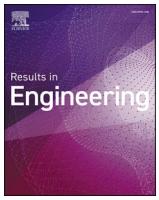
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Optimizing steam condenser efficiency: integrating logarithmic spiral search and greedy selection mechanisms in gazelle optimizer for PI controller tuning

Serdar Ekinci [a], Cebrail Turkeri [a], Davut Izci [a,b], Laith Abualigah [c,d], Mohit Bajaj [e,f,g,*], Vojtech Blazek [h]

[a] Department of Computer Engineering, Batman University, Batman, 72100, Turkey
[b] Applied Science Research Center, Applied Science Private University, Amman, 11931, Jordan
[c] Computer Science Department, Al al-Bayt University, Mafraq 25113, Jordan
[d] Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, 140401, Punjab, India
[e] Department of Electrical Engineering, Graphic Era (Deemed to be University), Dehradun, 248002, India
[f] College of Engineering, University of Business and Technology, Jeddah, 21448, Saudi Arabia
[g] Graphic Era Hill University, Dehradun, 248002, India
[h] ENET Centre, VSB—Technical University of Ostrava, 708 00 Ostrava, Czech Republic

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ABSTRACT

Steam condensers are critical for maintaining efficiency and stability in thermal power plants by converting exhaust steam back into water. Controlling the pressure within the condenser is essential for optimal performance and operational safety. This paper presents a dynamic model of a steam condenser, with pressure control achieved through a proportional-integral (PI) controller. The PI controller parameters are optimized using the gazelle optimization algorithm (GOA), which is applied for the first time to this system in the literature. Additionally, novel enhancements, the logarithmic spiral (Ls) search with greedy selection, are integrated into GOA to further enhance control effectiveness. The performance of the optimized PI controller is evaluated using nonlinear simulations, which include statistical analysis and fitness function assessments. To validate the effectiveness of the proposed approach, comparisons are made with other widely used optimization techniques. The results reveal that the GOA notably enhances control accuracy and stability, with the enhanced GOA (Ls-GOA) achieving the most significant improvements. This underscores its potential for enhancing steam condenser efficiency in thermal power plants.

1. Introduction

Steam condensers play a critical role in thermal power plants by converting exhaust steam from turbines into liquid water, which can be reused in the boiler [1,2]. This process not only improves the efficiency of the power generation cycle but also helps in maintaining the desired operational parameters of the system. The performance and reliability of a steam condenser directly impact the overall efficiency and stability of the power plant [3].

Controlling the pressure within a steam condenser is essential for maintaining optimal performance. If the pressure is not adequately controlled, it can lead to inefficient condensation, increased energy consumption, and potential damage to the condenser and associated equipment [4]. Therefore, precise control of condenser pressure is crucial to ensure the efficient operation of thermal power plants.

Various control methodologies have been explored in the literature to manage condenser pressure. Adaptive control methods, which can adjust controller parameters in real-time based on system behavior, offer significant advantages in dealing with nonlinearities and time-varying dynamics [5]. Additionally, robust control techniques aim to maintain system performance under a wide range of operating conditions and uncertainties, ensuring stability and reliability. Another noteworthy approach is the application of artificial neural networks in control systems. Artificial neural networks can model complex nonlinear

* Corresponding author.
E-mail addresses: serdar.ekinci@batman.edu.tr (S. Ekinci), cebrail.turkeri@batman.edu.tr (C. Turkeri), davutizci@gmail.com (D. Izci), aligah.2020@gmail.com (L. Abualigah), thebestbajaj@gmail.com (M. Bajaj), vojtech.blazek@vsb.cz (V. Blazek).

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relationships and have been applied to control problems in thermal power plants, demonstrating improved performance in handling nonlinearities and un-modeled dynamics [6]. Among these techniques, robust control strategies, such as those involving the use of proportional-integral (PI) controllers [7], have been extensively studied. Robust PI control methods are designed to maintain performance and stability despite variations in system parameters and external disturbances [8]. This makes them particularly suitable for applications in thermal power plants where operating conditions can change significantly. However, the performance of a PI controller heavily depends on the accurate tuning of its parameters (proportional gain K_P and integral gain K_I) [9].

To achieve optimal tuning of PI controller parameters, various optimization techniques have been employed. Classical methods such as Ziegler-Nichols [10] and Cohen-Coon [11] tuning rules offer heuristic approaches for parameter selection but may not always provide the best performance. For instance, the Ziegler-Nichols method is known for its simplicity and ease of use, providing a quick way to obtain initial parameter settings. However, it often results in aggressive tuning, leading to oscillatory responses and may not perform well for all systems. The Cohen-Coon method, another widely used classical technique, is particularly suited for first order plus dead time systems and provides more conservative tuning compared to Ziegler-Nichols [12]. Other classical methods include the Chien, Hrones, and Reswick method, which offers tuning rules for both set-point tracking and disturbance rejection [13], and the internal model control approach, which provides a more systematic way of tuning based on the internal model of the process [14].

Despite their widespread use, these classical methods have limitations and may not always yield optimal performance, especially for systems with complex dynamics. Therefore, modern optimization algorithms have gained attention for their ability to fine-tune controller parameters more effectively. Techniques such as genetic algorithm, particle swarm optimization, and differential evolution have been applied to optimize PI controller parameters, demonstrating significant improvements in control performance [15–17]. In the context of steam condensers, these advanced optimization methods have shown promise in achieving better control accuracy and stability, addressing the shortcomings of classical tuning approaches.

In line with the above discussion, this study presents a novel advanced tuning method by improving the structure of the gazelle optimization algorithm (GOA) [18] using the logarithmic spiral (Ls) search and greedy selection mechanisms [19–21]. GOA mimics the adaptive foraging behavior of gazelles to explore and exploit the search space, demonstrating effective performance in numerous optimization problems [21–24]. The logarithmic spiral search method is known for its efficient exploration capabilities, which help in avoiding local optima and enhancing the search process [25]. Considering the demonstrated ability of the GOA and the structure of the greedy selection based logarithmic spiral search method, this study aims to present an innovative approach by enhancing the GOA with logarithmic spiral search and greedy selection mechanisms (Ls-GOA). This integration aims to improve the balance between exploration and exploitation, leading to better optimization performance. The study involves dynamic modeling of a steam condenser, where the condenser pressure is controlled using a PI controller. The parameters of the PI controller are optimized using both GOA and Ls-GOA to achieve superior control performance. This paper contributes to the field of steam condenser pressure control and optimization in thermal power plants by:

i. Introducing the integration of the logarithmic spiral search and greedy selection mechanisms into the GOA, resulting in the novel Ls-GOA. The proposed approach significantly improves the exploration and exploitation balance during optimization.
ii. Developing a detailed dynamic model of a steam condenser system, which is essential for accurate pressure control in thermal power plants.
iii. Demonstrating the effectiveness of the GOA and Ls-GOA in tuning the PI controller parameters to achieve optimal pressure control in the steam condenser, with substantial improvements in system stability and performance.
iv. Conducting a rigorous comparison between the proposed methods (GOA and Ls-GOA) and other traditional optimization techniques (grey wolf optimization, particle swarm optimization, genetic algorithm, Ziegler-Nichols), highlighting the superiority of the proposed methodologies in terms of fitness function, settling time, and overshoot.
v. Offering new insights and benchmarks for further research in the optimization of control systems for thermal power plants, paving the way for future studies to build upon these findings.

