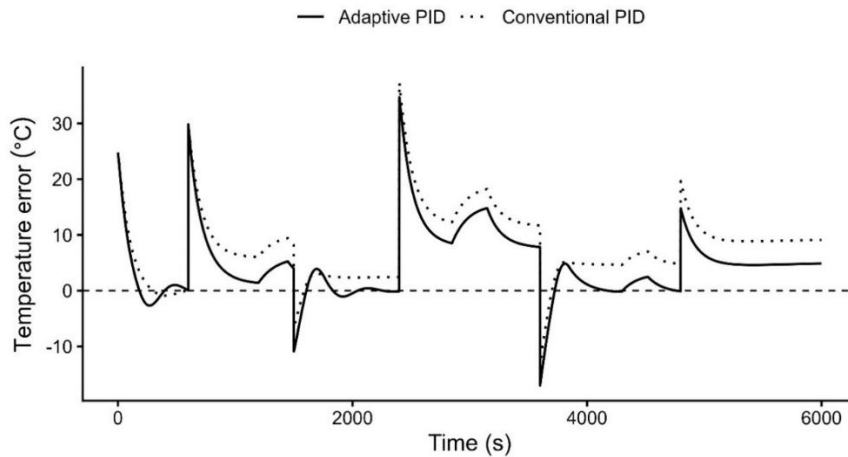


Figure 3. Comparison of Temperature Errors Between the Conventional PID and Adaptive PID Controllers Over Time.

3.3. Adaptation of PID Parameters.

Figure 4 presents the variations in K_p , K_i , and K_d throughout the control process. Unlike the conventional PID controller, which uses fixed gains, the adaptive PID controller updates its parameters according to the temperature error $e(k)$ and the error variation $\Delta e(k)$. In the simulation, the parameters are constrained within the predefined ranges of $2.0 \leq K_p \leq 2.8$, $0.05 \leq K_i \leq 0.08$, and $0.55 \leq K_d \leq 0.85$. For K_p , a pronounced increase occurs when large temperature errors arise, particularly following changes in the temperature setpoint (Figure 4a). At approximately 600 s and 2400 s, K_p increases from around 2.0 to approximately 2.6–2.7 before gradually decreasing as the error is reduced. Smaller increases are also observed at approximately 1500, 3600, and 4800 s. This behavior indicates that the proportional action is

strengthened when a rapid response to setpoint changes is required, whereas K_p returns toward its baseline value as the temperature approaches the desired state.

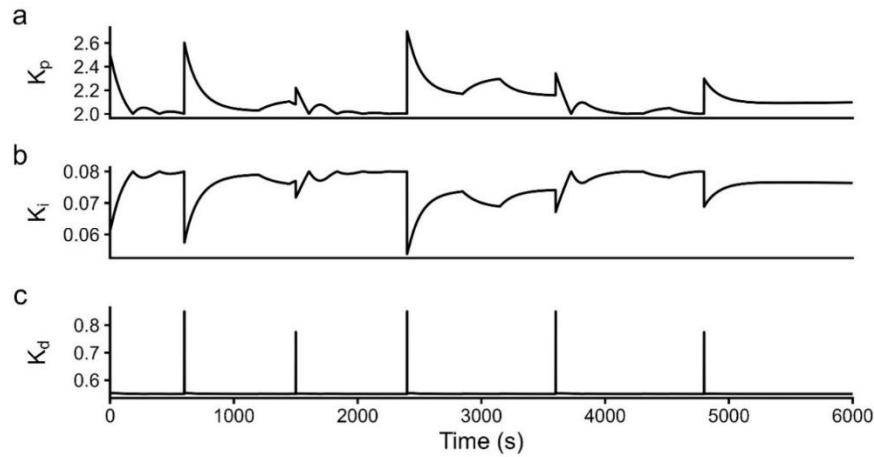


Figure 4. Variations in The Adaptive PID Parameters Over Time: (a) K_p , (b) K_i , and (c) K_d .

