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An advanced PID tuning method for temperature control in electric furnaces using the artificial rabbits optimization algorithm

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Abstract

In this study, we aim to enhance temperature control in electric furnaces, addressing key challenges in precision and response stability. We propose an integrated approach featuring a proportional–integral–derivative with *N* filter (PIDN) controller alongside the artificial rabbit's optimization (ARO) algorithm. The proposed PIDN controller incorporates adaptive tuning techniques designed to improve response accuracy and reduce overshoot, tailored specifically for the dynamic requirements of electric furnace applications. To optimize the PIDN parameters, we employ the ARO algorithm, a recent metaheuristic inspired by rabbit social behaviors, which has been customized for this control application. To evaluate the performance of the proposed framework, we introduce a modified objective function based on the integral of absolute error, emphasizing both transient and steady-state improvements. Comparative assessments with traditional controllers and metaheuristic algorithms, including the electric eel foraging optimization and whale optimization algorithm tuned by PIDN, genetic algorithm tuned by PID, Cohen–Coon algorithm tuned by PID, and direct synthesis algorithm tuned by PID, confirm the superior efficacy of our approach. Extensive tests including statistical analysis, noisy condition, and time and frequency domain evaluations demonstrate that our controller remains robust under nonideal conditions, such as measurement noise, external disturbances, and saturation. Results underscore the adaptability and effectiveness of this approach, marking a significant advancement in temperature control for electric furnaces.

Keywords Electric furnaces · Artificial rabbits optimizer · PID with *N* filter controller design · Temperature control · Tuning methods

Extended author information available on the last page of the article

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List of symbols

PI	Proportional–integral
PID	Proportional–integral–derivative
FOPID	Fractional-order PID
PIDN	Proportional–integral–derivative with N filter
ARO	Artificial rabbits optimization
WOA	Whale optimization algorithm
GA	Genetic algorithm
CC	Cohen–Coon
EEFO	Electric eel foraging optimization
DS	Direct synthesis
φ	Balancing coefficient
t_{set}	Settling time
HHO	Harris hawks optimization
PI-GPC	PI-based generalized predictive controller
EWOA+BE	Enhanced whale optimization algorithm with balloon effect
PSO	Particle swarm optimization
DOF	Degree-of-freedom
MPC	Model predictive control
FPFC	Fractional-order predictive functional control
mEEFO	Modified electric eel foraging optimizer
e^{-Ds}	Time delay
K_P	Proportional gain of controller
K_I	Integral gain of controller
K_D	Derivative gain of controller
OS	Overshoot
t_{rise}	Rise time
N	Controller filter
A	Computing an energy factor
E_{ss}	Steady-state error
r	Reference signal
y	Output system
F	Objective function
t_{sim}	Simulation time
σ	Stability factor
PSO	Particle swarm optimization
IAE	Integral absolute error
$N(s)$	Noise signal
$Y(s)$	Output signal
$U(s)$	Output signal from proposed controller
$E(s)$	Error between input and output signal
$R(s)$	Input signal
ZLG	Zwee-Lee-Gaing
SNR	Signal-to-noise ratio

1 Introduction

Effective temperature control in electric furnaces is crucial in industrial processes where high-precision heating is essential for producing metals, alloys, and other materials [1, 2]. However, maintaining stable temperatures presents challenges due to nonlinear dynamics, external disturbances, and variations in thermal loads [3]. These factors can lead to undesirable fluctuations, impacting the quality of the final product, increasing energy consumption, and elevating operational costs [4–6]. These challenges motivate the need for advanced control mechanisms that can enhance system stability and response accuracy in electric furnace applications.

Various control techniques have been employed for temperature regulation in electric furnaces, each with its unique advantages and limitations. The most common among these is the proportional–integral–derivative (PID) controller, valued for its simplicity and ease of implementation in industrial environments [7, 8]. More recent advancements include the fractional-order PID (FOPID) controller [9], which incorporates a fractional integrator order to offer enhanced control flexibility and adaptability, particularly when coupled with optimization algorithms like Harris hawks optimization (HHO) [10]. The implicit PI-based generalized predictive controller (PI-GPC) [11], optimized using the Lagrange multiplier method, has been effective in systems with time-delay constraints, allowing for real-time parameter adjustments and improved stability. Additionally, the PIDF controller, modified with a filter to mitigate transient effects, is particularly robust in electric furnace applications [12], especially when fine-tuned by algorithms. These advanced controllers address specific challenges, such as nonlinearity, coupling effects, and system disturbances, making them more suitable than conventional PID in demanding temperature regulation scenarios [7, 9].

Optimizing control parameters is a vital aspect of achieving high performance in temperature regulation systems [13]. Metaheuristic optimization algorithms, inspired by natural and evolutionary processes, have gained popularity due to their flexibility in handling complex, multidimensional search spaces [14]. Classic methods like genetic algorithm (GA) [15] and particle swarm optimization (PSO) [16] have demonstrated effectiveness, but newer approaches such as enhanced whale optimization algorithm with balloon effect (EWOA+BE) [17] and artificial rabbits optimization (ARO) offer additional enhancements in response accuracy and robustness [18]. The electric eel foraging optimization (EEFO) demonstrates superior performance in tuning controllers by leveraging social foraging behaviors, which optimizes temperature control in environments with nonlinear and time-delay characteristics [19]. By pairing these algorithms with advanced controllers, studies have achieved substantial improvements in tracking performance, rise time, and steady-state error, making them indispensable tools in electric furnace applications [7].

Industrial electric furnaces require advanced control systems to handle nonlinearities, time delays, and varying disturbances. Hussein et al. [17] proposed an adaptive control scheme integrating an EWOA+BE for online tuning of controller parameters, achieving superior performance in temperature control through minimized overshoot and improved settling times compared to traditional PID approaches. Other studies emphasize two-degree-of-freedom (2DOF) controllers for complex air temperature systems. In high-precision air temperature control systems, a two-degree-of-freedom (2DOF) controller integrates model predictive control (MPC) with loop shaping to enhance disturbance rejection, exemplifying how cascade architectures can achieve superior temperature stability [20]. The fractional-order predictive functional control (FPFC) method by Hu et al. [21] utilizes fractional calculus for predictive accuracy in managing large inertia and delay in industrial furnaces, outperforming integer-based control models. Additionally, Chen et al. [11] developed an implicit PI-GPC for multivariable temperature control systems with input constraints. This method demonstrates improved robustness through PI feedback integration and decoupling algorithms, tackling multivariable coupling effectively. Further advancements include a modified electric eel foraging optimizer (mEEFO) for optimizing PID tuning, enabling better temperature regulation and disturbance rejection in industrial settings [19]. Lastly, Feng et al. [22] implemented a hybrid intelligent control strategy for large heating furnaces, combining fuzzy and expert control to handle stable and fluctuating working conditions dynamically, significantly enhancing control precision and energy efficiency. Here is the literature review summary in Table 1:

This study presents an innovative framework for temperature control in electric furnaces, leveraging a refined PIDN controller optimized using the ARO algorithm. The main contributions of this work are as follows:

1. *Design PIDN controller* Development of an advanced PIDN controller specifically tailored for the high precision and stability requirements of electric furnace temperature regulation.
2. *Optimization technique* Integration of the ARO algorithm to optimize PID parameters effectively, ensuring fast, accurate, and stable control under varying operational conditions.
3. *Objective function enhancement* Design of a modified objective function aimed at minimizing integral error and enhancing the transient response, thereby achieving faster settling times and reducing overshoot.