The rest of this paper is organized as follows: Section 2 provides an overview of the dynamic modeling of the steam condenser. Section 3 delves into the GOA, while Section 4 introduces the Ls-GOA. Section 5 outlines the design of the PI controller using both the GOA and Ls-GOA algorithms. Section 6 presents the nonlinear simulation results, along with a discussion and comparison with other widely used metaheuristic methods. Finally, Section 7 offers the concluding remarks.

2. Dynamic modeling of steam condenser

The efficient operation of steam condensers is essential to the overall performance of thermal power plants. Among the different types of condensers, the shell-and-tube design is particularly favored for its sturdy construction and effective heat exchange capabilities [26]. The primary function of the steam condenser is to convert exhaust steam from the turbines back into liquid water, which can then be recirculated into the boiler, thereby sustaining the efficiency and stability of the power generation cycle.

2.1. Structure of shell-and-tube condenser

The shell-and-tube condenser consists of multiple tubes enclosed within a cylindrical shell. In this configuration, cooling water circulates through the tubes, while steam is introduced on the shell side. The standard design of a shell-and-tube condenser features several essential components, including the cooling water inlet, steam inlet, cooling water outlet, and condensate water outlet. Fig. 1 provides a structural diagram of the shell-and-tube condenser. The cooling water, typically sourced from a nearby water body, enters the condenser through the cooling water inlet. This water absorbs heat from the steam, facilitating its condensation. Exhaust steam from the turbine enters the condenser through the steam inlet. As the steam comes into contact with the cooler surfaces of the tubes, it releases its latent heat and condenses into water. After absorbing heat from the steam, the warmed cooling water exits the condenser through the cooling water outlet and is typically discharged back into the source or cooled for reuse. The condensed steam, now in liquid form, collects at the bottom of the condenser and exits through the condensate outlet. This water is then pumped back into the boiler for reuse in the power generation cycle.

2.2. Mathematical modelling of heat transfer and fluid flow

The dynamic characteristics of the steam condenser are delineated by modeling the processes of heat transfer and fluid flow. The thermal exchange between the steam and the cooling water involves intricate interactions, which can be mathematically described through a series of equations. The energy balance equation governs the rate at which heat is transferred from the steam to the cooling water.

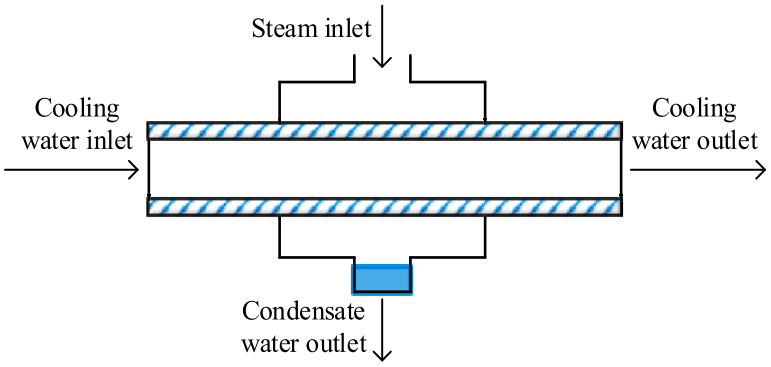


Fig. 1. Structure diagram of shell-and-tube condenser.

$$Q = F_c\lambda \tag{1}$$

where Q is the rate of heat transfer, F_c is the mass flow rate of the steam, λ is the specific latent heat of vaporization. The heat transfer rate is approximated by:

$$Q = UA\Delta T_m \tag{2}$$

where UA is the overall heat transfer coefficient, A is the heat transfer area, and ΔT_m is the logarithmic mean temperature difference, defined as:

$$\Delta T_m = \frac{T - T_{cw}}{\ln\left(\frac{T_c - T_{cw}}{T_c - T}\right)} \tag{3}$$

In this equation, T_c is the condensate temperature, T_{cw} is the cooling water inlet temperature, and T is the outlet temperature of the cooling water. The cooling water energy balance is given by:

$$\frac{dT}{dt} = \frac{F_{cw}}{M_{cw}}(T_{cw} - T) + \frac{Q}{M_{cw}C_P} \tag{4}$$

where F_{cw} is the mass flow rate of cooling water, M_{cw} is the cooling water holdup, and C_P is the heat capacity of the cooling water. According to the Wilson Plot method, the product of the overall heat transfer coefficient and area (UA) can be empirically approximated as:

$$\frac{1}{UA} = a_1 F_{cw}^{-0.8} + a_2 \tag{5}$$

where a_1 and a_2 are constants. a_2 is determined based on UA when $F_{cw} = \infty$. The mass balance equations for steam and condensate are based on the premise that their respective volumes remain constant. As a result, the outlet flow rate of the condensate is adjusted to maintain a stable condensate level within the condenser. The dynamic equation that governs the pressure within the condenser is given by:

$$\frac{dP}{dt} = \frac{RT_c}{V}(F_s - F_c) \tag{6}$$

where P is the condenser pressure, R is the specific gas constant, V is the condenser volume, and F_s is the steam mass flow rate. The relationship between condensate temperature and pressure is linearly approximated as:

$$T_c = \alpha P + \beta \tag{7}$$

where constant α and β are coefficients that are determined based on system specifications. Tables 1 and 2 show the value and unit of condenser parameters and variables, respectively.

Table 1
Condenser parameters [2,27].

Parameter	Value	Unit
R	0.461526	kJ/(kgK)
V	3	m^3
λ	2265.65	kJ/kg
UA	356.972	kW/K
M_{cw}	6500	kg
C_P	4.2	kJ/(kgK)
α	0.3162	K/kPa
β	68.0958	°C
a_1	0.087292	–
a_2	0.00073787	–

Table 2
Condenser Variables [2,27].