The variation in K_i generally exhibits an inverse trend relative to K_p (Figure 4b). When the temperature error is large, K_i decreases to approximately 0.055–0.060 and then gradually increases toward 0.078–0.080 as the error decreases. This mechanism limits excessive integral action during transient periods while strengthening the integral contribution as the system approaches the setpoint, thereby helping to reduce persistent tracking error. For K_d , the gain remains close to its baseline value of approximately 0.55 for most of the simulation period but exhibits short peaks reaching approximately 0.77–0.85 when the error changes rapidly (Figure 4c). Pronounced peaks occur near 600, 1500, 2400, 3600, and 4800 s, corresponding to the setpoint transition instants. This behavior is consistent with the adaptation law for K_d based on $|\Delta e(k)|$: the derivative action is strengthened when the error changes rapidly and quickly returns toward its baseline level as the system response stabilizes. Overall, the three PID parameters are adjusted according to the changing operating states of the system. These variations confirm that the proposed adaptive PID law operates according to its intended design mechanism and provide a basis for the improved temperature tracking performance compared with a conventional PID controller using fixed parameters.

3.4. Control Signal and Heater Power.

The control effort required by the two controllers is compared in Figure 5, which presents the heater-power profiles throughout the simulation. Heater power varies according to the thermal demand and is constrained within the prescribed range of 0–100%. During increases in the temperature setpoint, particularly at approximately 600 and 2,400 s, the heater power increases rapidly and approaches 100% before gradually decreasing as the temperature approaches the setpoint. Conversely, when the setpoint decreases, particularly at approximately 1,500 and 3,600 s, the heater power decreases to nearly 0% and subsequently increases to the level required to maintain the new operating temperature. During the three thermal load disturbance intervals, the heater power increases to compensate for the additional heat loss. As shown in Figure 5, the adaptive PID controller generally provides a stronger and more dynamic control action when the error increases because

K_p , K_i , and K_d are continuously adjusted according to the system state. After each disturbance is removed, the control signal gradually decreases to the level required to maintain stable operation. Throughout the simulation, heater power remains within the prescribed 0–100% actuator constraint. These results indicate that dynamic adjustment of the control signal contributes to the improved temperature tracking and reduced control error achieved by the adaptive PID controller.

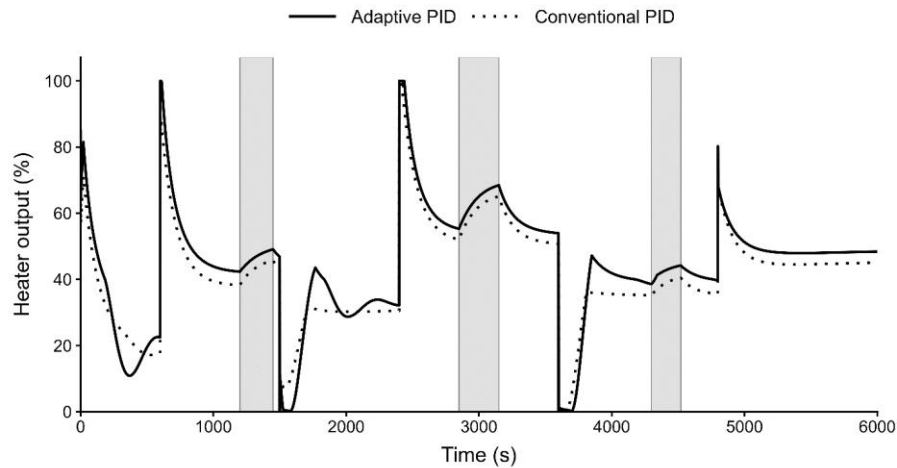


Figure 5. Comparison of Heater Power Between the Conventional PID and Adaptive PID Controllers Over Time.

During thermal load disturbances, the heater power tends to increase to compensate for the additional heat loss. After the disturbance is removed, the control signal gradually decreases to the level required to maintain stable operation. Throughout the simulation, the heater power remains within the prescribed range of 0–100%, consistent with the actuator constraints defined in the model. These results indicate that the dynamic adjustment of the control signal contributes to the improved temperature tracking and reduced control error achieved by the adaptive PID controller compared with the conventional PID controller.

3.5. Thermal Load Disturbance Rejection.

Figure 6 shows the temperature responses of the conventional PID and adaptive PID controllers during the three thermal load disturbance intervals. In all three cases, the disturbances cause the temperature to decrease below the setpoint. However, the adaptive PID controller maintains the temperature closer to the setpoint and exhibits a smaller temperature drop than the conventional PID controller. During the first disturbance, the adaptive PID controller maintains the temperature at approximately 75–78 °C, whereas the conventional PID response decreases to approximately 70–74 °C. A similar trend is observed during the second disturbance, where the adaptive PID controller maintains the temperature at approximately 85–91 °C, noticeably higher than that achieved by the conventional PID controller. During the third disturbance, the difference between the two controllers remains evident, with the adaptive PID maintaining the temperature at approximately 72–75 °C, while the conventional PID response decreases to approximately 68–70 °C. After each disturbance is removed, the adaptive PID controller exhibits faster temperature recovery and approaches the setpoint more closely. These results indicate that the online adjustment of K_p , K_i , and K_d enhances the controller's ability to compensate for disturbances and reduces the effects of thermal load variations.