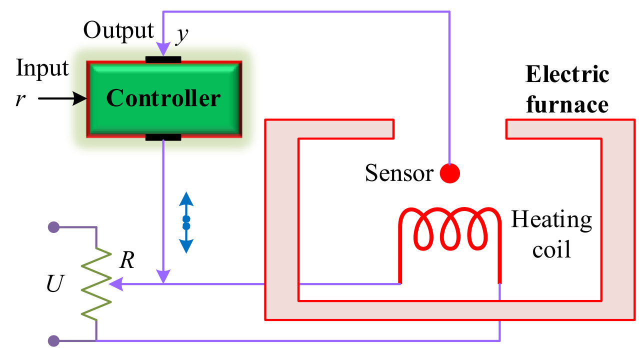

Fig. 1 Block diagram of temperature control system

Through extensive comparative analyses, including statistical validations and robustness tests under nonideal conditions, this study highlights the superiority of the proposed approach over existing methods. The framework not only enhances control performance but also contributes to the advancement of temperature control technology in industrial applications, setting a new benchmark in electric furnace regulation.

The structure of the paper is as follows: Sect. 2 covers the mathematical modeling of the electric furnace system. In Sect. 3, we present and explain about PIDN structure, optimized using ARO. Section 4 discusses the ARO optimization method, highlighting its suitability for parameter tuning. Section 5 showcases the simulation results and offers a comprehensive comparison with other popular controllers and metaheuristic optimization methods. Finally, Sect. 6 concludes the paper with a summary of key findings and potential future directions.

2 Mathematical modeling of electric furnace temperature control system

The temperature control system for an electric furnace can be represented by a simplified block diagram, as shown in Fig. 1. This system includes a controller, electric furnace, heating coil, and temperature sensor. The controller adjusts the input U to maintain the desired output temperature y, based on the error between the set point r and the measured temperature.

The transfer function $G(s)$ of the electric furnace system with time delay is given by:

$$G(s) = \frac{b_0}{a_2 s^2 + a_1 s + a_0} e^{-Ds} \tag{1}$$

where e^{-Ds} represents the time delay ($1.5s$) of the system. For this study, a first-order Pade approximation of the time

Table 1 Overview of utilizing controller and optimization method in the recent paper

Article	Controllers and optimizations type	Approaches	Findings
Hussein et al. [17]	Enhanced whale optimization algorithm balloon effect (EWOA+BE)	Enhanced whale optimization with adaptive tuning	Reduced overshoot, faster settling times, superior to traditional PID under load changes
Dong et al. [20]	Two-degree-of-freedom model predictive control with loop shaping (2DOF MPC)	Dual-loop structure with predictive control	Enhanced disturbance rejection for high-precision ATC systems under fluctuating loads
Hu et al. [21]	Fractional-order predictive functional control (FPFC)	Fractional calculus-based predictive control	Superior tracking for large inertia and delay; outperforms integer-based models
Chen et al. [11]	Implicit proportional–integral-based generalized predictive controller (PI = GPC) with decoupling	PI feedback, Lagrange multiplier method	Efficient multivariable control with input constraints, reducing coupling effects
Alzakari et al. [19]	Modified electric eel foraging optimization with PIDF controller (mEEFO with PIDF)	Electric eel foraging optimization (metaheuristic)	Effective temperature control with minimal energy consumption, optimized transient response
Feng et al. [22]	Hybrid intelligent control (Fuzzy + expert controller)	Condition-based switching for CSP furnaces	Dynamic adaptation to stable/fluctuating conditions, improving control accuracy

delay is used to simplify the control design, given by:

$$e^{-Ds} \cong \frac{2 - Ds}{2 + Ds} \tag{2}$$

Substituting this approximation into the transfer function yields:

$$G(s) = \frac{b_0(2 - Ds)}{\left(a_2 s^2 + a_1 s + a_0\right)(2 + Ds)} \tag{3}$$

For this study, with parameters $a_0 = 0.2$, $a_1 = 1.1$, $a_2 = 1$, $b_0 = 0.15$, and $D = 1.5$, the expanded transfer function becomes [19, 23, 24]:

$$G(s) = \frac{-0.1125s + 0.15}{0.75s^3 + 1.825s^2 + 1.25s + 0.2} \tag{4}$$

Finally, $G(s)$ provides a comprehensive model of the system's dynamics, incorporating the effects of system parameters and time delay, allowing for an effective control design. This transfer function accurately models the electric furnace's behavior by considering its dynamic elements such as the heat transfer properties and time delay allowing the controller to be designed and tuned for stable, efficient temperature regulation. By accounting for these factors, the system can achieve a responsive and precise temperature control, even under varying operating conditions. This model also facilitates advanced control strategies, potentially improving energy efficiency and prolonging the lifespan of the furnace components. Figure 2 demonstrates general schematic of electric furnaces system using ARO optimization method.

3 Structure of PIDN controller for temperature control system

The PIDN controller structure in this study is designed to enhance system stability and responsiveness by integrating a filtering component alongside the proportional, integral, and derivative terms. The transfer function for the PIDN controller is defined as:

$$C(s) = K_P + \frac{K_I}{s} + K_D \frac{Ns}{s + N} \tag{5}$$

where K_P, K_I, and K_D are the proportional, integral, and derivative gains, respectively, and N is the filter coefficient. This structure aids in reducing high-frequency noise effects, thereby improving control performance under various disturbances. The block diagram Fig. 3 represents this PIDN controller, showing its integration with the system and how it manages disturbances and measurement noise effectively.

To evaluate the performance of the PIDN controller, the closed-loop system response is analyzed. Using the Simulink PIDN tuner optimized parameters are $K_P = 2.5150$, $K_I = 0.4572$, $K_D = 2.2864$, $N = 86.5030$. The PIDN controller generated a controlled response that closely follows the temperature set point with minimal overshoot. The closed-loop equation represented as follows:

$$T_{\text{closed-loop}}(s) = \frac{C(s)G(s)}{1 + C(s)G(s)} \tag{6}$$

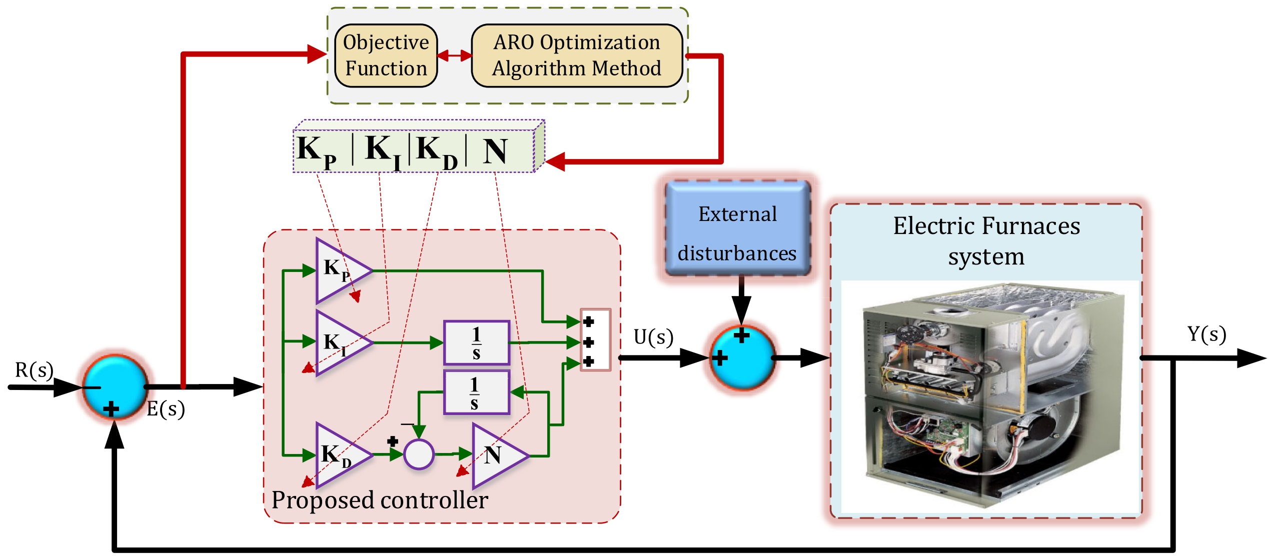

Fig. 2 General schematic of electric furnaces system using ARO optimization method