Parameter	Value	Unit	Description
F_s	4	kg/s	Steam flow rate
F_c	4	kg/s	Condensate flow rate
F_{cw}	107.8881	kg/s	Cooling water flow rate
P	90	kPa	Condenser pressure
T	80	°C	Cooling water outlet temperature
T_{cw}	60	°C	Cooling water inlet temperature
T_c	96.5538	°C	Condensate temperature
Q	9062.6	kW	Heat duty

3. Gazelle optimization algorithm

The GOA is an optimization technique inspired by the natural foraging behavior and social dynamics of gazelles. This method is designed to tackle complex optimization tasks by harnessing the collective decision-making and interaction strategies observed in gazelles, which enable effective resource searching and risk management. In GOA, the movement and actions of a group of gazelles are simulated within a multi-dimensional search space, with each gazelle representing a possible solution to the optimization problem. The positions of these gazelles are adjusted iteratively according to rules that replicate behaviors like following a leader, leading others, and evading threats. These strategies allow the algorithm to strike a balance between exploring new possibilities and exploiting known good solutions, thereby enhancing its effectiveness in finding optimal or near-optimal results.

The GOA is a population-based method that utilizes randomly initialized gazelles (X) as search agents. These agents are represented as an $n \times d$ matrix of potential solutions, as shown in Eq. (8). The algorithm employs the problem's constraints of the upper bound (UB) and lower

bound (*LB*) to define the range within which the population vector can vary stochastically.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d-1} & x_{1,d} \\ x_{2,1} & x_{2,2} & & x_{2,d-1} & x_{2,d} \\ \vdots & & \ddots & \vdots & \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d-1} & x_{n,d} \end{bmatrix} \tag{8}$$

Here, X is the matrix representing the position vectors of the candidate population. Each position vector is randomly generated using Eq. (9), where $x_{i,j}$ is the position vector of the i-th individual in the j-th dimension, n is the number of gazelles, and d denotes the search space's dimensionality.

$$x_{i,j} = rand \times \left(UB_j - LB_j\right) + LB_j \tag{9}$$

where *rand* is a random number between 0 and 1, UB_j is the upper bound for the j-th dimension and LB_j is the lower bound for the j-th dimension. In each iteration, every $x_{i,j}$ generates a potential solution, and the best solution found so far is selected as the top gazelle. This best solution is crucial in constructing an *Elite* $n \times d$ matrix (as described in Eq. (10), which guides the search process.

$$Elite = \begin{bmatrix} x'_{1,1} & x'_{1,2} & \cdots & x'_{1,d-1} & x'_{1,d} \\ x'_{2,1} & x'_{2,2} & & x'_{2,d-1} & x'_{2,d} \\ \vdots & & \ddots & \vdots & \\ x'_{n,1} & x'_{n,2} & \cdots & x'_{n,d-1} & x'_{n,d} \end{bmatrix} \tag{10}$$

The matrix $x'_{i,j}$ represents the position vector of the top-performing gazelle. The algorithm considers both the predator and gazelles as search agents. When a predator is detected, both the predator and gazelles move towards a haven, with the Elite matrix being updated at each iteration if a better-performing gazelle is found. The movement of gazelles incorporates Brownian motion, which is a type of random motion where displacement follows a Gaussian probability distribution with mean $\mu = 0$ and variance $\sigma^2 = 1$ [28]. This is mathematically represented in Eq. (11).

$$f(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{x^2}{2}\right) \tag{11}$$

where x is the position in the space and $f(x, \mu, \sigma)$ is the probability density function of the Brownian motion. Additionally, the algorithm utilizes Lévy flight, which is a random walk characterized by Lévy distribution [29], as depicted in Eq. (12).

$$\mathrm{L}(\mathrm{x_j}) \approx \left|\mathrm{x_j}\right|^{1-\alpha} \tag{12}$$

where x_j denotes the flight distance and α is the power-law exponent, typically between 1 and 2. The Lévy stable process, an integral part of this algorithm, is defined by the following form [30]:

$$f_L(x, \alpha, \gamma) = \frac{1}{\pi} \int_0^{\infty} exp(-\gamma q^{\alpha}) \cos(qx) dq \tag{13}$$

where γ is a scale factor that affects the spread of the distribution and α controls the motion's distribution index (values ranging between 0.3 and 1.99) [30]. The algorithm employs a stable Lévy motion as defined by Eq. (14).

$$Levy(\alpha) = 0.05 \times \frac{x}{|y|^{1/\alpha}} \tag{14}$$

Here, x and y are normal random variables, and $\alpha = 1.5$, with r_x and r_y given as follows:

$$r_x = \left[\frac{\Gamma(1+\alpha)\sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma\left(\frac{1+\alpha}{2}\right)\alpha 2^{\frac{\alpha-1}{2}}}\right]^{\frac{1}{\alpha}}, \; r_y = 1 \tag{15}$$

The optimization process simulates the survival behavior of gazelles, which includes grazing without a predator and fleeing when a predator is detected. When no predator is present, the gazelles move according to Brownian motion, as shown in Eq. (16).

$$gazelle_{i+1} = gazelle_i + s \times R \times R_B(Elite_i - R_B \times gazelle_i) \tag{16}$$

where $gazelle_{i+1}$ is the position of the gazelle in the next iteration, $gazelle_i$ is the current position of the gazelle, R is a vector of uniform random numbers [0, 1], s represents the grazing speed of the gazelle and R_B is a vector of random numbers representing the Brownian motion. However, when a predator is detected, the gazelles react by taking Lévy flights, while the predator initially follows Brownian motion before also switching to Lévy flights. This behavior is mathematically modeled by Eq. (17).

$$gazelle_{i+1} = gazelle_i + S \times R \times \lambda \times R_L \times (Elite_i - R_L \times gazelle_i) \tag{17}$$

where S is the maximum speed of the gazelle, λ represents the change of direction, R_L is a vector of random numbers based on the Lévy distribution. The predator's chase behavior is captured by Eq. (18).

$$gazelle_{i+1} = gazelle_i + S \times \lambda \times CF \times R_B \times (Elite_i - R_L \times gazelle_i) \tag{18}$$

where CF is the cumulative effect of the predator, defined as:

$$CF = \left(1 - \frac{iter}{Max\ iter}\right)^{(2 \cdot iter/Maxiter)} \tag{19}$$

Finally, the algorithm accounts for Predator Success Rates (PSRs), which influence the likelihood of a gazelle escaping. The effect is modeled by Eq. (20).

$$gazelle_{i+1} = \begin{cases} gazelle_i + CF \times [LB + R \times (UB - LB)] \times U; & \text{if } r \leq PSRs \\ gazelle_{i+1} + [PSRs(1-r) + r] \times (gazelle_{r1} - gazelle_{r2}); & otherwise \end{cases} \tag{20}$$

Here, U is a uniform random number between [0, 1]. This comprehensive approach ensures that the algorithm can effectively search the solution space while avoiding local minima, thus optimizing the overall performance.