Overall, the adaptive PID controller demonstrates better disturbance rejection performance than the conventional PID controller under all three investigated disturbance scenarios.

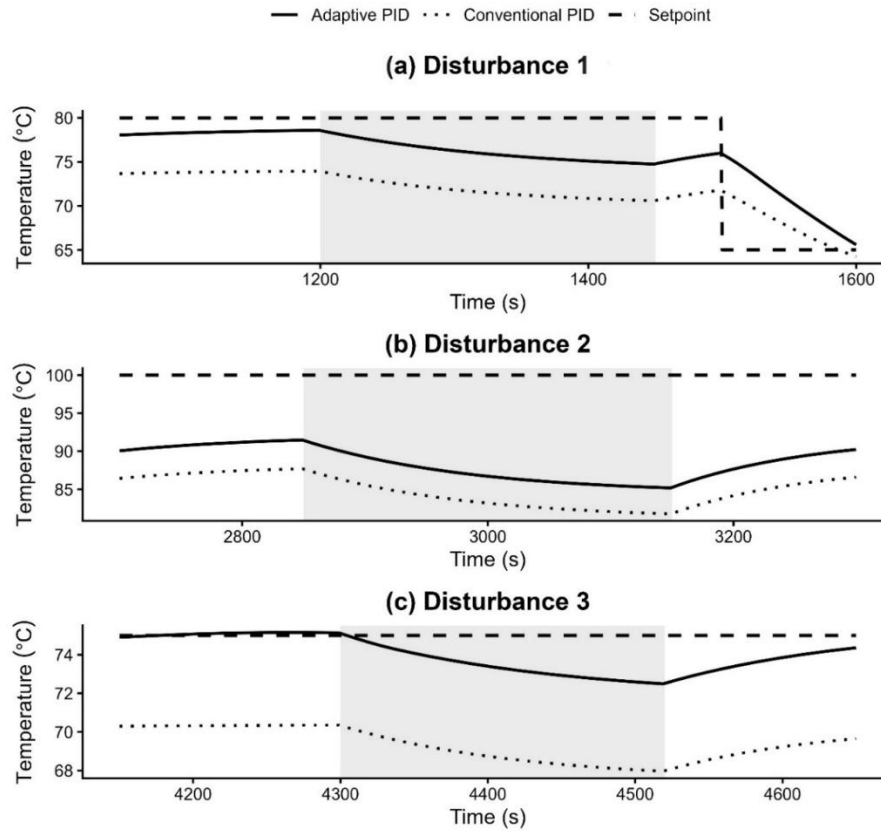


Figure 6. Comparison of the Temperature Responses of the Conventional PID and Adaptive PID Controllers Under Thermal Load Disturbances: (a) Disturbance 1, (b) Disturbance 2, and (c) Disturbance 3.

3.6. Quantitative Evaluation of Control Performance.

The performance of the conventional PID and adaptive PID controllers was evaluated using cumulative error indices and dynamic response characteristics. The results are summarized in Table 2. The results show that the adaptive PID controller improves all overall error-based performance indices. MAE and RMSE are reduced by 34.90% and 23.86%, respectively, while IAE and ISE decrease by 34.90% and 42.03%, respectively. In particular, the mean steady-state error decreases from 6.251 to 3.081 °C, corresponding to an improvement of approximately 50.72%. This result indicates that the adaptive PID controller maintains the system temperature closer to the desired setpoint. Regarding transient performance, the maximum overshoot decreases from 28.14% to 25.96%, corresponding to an improvement of 7.75%. However, the results for individual setpoint transitions indicate that this improvement is not consistent across all operating conditions. For the 80→65 °C transition, the adaptive PID controller produces an overshoot of 25.96%, which is higher than the 21.07% obtained with the conventional PID controller. In contrast, for the 100→75 °C transition, the overshoot decreases from 28.14% to 19.46%. Using a settling criterion of $\pm 2\%$ of the step amplitude maintained for at least 30 s, the conventional PID controller does not satisfy the settling requirement for any of the five setpoint transitions, whereas the adaptive PID controller satisfies the criterion for two decreasing transitions, 80→65 °C and 100→75 °C, with settling

times of 515 and 474 s, respectively. The increasing setpoint transitions do not satisfy this criterion within the investigated time intervals, primarily reflecting the slow thermal dynamics and heating power limitations of the model. Overall, the quantitative results demonstrate that the adaptive PID controller substantially improves temperature tracking accuracy and reduces cumulative control errors compared with the conventional PID controller. However, settling performance and overshoot remain dependent on the direction and magnitude of the setpoint change, indicating that further optimization of the adaptation law may provide additional performance improvements.