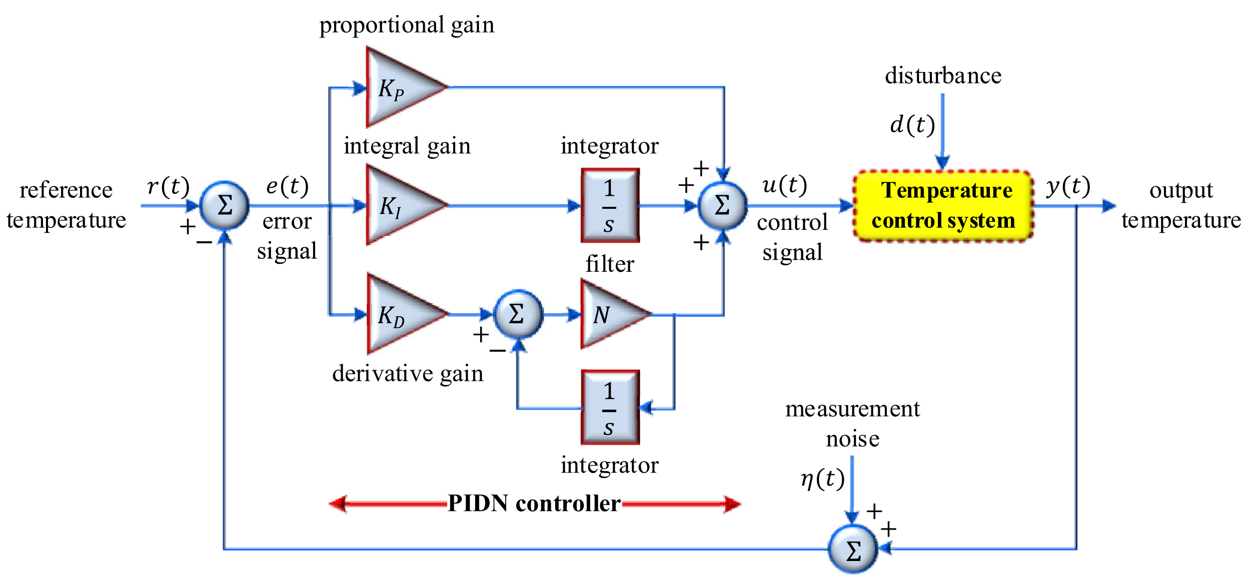

Fig. 3 Block diagram of a PIDN-controlled system incorporating disturbance and measurement noise

$$T_{\text{closed-loop}}(s) = \frac{-22.53s^3 + 5.518s^2 + 28.25s + 5.932}{0.75s^5 + 66.7s^4 + 136.6s^3 + 113.8s^2 + 45.55s + 5.932} \quad (7)$$

Figure 4 shows the closed-loop system response optimized using the PIDN controller. The key metrics observed include a rise time (t_{rise}) of approximately 3.0587s, a settling time (t_{set}) of 9.2888s, and an overshoot (OS%) of 3.6591%. However, the obtained values through Simulink PIDN tuner are not good and needs to be improved via a more effective new control strategy such that the PIDN tuning effectively balances response speed and stability, which is crucial for precise temperature control in industrial applications. The proposed control methodology with this work aims to provide a combination of approximation, advanced controller structure, and tuning to provide a comprehensive approach to managing temperature in electric furnaces, aligning well with the requirements for both accuracy and robustness in industrial settings.

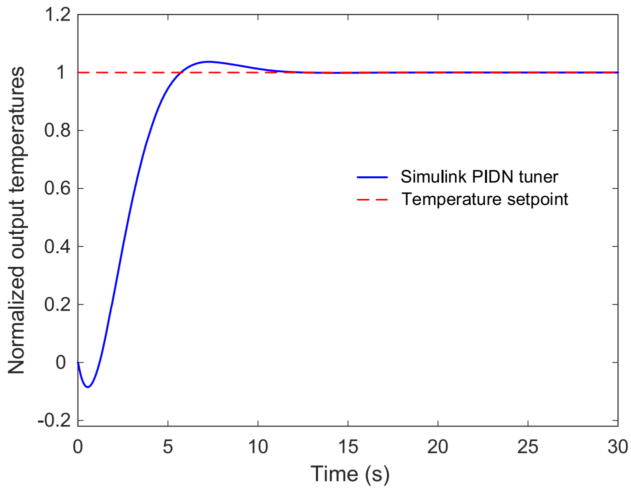

Fig. 4 Closed-loop system response optimized using the Simulink PIDN tuner

4 Optimization method and definition of the problem

4.1 Artificial rabbits optimization

The artificial rabbits optimization (ARO) is inspired by the survival strategies of rabbits, specifically through detour foraging and random hiding behaviors [25]. This algorithm models' rabbits' tendency to forage away from their nests to avoid detection by predators and their habit of digging multiple burrows to evade capture. Each rabbit in the population performs exploratory detour foraging, where it moves toward other regions in the search space, and exploitative random hiding, selecting burrows randomly to minimize predation risk [25]. The ARO algorithm effectively balances exploration and exploitation phases by adapting these behaviors, enhancing global and local search capabilities, respectively [18, 25, 26].

The operational framework of ARO begins by computing an energy factor (A) to determine whether the foraging or hiding strategy will be executed. If $A > 1$, the algorithm initiates detour foraging, where rabbits explore distant regions to gather resources. If $A \leq 1$, random hiding is triggered, allowing rabbits to use their burrows as protective measures while exploiting local areas. Through this approach, the algorithm continually assesses the fitness function and updates the best solution iteratively until termination conditions are met, ensuring effective convergence and solution optimization across complex search spaces. Figure 5 shows the flowchart of ARO optimization method. The application of ARO has shown notable results in various optimization tasks, as highlighted in the literature [18, 25, 26].

4.2 ARO-based controller design utilizing a modified objective function for enhanced performance

This section presents the development of an ARO-based controller, utilizing a modified objective function to achieve enhanced performance in a temperature regulation system. By leveraging ARO principles, this controller aims to dynamically adjust its parameters, ensuring robustness and stability across various operational conditions.

4.2.1 Objective function (F)

To improve the temperature control performance of the electric furnace system, this study employs the IAE as a primary objective function for minimization, as defined in Eq. (8). The IAE represents the total absolute difference between the reference signal $r(t)$ and the system output $y(t)$ over time, offering a direct measure of control accuracy [27]:

$$\mathrm{IAE} = \int_0^{t_{\mathrm{sim}}} |e(t)|\mathrm{d}t \tag{8}$$

$$F = \sigma \int_0^{t_{\mathrm{sim}}} |e(t)|\mathrm{d}t + (1-\sigma)t_{\mathrm{set}} \tag{9}$$

where $\sigma = 0.70$ is stability factor and simulation time is $t_{\mathrm{sim}} = 100s$.

$$\text{Error signal} = e(t) = r(t) - y(t) \tag{10}$$

Here, $e(t)$ is the error between the input and output signals. In temperature control applications for the electric furnace system, minimizing this error is essential to achieve a rapid response with minimal overshoot and a swift settling time. To address these criteria, this study introduces a novel cost function (F), as shown in Eq. (9), which combines the IAE with the system's t_{set}. This approach captures both accuracy and responsiveness in a single metric: The bounds for the PIDN controller parameters are chosen to balance responsiveness and stability while minimizing control effort. Table 2 outlines the ranges for each parameter, indicating the upper and lower bounds considered in the design:

The ARO-based PIDN controller's operational structure is depicted in Fig. 6, a block diagram illustrating the interaction between the controller and the temperature regulation system. Each block in the diagram represents a specific function, including error detection, parameter adjustment, and optimization. The ARO block dynamically tunes the PIDN parameters in response to real-time error and stability feedback, adapting to maintain desired temperature levels while minimizing power consumption and ensuring consistent response across changing conditions.