4. Novel Ls-GOA approach

The Ls-GOA integrates the conventional GOA with the logarithmic spiral search and greedy selection mechanisms to enhance its exploration and exploitation capabilities [31]. This section elaborates on the fundamental principles of the logarithmic spiral search model and its integration into the GOA framework. The logarithmic spiral is a mathematical curve that appears frequently in nature, defined by the polar form given in Eq. (21):

$$r(\theta) = ae^{b\theta} \tag{21}$$

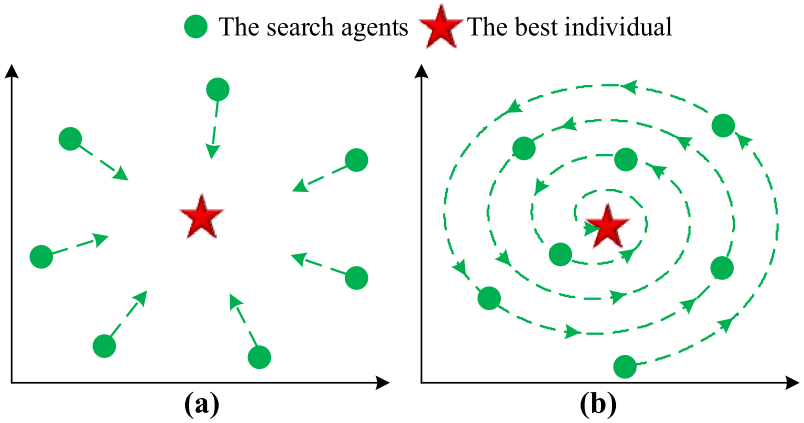


Fig. 2. Basic search model (a) and logarithmic spiral search model (b).

where r is the radius, θ is the angle, and a and b are constants that control the shape of the spiral. This spiral has desirable properties for optimization algorithms, particularly in maintaining a balance between exploration and exploitation. In terms of logarithmic spiral search mechanism, the mathematical expression given by Eq. (22). Here, l is a random variable within the range $[-1,1]$, α is a constant set to 1, and $x_{best}(t)$ represents the optimal position in the current iteration.

$$x_i^{Ls}(t) = |x_{best}(t) - x_i(t)| \cdot e^{\alpha l} \cdot \cos(2\pi l) + x_{best}(t) \quad (22)$$

GOA may face difficulties with maintaining population diversity, which can result in premature convergence to local optima. This is particularly problematic when the search agents follow straight-line

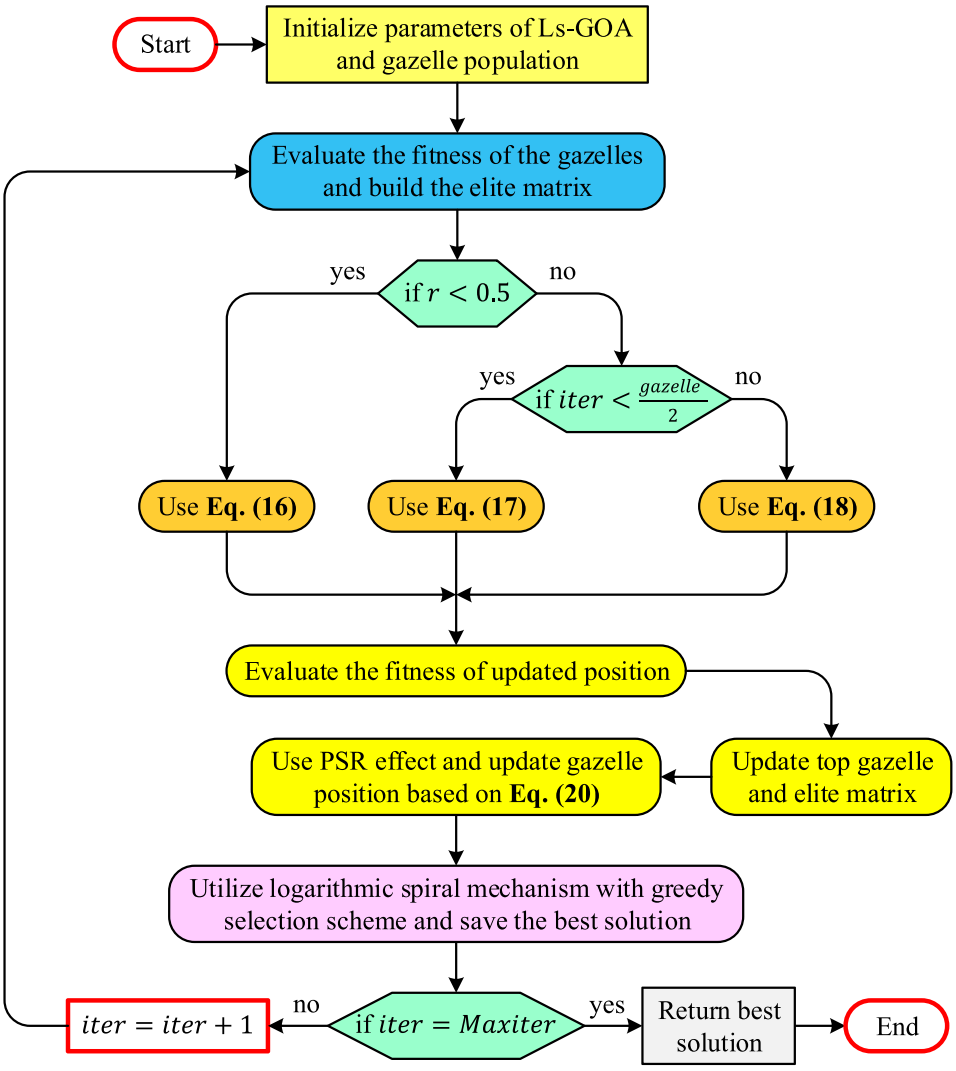


Fig. 3. Flowchart of Ls-GOA.

paths towards the optimal solution, as shown in Fig. 2(a). While this method exhibits strong intensification capabilities, enabling focused refinement around the best-known solution, it also limits the exploration of the broader search space. To mitigate this problem and improve the exploration capability of GOA, we propose incorporating a logarithmic spiral search mechanism, as depicted in Fig. 2(b). This approach allows search agents to follow a spiral trajectory towards the optimal solution rather than a direct line. The logarithmic spiral pattern promotes greater diversity among the search agents, thereby reducing the likelihood of the algorithm becoming trapped in local optima and improving its complete performance in global search.