Table 2. Quantitative comparison of the performance of the conventional PID and adaptive PID controllers

Performance metric	Conventional PID	Adaptive PID	Improvement (%)
MAE (°C)	8.419	5.481	34.90
RMSE (°C)	10.236	7.793	23.86
IAE (°C·s)	50,516.455	32,886.760	34.90
ISE (°C ² ·s)	628,646.340	364,404.270	42.03
Maximum overshoot (%)	28.14	25.96	7.75
Number of settled transitions ($\pm 2\%$, ≥ 30 s)	0/5	2/5	—
Mean steady-state error (°C)	6.251	3.081	50.72

3.7. Discussion.

PID control continues to play an important role in industrial thermal systems due to its simple structure, high reliability, low computational requirements, and ease of implementation on existing control platforms [17]. However, PID performance strongly depends on the selection of K_p , K_i , and K_d , whereas the characteristics of thermal processes may vary with temperature setpoints, thermal loads, and operating conditions. Therefore, online parameter adjustment represents an appropriate approach for preserving the advantages of the PID structure while enhancing controller adaptability [18].

In this study, the adaptation mechanism based on the error $e(k)$ and the error variation $\Delta e(k)$ enables the controller to modify its control action according to the system state, following a principle similar to online tuning in fuzzy adaptive PID control [2]. When the error is large, increasing K_p strengthens the control action, while reducing K_i limits excessive accumulation of the integral term. As the temperature approaches the setpoint, the integral contribution is increased to compensate for the remaining tracking error. Meanwhile, K_d responds primarily to rapid changes in the error, thereby contributing to improved transient response. This mechanism is conceptually consistent with adaptive and fuzzy adaptive PID approaches applied to thermal processes, in which K_p , K_i , and K_d are adjusted online to improve system dynamics and adaptability [2, 19]. Although the proposed method is conceptually related to existing self-tuning and fuzzy adaptive PID strategies [15, 16, 18, 19, 26], its distinguishing feature lies in the simplicity of the adaptation mechanism rather than in a fundamentally new adaptive-control principle. Self-tuning PID approaches adjust controller parameters online according to changes in process conditions [15, 18], while fuzzy adaptive PID methods typically employ error-related information together with fuzzy rules and inference mechanisms to modify the PID gains [16, 19, 26]. In contrast, the present method directly maps the normalized error $e(k)$ and error variation $\Delta e(k)$ to bounded K_p , K_i , and K_d values through explicit algebraic relationships, without requiring a fuzzy inference system or online process identification. Therefore, the contribution of the proposed approach is its simple and transparent implementation while retaining the conventional PID structure, together with its evaluation under multiple temperature setpoints and thermal load disturbances.

Online parameter adjustment is particularly important when the system is subjected to thermal load disturbances. In heating processes, load variations disturb the balance between the supplied heating power and heat losses; consequently, a fixed set of PID gains may no longer be suitable for the new operating condition. The simulation results indicate that the adaptive approach tends to maintain the temperature closer to the setpoint and increase the heating action in response to disturbances. This trend is consistent with previous studies on adaptive and fuzzy adaptive PID control for thermal systems, where online parameter adjustment has been shown to improve system adaptability and disturbance rejection capability [2, 20].

In terms of overall performance, the reductions in MAE and IAE of approximately 34.9%, together with a 42.03% reduction in ISE, indicate that the main benefit of the proposed method lies in reducing tracking errors and suppressing large-magnitude deviations. However, the improvement is not consistent across all transient characteristics, as relatively large overshoot is still observed for some setpoint transitions. This indicates that reducing the overall tracking error does not necessarily imply simultaneous optimization of response speed, overshoot, and settling time. Such trade-offs among performance criteria have also been reported in multi-objective optimization studies of PID controllers [21, 22]. Therefore, the adaptation law should be considered as a compromise among multiple control objectives rather than as an approach for optimizing a single performance criterion. The higher overshoot during the 80→65 °C transition is mainly attributed to thermal inertia and the absence of active cooling. After the setpoint decreases, stored thermal energy cannot be dissipated immediately, while the adaptive gains and accumulated integral action temporarily affect the response. Therefore, improved overall tracking accuracy does not necessarily result in lower overshoot for every transition.