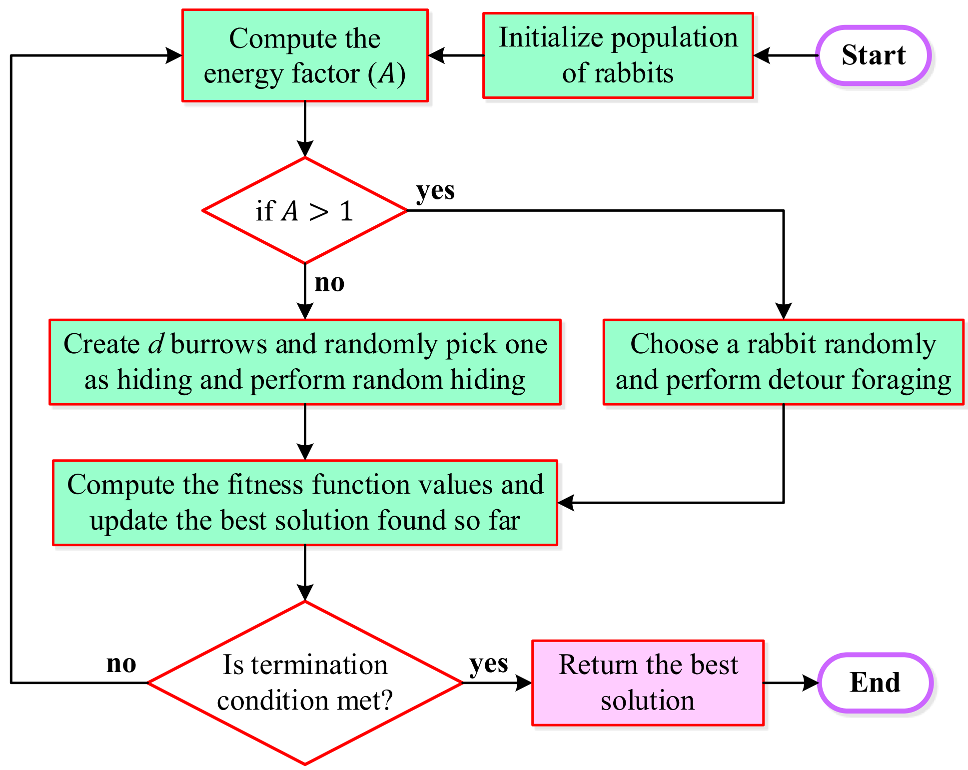

Fig. 5 Operational framework of ARO

Table 2 Bounds of PIDN controller

Range of parameters	K_P	K_I	K_D	N
Lower bound (Min)	1	0	3	10
Upper bound (Max)	4	2	7	500

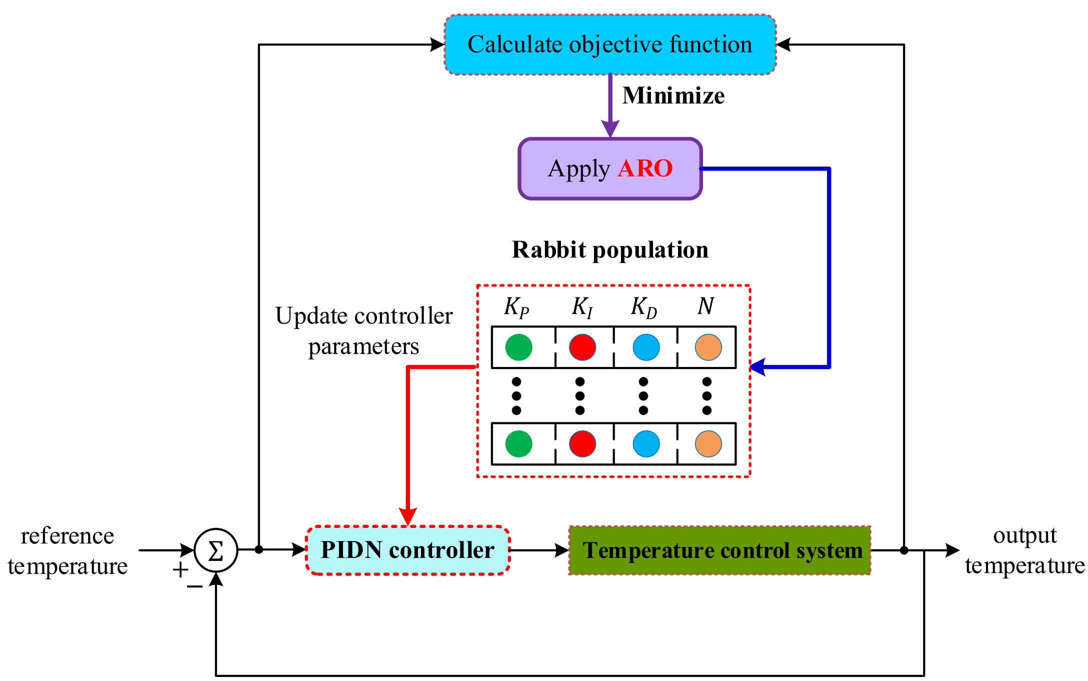

Fig. 6 Block diagram of ARO-optimized PIDN controller for temperature regulation system

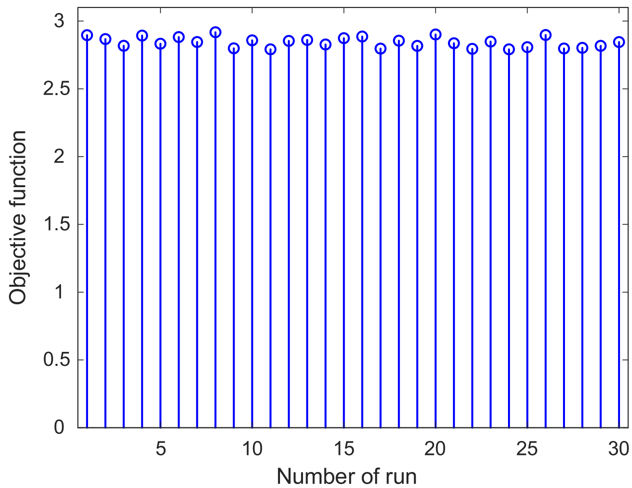

Fig. 7 Objective function values obtained using ARO

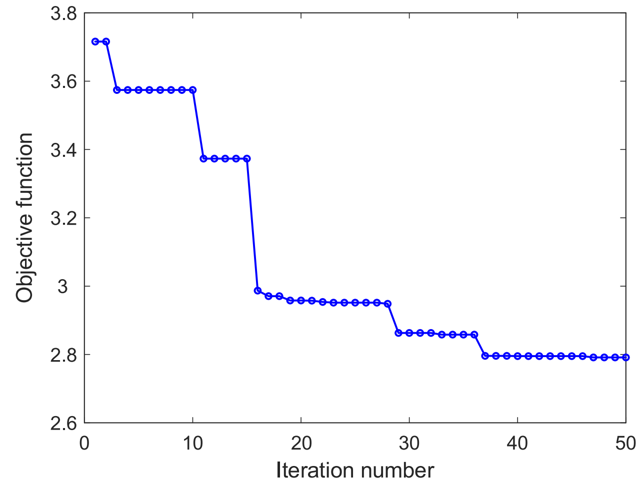

Fig. 8 Convergence graph of objective function

Table 3 Statistical metrics of F objective functions minimized by ARO algorithm

Statistical measures	Value
Maximum	2.9173
Minimum	2.7914
Average	2.8435
Standard division	0.0380
Median	2.8452

5 Simulation results

5.1 Statistical performance evaluation of ARO

To evaluate the performance of the ARO algorithm, we conducted a statistical analysis based on 30 independent runs. Each run used a rabbit population of 30 and a maximum iteration count of 50. This statistical evaluation aims to assess the consistency and robustness of the ARO algorithm in optimizing the objective functions. Figure 7 shows the objective function values obtained using ARO after 30 runs.