The integration of the logarithmic spiral into the GOA involves modifying the position update rules to incorporate the logarithmic spiral search mechanism. This integration can be mathematically described by augmenting the position update equations of GOA with the logarithmic spiral trajectory equations. As seen in Fig. 2(b), individuals continuously adjust their positions in each iteration, gradually moving closer to the target in a spiral pattern, while yet maintaining the diversity of the population. This strategy enhances the algorithm's ability to explore. Additionally, the suggested algorithm integrates a greedy selection framework to further optimize its efficiency. Therefore, the position update mechanism is modified using the definition in Eq. (23), where $x_i(t+1)$ denotes the i^{th} gazelle in the next iteration. The proposed approach is illustrated in the flowchart shown in Fig. 3.

$$x_i(t+1) = \begin{cases} x_i^{Ls}(t), & fitness\left(x_i^{Ls}(t)\right) \le fitness(x_i(t)) \\ x_i(t), & fitness\left(x_i^{Ls}(t)\right) > fitness(x_i(t)) \end{cases} \tag{23}$$

5. PI controller design via GOA and Ls-GOA algorithms

This section details the design process of the PI controller for the nonlinear steam condenser system using the GOA and its enhanced variant, the Ls-GOA. The focus is on optimizing the proportional (K_P) and integral (K_I) gains of the PI controller to achieve precise and stable pressure control within the condenser. The transfer function of the PI controller ($C_{PI}(s)$) is expressed as follows:

$$C_{PI}(s) = K_P + \frac{K_I}{s} \tag{24}$$

The primary objective for GOA is to minimize the integral of time-weighted absolute error (ITAE) performance index, defined as [32]:

$$F_{ITAE} = \int_0^\infty t|e(t)|dt \tag{25}$$

where $e(t)$ represents the error between the desired and actual pressure within the condenser, and t is time. The bounds for the PI controller gains are set as follows:

$$0.1 \le K_P \le 20 \text{ and } 0.05 \le K_I \le 10 \tag{26}$$

These constraints are chosen to ensure realistic and effective control actions. The design was implemented using a Simulink-based model of the nonlinear steam condenser system, which is illustrated in Fig. 4.

The model includes a closed-loop response to a step change in the pressure setpoint from 90 kPa to 95 kPa, simulating typical operational conditions in a thermal power plant. The optimization was carried out with a population size of 30, over 40 iterations, and with 25 runs for each algorithm. Both GOA and Ls-GOA were applied to fine-tune the PI controller parameters. Fig. 5. depicts the application of these algorithms to the PI-controlled system, showcasing the iterative adjustment process of K_P and K_I within the specified constraints.

6. Nonlinear simulation results and discussion

6.1. Statistical analysis

A detailed statistical evaluation of the ITAE fitness function is presented, comparing the performance of the GOA and its enhanced variant, the Ls-GOA. The primary focus is to assess each algorithm's effectiveness in tuning the PI controller parameters for a nonlinear steam condenser system. Optimized ITAE fitness function from all runs is depicted in Fig. 6. The results depicted in Fig. 6 clearly demonstrate that the ITAE values obtained by Ls-GOA fluctuate within a narrower range, approximately between 19.2 and 21.3, suggesting a more stable and consistent performance. In contrast, the ITAE values obtained from GOA are consistently higher, ranging from 22 to 23.9, reflecting less stability and higher variability in the optimization outcomes.

Table 3 summarizes key statistical measures for both algorithms, including the minimum, maximum, average, standard deviation, and p-value of the ITAE fitness function. The data reveals that Ls-GOA

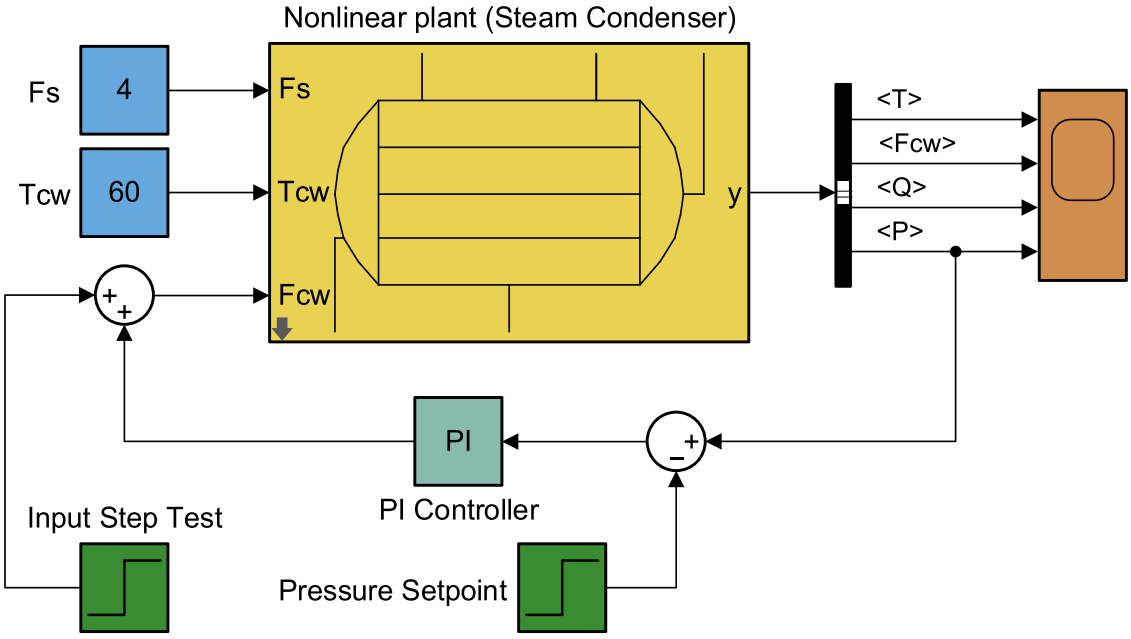


Fig. 4. Simulink-based model of the nonlinear steam condenser system.

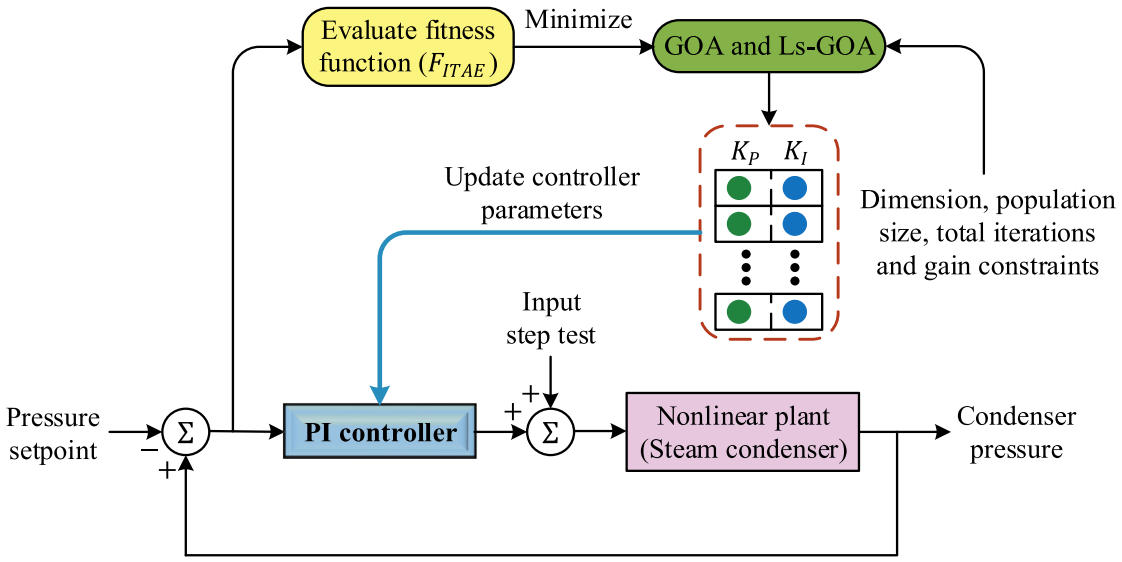


Fig. 5. Application of GOA and Ls-GOA algorithms to PI controlled system.