Another important factor is the physical limitation of the heating system. When the control output reaches its upper limit of 100%, further increases in control action cannot deliver additional energy to the thermal process. Conversely, when a rapid temperature reduction is required, the system can only reduce the heating power to 0% and cannot provide active cooling. Actuator saturation and the absence of an active cooling mechanism are important characteristics of thermal control systems [23]. Consequently, thermal inertia and actuator saturation can still dominate the system response, particularly during large temperature setpoint changes. Large thermal inertia has also been reported to contribute to increased overshoot and prolonged settling time [24]. These limitations partly explain why some setpoint transitions do not satisfy the strict settling criterion despite the overall improvement in temperature tracking performance.

Compared with offline PID optimization approaches such as PSO-PID, the proposed method updates the controller gains continuously during operation rather than relying on a fixed set of optimized gains [25]. Fuzzy adaptive PID methods also provide online parameter adjustment but generally employ fuzzy membership functions, rule bases, and inference mechanisms [2, 26]. In contrast, the present method directly maps $e(k)$ and $\Delta e(k)$ to bounded PID gains through a simple algebraic adaptation law, thereby retaining a relatively simple control structure. Nevertheless, because different controller architectures require independent tuning and the models and test conditions differ among published studies, their reported quantitative performance indices cannot be directly compared. A direct comparison with Fuzzy-PID and PSO-PID under the same thermal model and identical operating conditions

would therefore provide a more comprehensive benchmark and should be considered in future work.

Regarding closed-loop stability, the online adaptation is constrained by predefined finite ranges of K_p , K_i , and K_d , which prevents unbounded gain variation during operation. In addition, the control signal is limited to 0–100%, and the anti-windup mechanism restricts excessive accumulation of the integral term during actuator saturation. The gain ranges were empirically selected through preliminary simulations to maintain stable closed-loop operation over the investigated operating conditions. Under the multiple setpoint changes and thermal load disturbances considered in this study, the controller gains remained bounded and the temperature responses showed no sustained oscillation or divergence. These results provide numerical evidence of stable operation within the investigated parameter and operating ranges; however, they should not be interpreted as a general analytical proof of stability for arbitrary gain variations or operating conditions.

This study has several limitations. The current results were obtained from simulations and have not yet been validated on an actual industrial heating system. The thermal model was simplified and does not fully account for nonlinearities, time delays, variations in thermal parameters under different operating conditions, sensor errors, or complex disturbance patterns. In addition, the adaptation laws for K_p , K_i , and K_d are relatively simple, and their associated coefficients have not been optimized with respect to multiple control objectives.

Future studies should validate the proposed controller on an experimental heating system and evaluate its performance over a wider range of operating conditions. Further improvements in transient performance may be achieved by incorporating enhanced anti-windup mechanisms, derivative filtering, and optimization algorithms for tuning the parameters of the adaptation law. Moreover, direct comparisons with Fuzzy-PID, PSO-PID, and model predictive control (MPC) using the same thermal process and identical test conditions would provide a more comprehensive basis for assessing the effectiveness and industrial applicability of the proposed method.

4. Conclusions

This study proposed an adaptive PID controller for a heating system, in which K_p , K_i , and K_d are updated online based on the temperature error and its rate of change. Simulation results under varying setpoints and thermal load disturbances showed that the proposed method improved temperature tracking performance compared with the conventional PID controller. The adaptive controller maintained the temperature closer to the setpoint and exhibited better recovery under the investigated thermal load disturbances. However, improvements in overshoot and settling performance were not consistent across all setpoint transitions, mainly due to thermal inertia and heating power limitations. Overall, the results demonstrate the potential of the simple error-based adaptation law to improve temperature control performance under the simulated operating conditions without substantially increasing the complexity of the conventional PID structure. Nevertheless, since the present findings are based entirely on simulation, the practical applicability of the proposed controller should be further verified through experimental validation on an actual heating system. Future work should therefore focus on experimental validation, optimization of the parameter adaptation law, and evaluation over a wider range of operating conditions.

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Author Contribution

Nguyen Anh Quang: Conceptualization, Methodology, Writing, Supervision; Duong Duy Hoang: Data Collection, Data Analysis, Writing.

Competing Interest

The authors declare no competing interests.

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