Table 3 presents the statistical metrics of the objective functions minimized by the ARO algorithm, including the maximum, minimum, average, standard deviation, and median values. These metrics are crucial in understanding the reliability of ARO across multiple trials and identifying the best achievable performance.

5.2 Convergence curve of objective function and extracted PIDN controller parameters optimized by ARO

The following section highlights the optimization process of a PIDN controller using the ARO method, illustrating its effectiveness through convergence graphs and parameter evolution. Additionally, it compares the ARO-optimized parameters to those obtained by other well-known tuning techniques, providing a clear benchmark of performance. Figure 8 displays the convergence of the objective function over the course of the optimization process. This graph shows the progressive reduction in the objective function's value as the ARO algorithm iterates toward an optimal solution. The decreasing trend indicates that the algorithm is effectively minimizing the objective function, thus enhancing the PIDN controller's performance. As the curve stabilizes, it signifies that the ARO method has identified parameters that balance control accuracy, stability, and responsiveness, achieving a near-optimal configuration for the system. Figure 9 illustrates the adjustments in the PIDN controller parameters as the optimization progresses. Each parameter is fine-tuned in response to the algorithm's feedback, indicating a dynamic adjustment that brings the controller closer to its optimal configuration. This evolution of parameters demonstrates the adaptability and responsiveness of the ARO method in achieving precise tuning. By the end of the process, each parameter has been set to a value that enhances the overall performance, stability, and robustness of the control system.

Table 4 compares the PIDN controller parameters obtained through ARO optimization with those achieved by other popular tuning techniques, including EEFO, WOA, GA, CC, and DS. Each method produces different values for the controller parameters, which can significantly impact control performance. The table reveals the following insights:

From this comparison, it is evident that the ARO-optimized PIDN parameters provide a balanced and effective configuration compared to other methods. While some methods yield values that diverge from the optimal range, ARO maintains parameters that contribute to a stable, responsive,

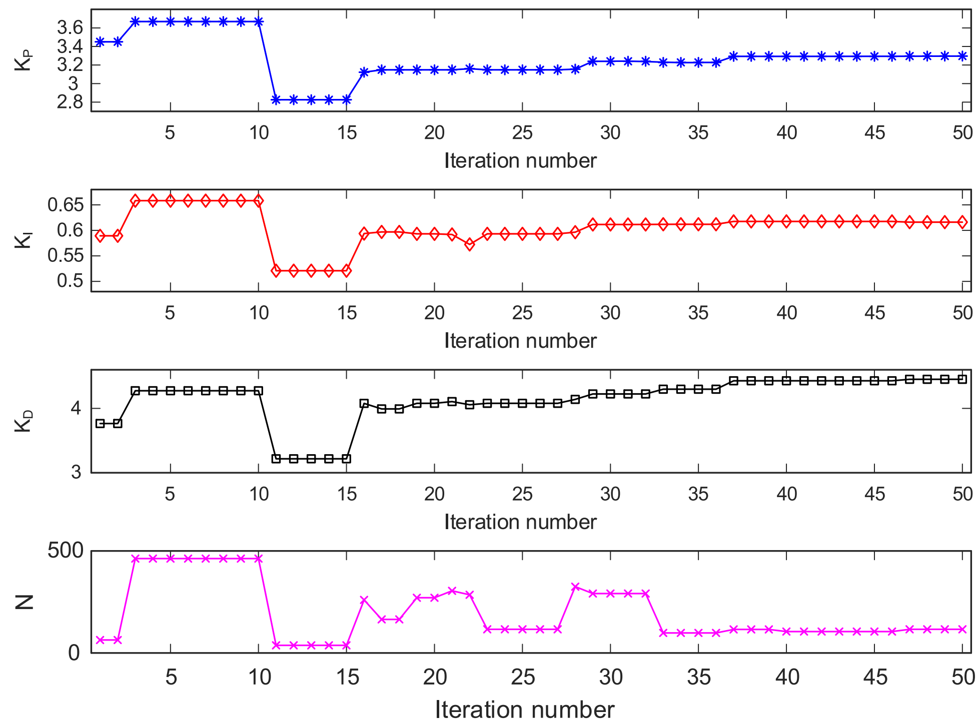

Fig. 9 Change of PIDN controller parameters

Table 4 Optimal parameters obtained by various tuning method

Tuning method	K_P	K_I	K_D	N
ARO-optimized PIDN (proposed)	3.2961	0.6162	4.4519	116.0697
EEFO-optimized PIDN [19]	3.1365	0.5925	4.1063	482.4784
WOA-optimized PIDN [19]	3.3376	0.5802	4.0353	86.5032
GA-optimized PID [23]	3.4066	0.6221	6.7512	–
CC-optimized PID [24]	3.9931	0.4144	2.6267	–
DS-optimized PID [24]	2.5150	0.4572	2.2864	–

and efficient control system. Notably, the noise (N) parameter, which directly impacts system stability in the presence of high-frequency disturbances, is more effectively managed in the ARO-optimized PIDN than in methods such as EEFO, where the noise parameter is significantly higher. The ARO algorithm has proved to be a powerful and reliable method for optimizing PIDN controller parameters, as evidenced by both the convergence curve and parameter comparison. By tuning each parameter to ideal values, ARO enhances the controller's stability, accuracy, and adaptability, offering a superior alternative to traditional optimization techniques.

5.3 Closed-loop time response performance

This section explores the time-domain performance of various optimization algorithms by examining their step responses. The step response serves as a vital indicator of system performance, reflecting aspects like stability, response speed, and accuracy. Figure 10 presents the step responses of different algorithms, offering insights into their dynamic characteristics. In addition, Fig. 11 provides a detailed view of the step responses in Fig. 10, highlighting essential performance metrics such as OS%, t_{rise}, and t_{set}.

Table 5 provides a detailed summary of the optimal controller parameters derived from the optimization process for each algorithm. This table also includes the corresponding closed-loop transfer functions, shedding light on the dynamic properties of the optimized controllers. These parameters are essential for attaining optimal closed-loop performance in the temperature control system. By jointly analyzing convergence behavior and the obtained controller parameters, a comprehensive view of the optimization algorithms' effectiveness in designing controllers for the electric furnace temperature regulation is achieved. The strong performance of ARO in both convergence and parameter optimization highlights its suitability for practical application in real-world control systems.