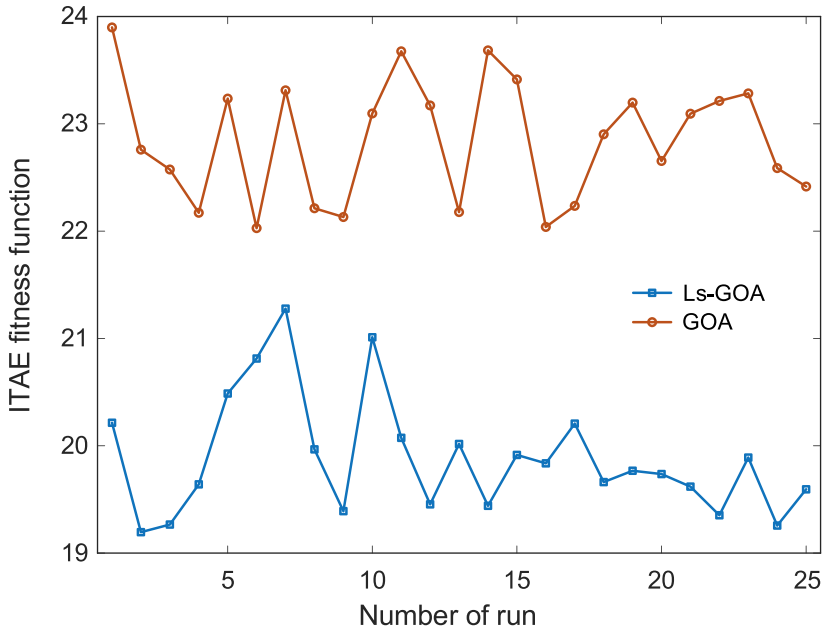


Fig. 6. Optimized F_{ITAE} fitness function from all runs.

Table 3
Key statistical measures for GOA and Ls-GOA algorithms.

Tuning method	Minimum	Maximum	Average	Standard deviation	p-value
Ls-GOA	19.1952	21.2779	19.8835	0.5467	1.2290E−05 (Winner: Ls-GOA)
GOA	22.0283	23.8985	22.8469	0.5683	

consistently yields lower ITAE values, with reduced average and standard deviation, signifying superior convergence behavior and robustness compared to GOA. The p-value further confirms the statistical significance of Ls-GOA's enhanced performance, positioning it as a more effective optimization strategy for this control application. The statistical analysis clearly demonstrates that Ls-GOA provides a more reliable and efficient solution for optimizing the PI controller, offering improved accuracy and stability in the control of the steam condenser system.

6.2. Evolution of fitness function

This section explores the progression of fitness function values throughout the optimization process, with a focus on the ITAE as the primary performance metric. Fig. 7 illustrates the changes in ITAE values over 40 iterations for both Ls-GOA and the traditional GOA. In this figure, both Ls-GOA and GOA exhibit a downward trend, signifying that the fitness function improves with increasing iterations. However, the rate of improvement is more pronounced in Ls-GOA than in GOA, underscoring the superior convergence speed and effectiveness of the Ls-GOA method.

This steeper decline suggests that Ls-GOA is better at fine-tuning the PI controller parameters, leading to quicker and more significant improvements in system performance. The comparison between the two algorithms shows that while both are capable of optimizing the controller parameters, Ls-GOA consistently outperforms GOA, achieving lower ITAE values at each iteration step. This indicates that the

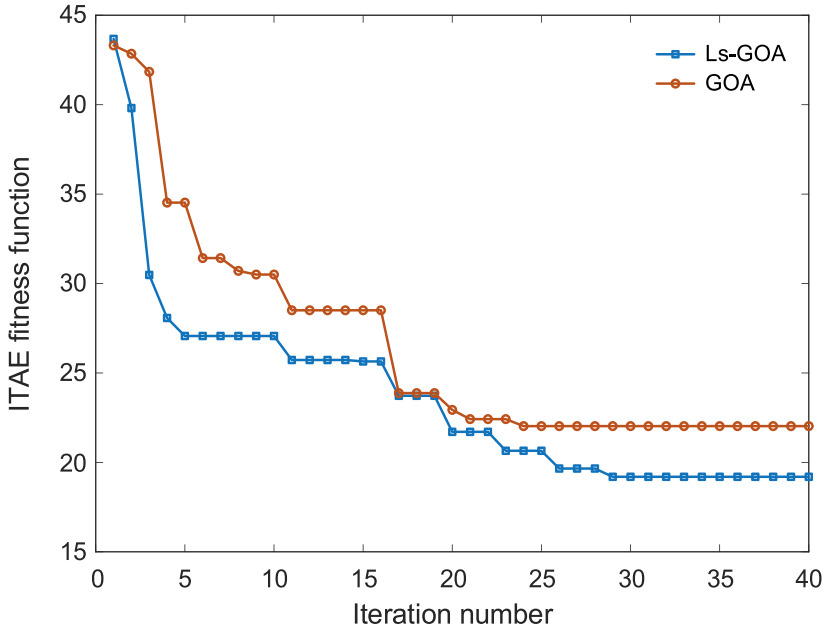


Fig. 7. Change of F_{ITAE} fitness function.

Table 4
Optimized PI controller parameters for dynamic steam condenser.

Tuning method	K_P	K_I
Ls-GOA (proposed)	3.1092	0.6173
GOA (proposed)	3.9506	0.8207
GWO	4.47	0.89
PSO	7.07	1.04
GA	8.53	0.91
ZN	10.8	4.22

incorporation of the logarithmic spiral mechanism into the GOA framework provides a more robust and efficient approach for optimization, particularly in complex control applications such as steam condenser pressure regulation.

6.3. Comparisons with reported approaches

The proposed optimization methods, GOA and its enhanced version, Ls-GOA, are compared with traditional techniques such as grey wolf optimizer (GWO) [27], particle swarm optimization (PSO) [27], genetic algorithm (GA) [27], and Ziegler-Nichols (ZN) [27] tuning schemes. The analysis evaluates how effectively each method optimizes the PI controller parameters in the context of the nonlinear steam condenser system. Table 4 details the optimized PI controller parameter values K_P and K_I obtained using each optimization method.

Figs. 8, 9, 10, and 11 showcase the dynamic response of the steam condenser system as the PI controllers which are tuned according to each optimization method. These figures compare the output response curves for different optimized PI controlled systems. The figures presented in this section illustrate that both the GOA and its variant, the Ls-

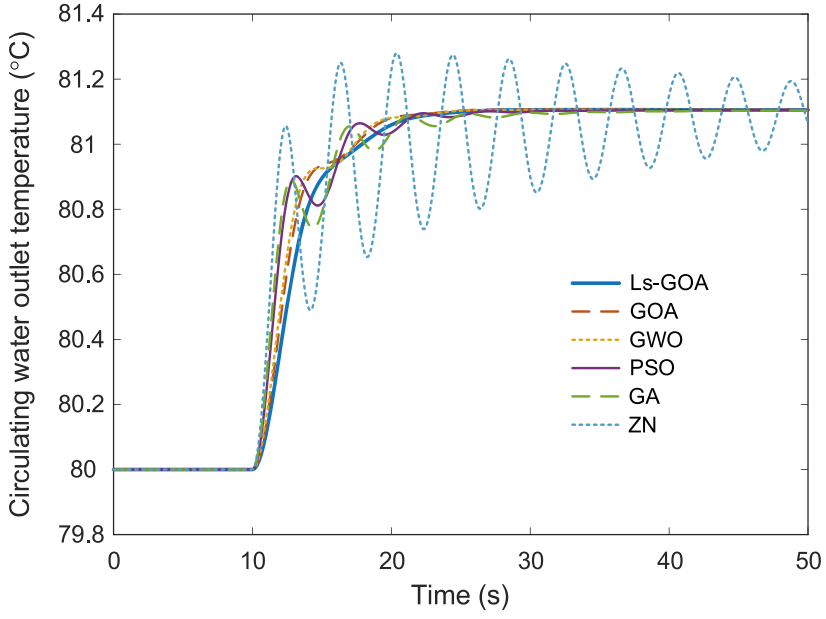


Fig. 8. Output response curves of outlet temperature of cooling water.

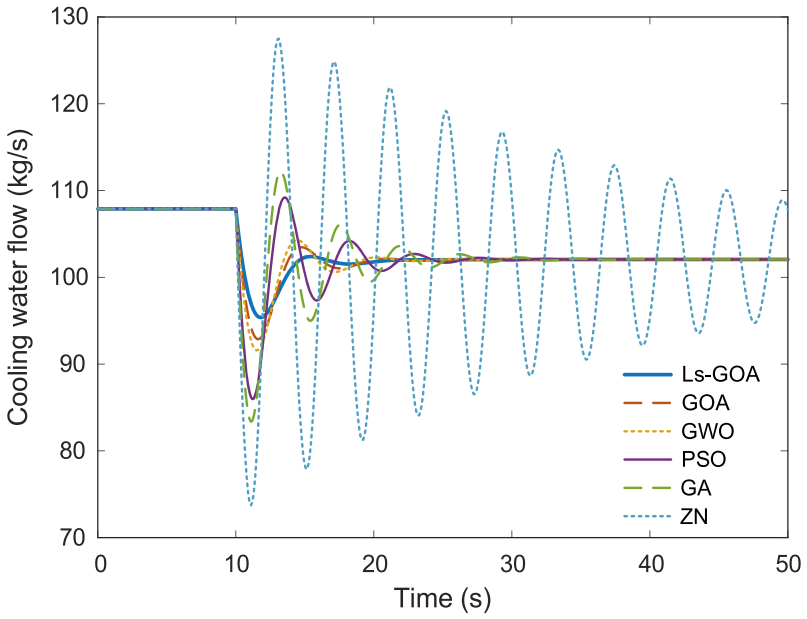


Fig. 9. Output response curves of circulating water flow.

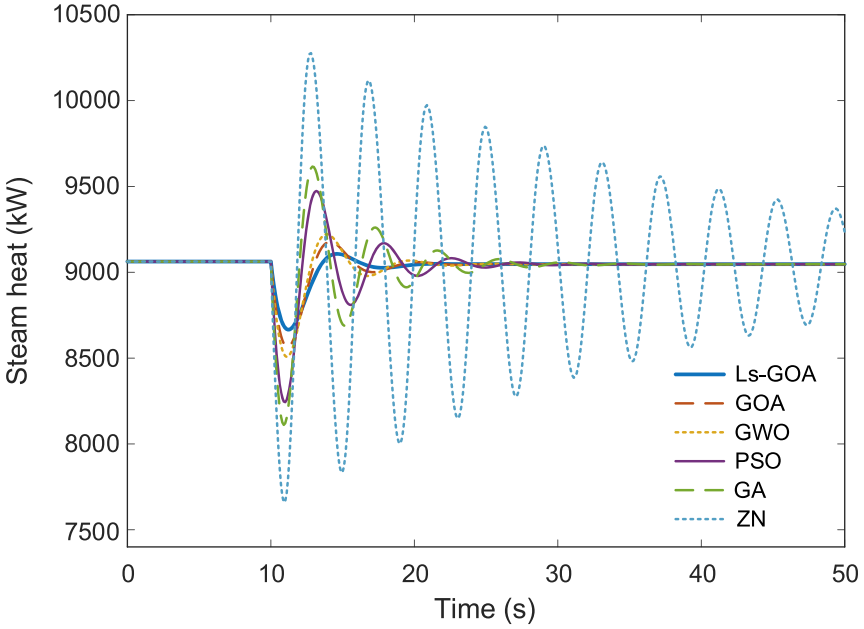


Fig. 10. Output response curves of steam heat output.

GOA, outperform traditional optimization methods such as GWO, PSO, GA, and ZN in tuning the PI controller for the steam condenser system. Among these proposed methods, Ls-GOA demonstrates further enhancements over GOA, achieving faster stabilization, reduced overshoot, and more accurate responses across various system parameters, including the outlet temperature of the cooling water, circulating water flow, steam heat output, and pressure. This comparison highlights the effectiveness of Ls-GOA in providing superior control performance, building upon the already strong foundation established by GOA.