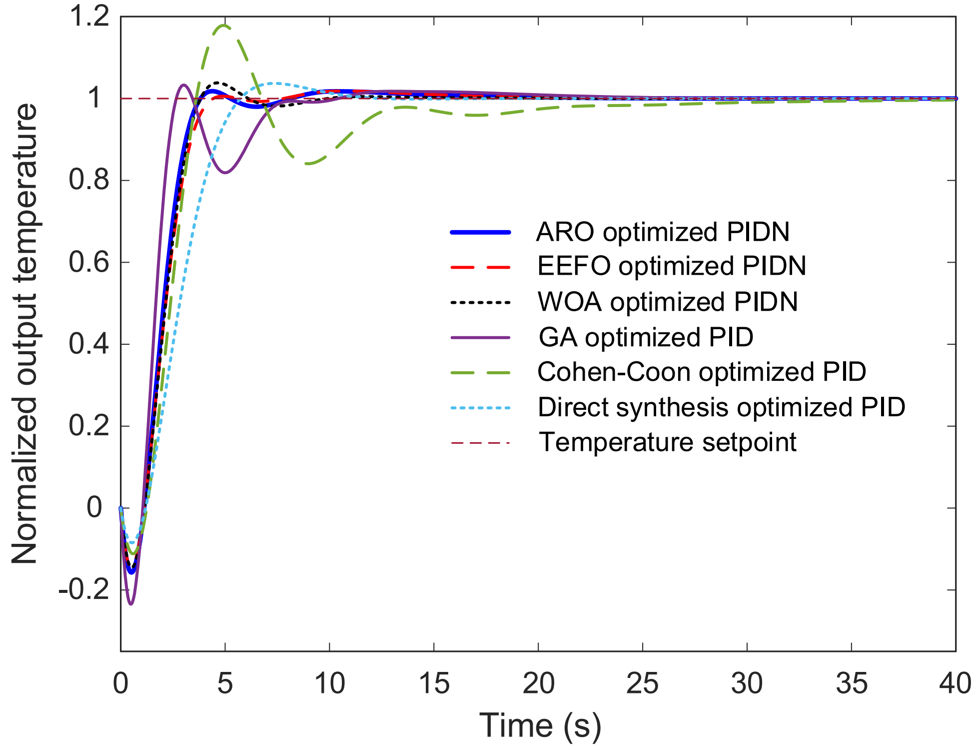

Fig. 10 Comparative time responses

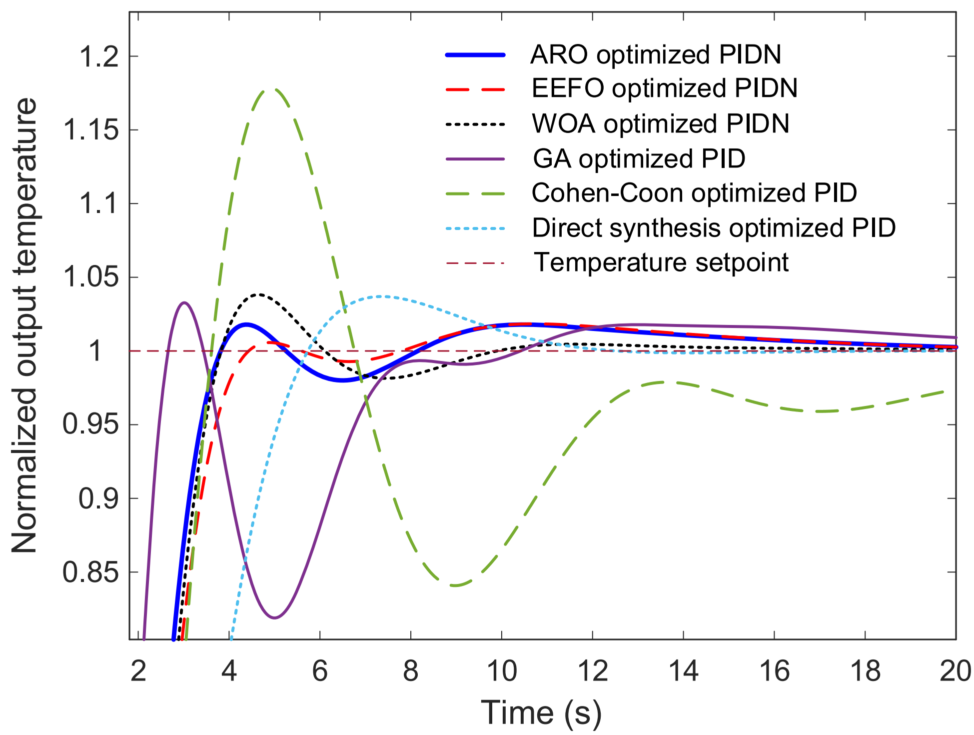

Fig. 11 Enlarged view of time responses

Table 5 Closed-loop transfer function of the system optimized by various tuning method

Tuning method	Closed-loop transfer function
ARO-optimized PIDN (proposed)	$\frac{-58.5s^3+34.89s^2+49.43s+10.73}{0.75s^5+88.88s^4+154.6s^3+180.2s^2+72.65s+10.73}$
EEFO-optimized PIDN [19]	$\frac{-223.2s^3+127.3s^2+194.9s+42.88}{0.75s^5+363.7s^4+658.5s^3+730.6s^2+291.4s+42.88}$
WOA-optimized PIDN [19]	$\frac{-39.65s^3+20.32s^2+37.75s+7.528}{0.75s^5+66.7s^4+119.5s^3+128.6s^2+55.05s+7.528}$
GA-optimized PID [23]	$\frac{-0.7595s^3+0.6294s^2+0.441s+0.09331}{0.75s^4+1.065s^3+1.879s^2+0.641s+0.09331}$
CC-optimized PID [24]	$\frac{-0.2955s^3-0.05522s^2+0.5523s+0.06216}{0.75s^4+1.529s^3+1.195s^2+0.7523s+0.06216}$
DS-optimized PID [24]	$\frac{-0.2572s^3+0.06002s^2+0.3258s+0.06858}{0.75s^4+1.568s^3+1.31s^2+0.5258s+0.06858}$

Table 6 Comparison of transient response specifications

Tuning method	Rise time (s)	Settling time (s)	Overshoot (%)	Steady-state error (%)
ARO-optimized PIDN (proposed)	1.7956	3.5982	1.7923	1.4322E−12
EEFO-optimized PIDN [19]	2.0330	4.0212	1.8421	6.8168E−12
WOA-optimized PIDN [19]	1.8674	5.4821	3.8198	3.0287E−11
GA-optimized PID [23]	1.1378	7.3185	3.2725	1.6148E−07
CC-optimized PID [24]	1.7853	21.4023	17.8485	0.0012
DS-optimized PID [24]	3.0806	9.3605	3.6937	4.5408E−12

Table 6 presents a numerical evaluation of time-domain performance metrics, providing quantitative values for overshoot, rise time, and settling time across each algorithm. These values reveal that ARO achieves the lowest overshoot at 1.7923%, demonstrating enhanced control over transient oscillations compared to other algorithms. Moreover, ARO shows the fastest rise time at 1.7956 s, reflecting a quicker response to changes in the reference signal than its counterparts. With a settling time of 3.5982 s, ARO also surpasses other algorithms in reaching stability and precision within a shorter duration. Collectively, these results indicate that ARO not only excels in optimization but also delivers outstanding dynamic performance in the time domain. This analysis of step response, supported by numerical data, highlights ARO's effectiveness in achieving precise and efficient temperature control for the electric furnace system.

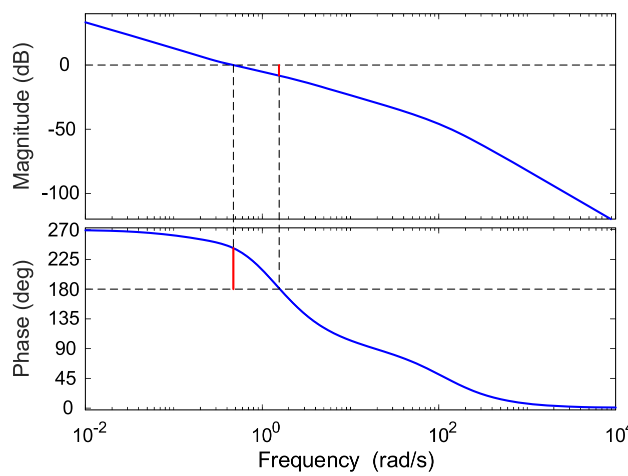

Fig. 12 Bode plot of open-loop PIDN-controlled system optimized by ARO

5.4 Frequency response performance

This section examines the frequency domain performance of various optimization algorithms through Bode diagram analysis. Figure 12 presents the Bode diagrams for proposed controller tuned by ARO algorithm, illustrating their frequency response characteristics and offering a visual comparison. Additionally, Table 7 provides a numerical evaluation of essential frequency domain parameters, including phase margin, gain margin, and bandwidth, enabling a detailed assessment of each algorithm's stability and responsiveness.

The results in Table 7 show that the ARO-optimized PIDN tuning method offers a strong balance across key frequency response specifications. With a phase margin of 62.6683°, a gain margin of 8.2582 dB, and a bandwidth of 1.4567 rad/s, the ARO-optimized PIDN achieves a good compromise between stability and responsiveness. While it does not reach the highest phase margin observed in the

Table 7 Comparison of frequency response specifications

Tuning method	Phase margin (°)	Gain margin (dB)	Bandwidth (rad/s)
ARO-optimized PIDN (proposed)	62.6683	8.2582	1.4567
EEFO-optimized PIDN [19]	63.0627	8.9281	1.3027
WOA-optimized PIDN [19]	60.4229	8.5523	1.3379
GA-optimized PID [23]	68.9974	5.8858	2.2322
CC-optimized PID [24]	45.8826	7.5116	1.1753
DS-optimized PID [24]	61.1560	11.7940	0.7403

GA-optimized PID (68.9974°) or the highest gain margin seen in the DS-optimized PID (11.7940 dB), it maintains a well-rounded performance with competitive bandwidth, outperforming several other methods like the EEFO- and WOA-optimized PIDNs. This balanced profile highlights the effectiveness of ARO optimization in achieving robust and responsive control performance.

5.5 Well-known performance indicators

The performance indicators presented here, IAE and Zwee-Lee-Gaing (ZLG), are widely recognized metrics for evaluating control system performance. The IAE measures the cumulative error over the simulation time, providing a quantitative assessment of accuracy by IAE, $|e(t)|$ over time. A lower IAE value indicates that the system effectively minimizes error throughout its operation, which is crucial for applications requiring high precision. The ZLG indicator combines multiple aspects of dynamic response, including %OS, steady-state error ($\%E_{\text{ss}}$), t_{set}, and t_{rise}. It incorporates a balancing coefficient $\varphi = e^{-1} = 0.3679$ to adjust the weighting between overshoot, steady-state error, and timing characteristics, making it a comprehensive measure of both accuracy and responsiveness. The ZLG metric is particularly useful for evaluating how well a system balances rapid response with minimal overshoot and error, which are critical qualities for stable and efficient control [27].

$$\text{IAE} = \int_0^{t_{\text{sim}}} |e(t)|\text{d}t \tag{11}$$

$$\text{ZLG} = (1-\varphi)\left(\frac{\%\text{OS} + \%E_{\text{ss}}}{100}\right) + \varphi(t_{\text{set}} - t_{\text{rise}}) \tag{12}$$

Table 8 Comparison of IAE and ZLG performance indicators

Tuning method	IAE	ZLG
ARO-optimized PIDN (proposed)	2.4456	0.6745
EEFO-optimized PIDN [19]	2.5236	0.7431
WOA-optimized PIDN [19]	2.4627	1.3539
GA-optimized PID [23]	2.5095	2.2944
CC-optimized PID [24]	3.9343	7.3295
DS-optimized PID [24]	3.1692	2.3336

Table 8 highlights the comparison of well-known performance indicators, IAE and ZLG, across different tuning methods. The ARO-optimized PIDN demonstrates the lowest IAE value at 2.4456, indicating superior error minimization over the simulation period compared to other methods. Additionally, the ARO-optimized PIDN achieves the lowest ZLG value of 0.6745, reflecting an excellent balance between overshoot, steady-state error, and response times. In contrast, other methods such as the GA- and DS-optimized PIDs show higher ZLG values, indicating less desirable dynamic response characteristics. The overall results underline the effectiveness of the ARO-optimized PIDN in achieving minimal error and a balanced dynamic response, positioning it as a strong choice for applications requiring precise control performance.

6 Reference signal tracking performance

In an electric furnace temperature control system, precise input signal tracking is essential for sustaining optimal performance, especially within dynamic conditions. As illustrated in Fig. 13, the ARO-based PIDN controller exhibits exceptional accuracy in tracking input temperature signals. Figure 13 further emphasizes the controller's effectiveness in delivering high-performance results. Achieving this level of precision is vital for maintaining process stability and achieving the desired temperature outcomes in real-time applications, ensuring reliable and efficient operation.

6.1 Assessment of performance under nonideal conditions

6.1.1 Disturbance and measurement noise rejection

Within the scope of this investigation, a more realistic model for managing the temperature within an electric furnace system was also investigated. This was done in order to better demonstrate the efficacy of the strategy that was provided. Among the more practical factors that are incorporated into this model are measurement noise as a disturbance factor,

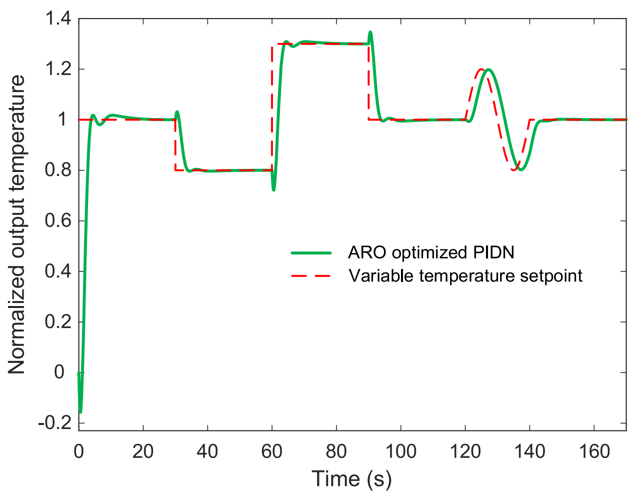

Fig. 13 Input signal tracking capability of ARO-optimized PIDN controller

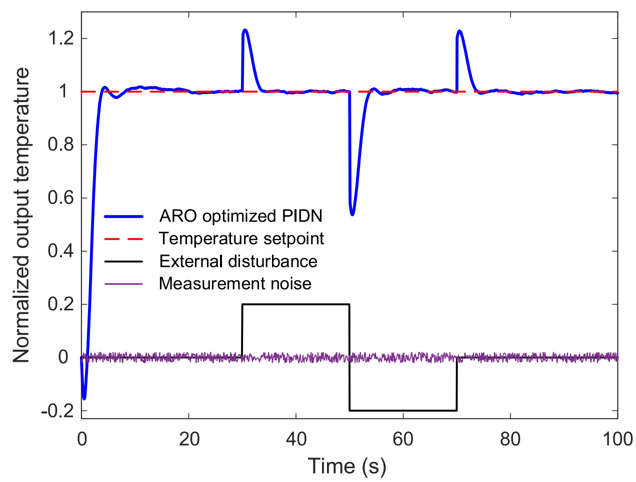

Fig. 15 Disturbance and noise rejection capability of ARO-optimized PIDN

external disturbances, and input saturation as a nonlinear influence on the temperature control system of the furnace. Figure 14 depicts the system in its current state, which is considerably less than optimal.

Regarding the noise that was present in the measurements, white Gaussian noise was utilized, and the signal-to-noise ratio (SNR) was set at 20 decibels. The normalized output temperature variations are shown in Fig. 15, which depicts the conditions under which the output temperature varies. As can be seen in this picture, the proposed strategy is able to successfully manage the nonlinear effects by swiftly recovering the output that is intended.

7 Conclusion and future work

This study introduces a novel framework for electric furnace temperature control, combining a PIDN controller tuned using a powerful optimization method known as the ARO algorithm. Extensive testing demonstrates that this approach significantly outperforms traditional controllers and meta-heuristic algorithms, including the EEFO and WOA tuned by PIDN, GA tuned by PID, CC algorithm tuned by PID, and DS algorithm tuned by PID. The robustness and adaptability of the proposed method are demonstrated through comprehensive statistical analysis, examining its behavior under varying conditions such as disturbances and noise entering the system. The analysis includes evaluating the system's response and performance across both time and frequency domains. The results indicate a marked improvement over previous methods, showing significant advancements in regulating electric furnaces. The analysis also highlights a number of intriguing avenues for further investigation in the future. In order to gain significant insights into the framework's applicability in the real world, it would be beneficial to evaluate

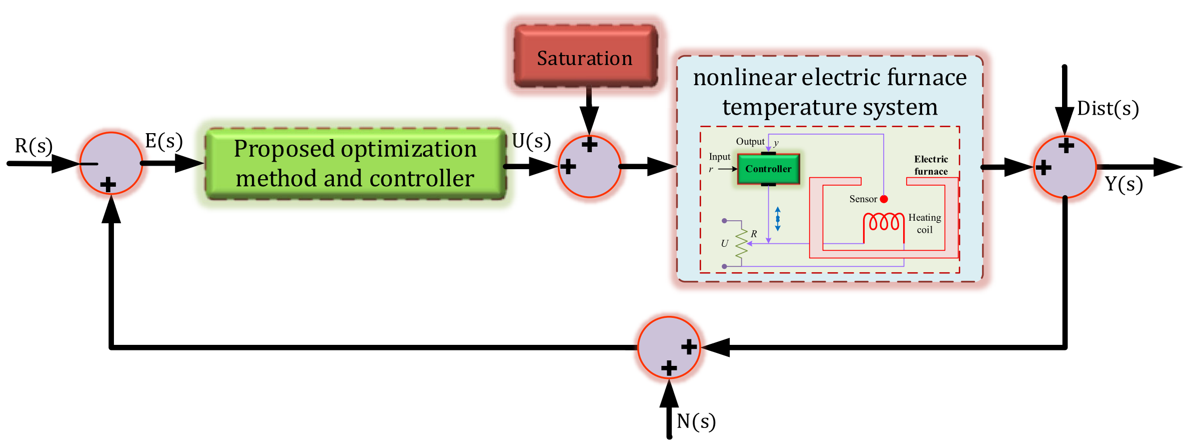

Fig. 14 Accurate model for regulating temperature in an electric furnace system

the adaptability and performance of this framework in industrial settings. It is also possible that further strengthening its resilience might be accomplished by analyzing the impact of different environmental conditions and system uncertainty. Further development of the ARO algorithm, in conjunction with the investigation of several alternative objective functions, may result in the creation of even more sophisticated control strategies. The incorporation of this framework into industrial automation systems would be made easier by the collaborative efforts of control engineers and practitioners from the industry. In conclusion, a more in-depth comprehension of the approach's potential in complex industrial settings would be facilitated by the expansion of the method to include multivariable systems, as well as the consideration of nonlinearities and external disturbances.

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Declarations

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this paper.

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References

1. Zhou D et al (2022) Intelligent manufacturing technology in the steel industry of China: a review. Sensors 22(21):8194
2. Singh S, Berndt CC, Singh Raman R, Singh H, Ang AS (2023) Applications and developments of thermal spray coatings for the iron and steel industry. Materials 16(2):516
3. Behzadi A, Holmberg S, Duwig C, Haghighat F, Ooka R, Sadrizadeh S (2022) Smart design and control of thermal energy storage in low-temperature heating and high-temperature cooling systems: a comprehensive review. Renew Sustain Energy Rev 166:112625
4. Seferlis P, Varbanov PS, Papadopoulos AI, Chin HH, Klemeš JJ (2021) Sustainable design, integration, and operation for energy high-performance process systems. Energy 224:120158
5. Meliani M, Barkany AE, Abbassi IE, Darcherif AM, Mahmoudi M (2021) Energy management in the smart grid: state-of-the-art and future trends. Int J Eng Bus Manag 13:18479790211032920
6. Sepasi S, Talichet C, Pramanik AS (2023) Power quality in microgrids: a critical review of fundamentals, standards, and case studies. IEEE Access 11:108493–108531
7. Jabari M, Izci D, Ekinci S, Bajaj M, Zaitsev I (2024) Performance analysis of DC-DC Buck converter with innovative multi-stage PIDn (1+ PD) controller using GEO algorithm. Sci Rep 14(1):25612
8. Rojas JD, Arrieta O, Vilanova R (2021) Industrial PID controller tuning. Springer, Cham
9. Jabari M, Rad A (2024) Optimization of speed control and reduction of torque ripple in switched reluctance motors using metaheuristic algorithms based PID and FOPID controllers at the edge. Tsinghua Sci Technol. https://doi.org/10.26599/TST.2024.9010021
10. Idir A, Zemmit A, Akroum H, Nesri M, Guedida S, Canale L (2024) Enhancing temperature control of electric furnaces using a modified PID controller design strategy
11. Chen Z, Cui J, Lei Z, Shen J, Xiao R (2020) Design of an improved implicit generalized predictive controller for temperature control systems. IEEE Access 8:13924–13936
12. Abualigah L, Ekinci S, Izci D (2024) Aircraft pitch control via filtered proportional-integral-derivative controller design using sinh cosh optimizer. Int J Robot Control Syst 4(2):746–757
13. Abdrakhmanov R, Alchinbayeva O (2024) Optimizing microclimate comfort in smart constructions using an intelligent fuzzy-PID temperature regulation system. In: 2024 IEEE 4th international conference on smart information systems and technologies (SIST). IEEE, pp 290–295
14. Gharehchopogh FS (2023) Quantum-inspired metaheuristic algorithms: comprehensive survey and classification. Artif Intell Rev 56(6):5479–5543
15. Gen M, Lin L (2023) Genetic algorithms and their applications. In: Pham H (ed) Springer handbook of engineering statistics. Springer, Cham, pp 635–674
16. Gad AG (2022) Particle swarm optimization algorithm and its applications: a systematic review. Arch Comput Methods Eng 29(5):2531–2561
17. Hussein MM et al (2022) Modern temperature control of electric furnace in industrial applications based on modified optimization technique. Energies 15(22):8474
18. Rizk-Allah RM, Ekinci S, Izci D (2023) An improved artificial rabbits optimization for accurate and efficient infinite impulse response system identification. Decis Anal Jo 9:100355
19. Alzakari SA, Izci D, Ekinci S, Alhussan AA, Hashim FA (2024) A new control scheme for temperature adjustment of electric furnaces using a novel modified electric eel foraging optimizer. AIMS Mathematics 9(5):13410–13438
20. Dong H, Li X, He X, Zeng Z, Wen G (2023) A two-degree-of-freedom controller for a high-precision air temperature control system with multiple disturbances. Case Stud Therm Eng 50:103442
21. Hu X, Zou Q, Zou H (2018) Design and application of fractional order predictive functional control for industrial heating furnace. IEEE Access 6:66565–66575
22. Feng Y et al (2021) Hybrid intelligent control based on condition identification for combustion process in heating furnace of compact strip production. IEEE Trans Industr Electron 69(3):2790–2800
23. Gani MM, Islam MS, Ullah MA (2019) Optimal PID tuning for controlling the temperature of electric furnace by genetic algorithm. SN Appl Sci 1:1–8
24. Sinlapakun V, Assawinchaichote W (2015) Optimized PID controller design for electric furnace temperature systems with Nelder Mead algorithm. In: 2015 12th International conference on electrical engineering/electronics, computer, telecommunications and information technology (ECTI-CON). IEEE, pp 1–4
25. Wang L, Cao Q, Zhang Z, Mirjalili S, Zhao W (2022) Artificial rabbits optimization: a new bio-inspired meta-heuristic algorithm for solving engineering optimization problems. Eng Appl Artif Intell 114:105082
26. Izci D, Rizk-Allah RM, Snášel V, Ekinci S, Hashim FA, Abualigah L (2023) A novel control scheme for automatic voltage regulator using novel modified artificial rabbits optimizer. E-Prime-Adv Electr Eng Electron Energy 6:100325
27. Izci D, Ekinci S, Hekimoğlu B (2022) A novel modified Lévy flight distribution algorithm to tune proportional, integral, derivative and acceleration controller on buck converter system. Trans Inst Meas Control 44(2):393–409

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