The results from the figures are further quantified in Table 5, which compares the ITAE, normalized settling time, and normalized overshoot for each tuning method. From the data, it is evident that the Ls-GOA method consistently delivers the lowest ITAE values, reflecting its superior capability in minimizing the error over time. Additionally, Ls-GOA achieves the shortest normalized settling time and the lowest normalized overshoot among all methods, indicating that it does not only stabilize the system more rapidly but also with minimal deviation from the desired performance. These results clearly demonstrate that the proposed Ls-GOA method offers significant improvements over traditional optimization techniques in tuning the PI controller for a nonlinear steam condenser system.

7. Conclusion and future research directions

This study offers an in-depth analysis of the dynamic modeling and optimization of steam condenser pressure, utilizing PI controllers tuned by the GOA and its innovative enhancement, the Ls-GOA mechanism. The main objective was to enhance the control accuracy and stability of the steam condenser, which is crucial for ensuring the efficiency and operational safety of thermal power plants. A dynamic model of the

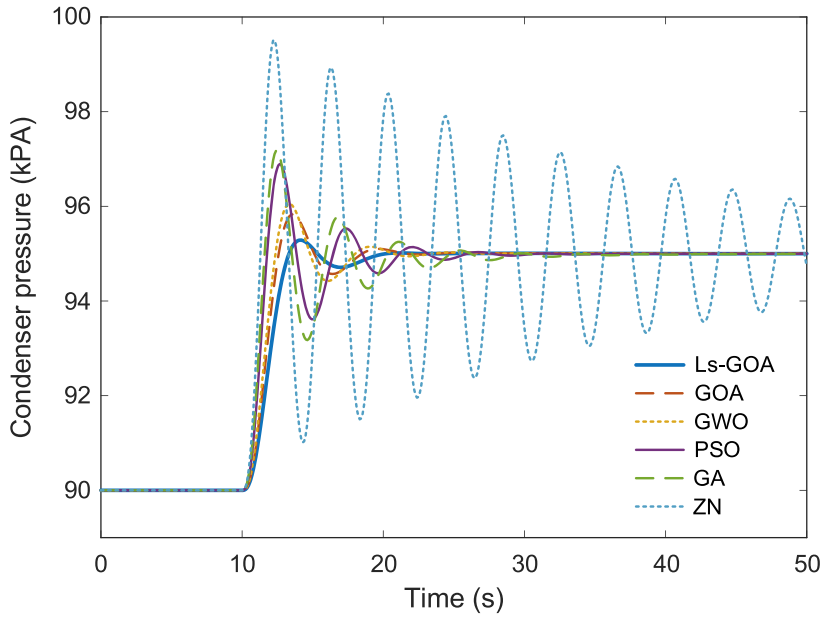


Fig. 11. Output response curves of condenser pressure.

Table 5
Values of F_{ITAE}, normalized settling time, and normalized overshoot for different methods.

Tuning method	F_{ITAE}	Normalized settling time (s)	Normalized overshoot (%)
Ls-GOA (proposed)	**19.1952**	**18.9191**	5.7235
GOA (proposed)	22.0283	19.7634	16.6151
GWO	23.8138	19.8218	21.0654
PSO	43.0814	24.9358	37.8907
GA	64.5673	28.1829	43.7486
ZN	985.3519	49.9426	101.5948

steam condenser was created to accurately capture its key dynamics, laying the groundwork for the development of an effective pressure control system. The PI controller, chosen for its simplicity and effectiveness in industrial applications, was optimized using GOA. The introduction of the Ls mechanism into GOA resulted in a novel approach, enhancing the algorithm's exploration and exploitation capabilities. The Ls-GOA demonstrated significant improvements over traditional optimization methods, as evidenced by statistical analysis, fitness function evaluation, and comparative studies. Notably, the Ls-GOA optimized PI controller achieved the highest level of improvement in controlling steam condenser pressure, underscoring its potential for broader applications in complex engineering systems. The success of integrating the Ls mechanism into GOA highlights its robustness and effectiveness, paving the way for future research in optimizing control systems for advanced industrial applications.

The promising results achieved using the Ls-GOA for steam condenser pressure control in thermal power plants open up several avenues for future research. One potential direction is the integration of Ls-GOA with other advanced control strategies, such as model predictive control or adaptive control systems, to further enhance robustness and performance under varying operating conditions. Additionally, extending the application of Ls-GOA to other complex industrial processes, such as chemical reactors or large-scale renewable energy systems, could provide valuable insights into its versatility and effectiveness across different domains. Another area worth investigating is the real-time implementation of Ls-GOA in actual plant environments, focusing on the computational efficiency and scalability of the algorithm in dynamic and high-stakes operational settings. Moreover, comparative studies with other emerging optimization algorithms could help refine the approach and identify the most suitable contexts for its application. Finally, incorporating machine learning techniques to predict system behavior and adapt the optimization process dynamically could open new frontiers in intelligent control systems, paving the way for further advancements in industrial automation and optimization.

Availability of data and materials

The data supporting the findings of this study are available within the article.

CRediT authorship contribution statement

Serdar Ekinci: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cebrail Turkeri:** Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Davut Izci:** Writing – original draft, Supervision, Project administration, Investigation, Formal analysis, Data curation, Conceptualization. **Laith Abualigah:** Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Mohit Bajaj:** Writing – review & editing, Visualization, Supervision, Project administration. **Vojtech Blazek:** Writing – review & editing, Visualization, Supervision, Project administration, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

References

[1] Yu.M. Brodov, K.E. Aronson, A.Yu. Ryabchikov, M.A. Nirenshteyn, Current state and trends in the design and operation of water-cooled condensers of steam turbines for thermal and nuclear power stations (review), Thermal Eng. 66 (2019) 16–26, https://doi.org/10.1134/S0040601519010026.

[2] S.A. Alzakari, D. Izci, S. Ekinci, A.A. Alhussan, F.A. Hashim, Nonlinear FOPID controller design for pressure regulation of steam condenser via improved metaheuristic algorithm, PLoS. One 19 (2024) e0309211, https://doi.org/10.1371/journal.pone.0309211.

[3] E. Martelli, F. Alobaid, C. Elsido, Design optimization and dynamic simulation of steam cycle power plants: a review, Front. Energy Res. 9 (2021), https://doi.org/10.3389/fenrg.2021.676969.

[4] B. Girirajan, D. Rathikarani, Optimal CRONE controller using meta-heuristic optimization algorithm for shell and tube Heat Exchanger, IOP. Conf. Ser. Mater. Sci. Eng. 1166 (2021) 012058, https://doi.org/10.1088/1757-899X/1166/1/012058.

[5] J.T. Spooner, M. Maggiore, R. Ordóñez, K.M. Passino, Stable Adaptive Control and Estimation for Nonlinear Systems, Wiley, 2002, https://doi.org/10.1002/0471221139.

[6] H. Salim, K. Faisal, R. Jawad, Enhancement of performance for steam turbine in thermal power plants using artificial neural network and electric circuit design, Appl. Comput. Intell. Soft Comput. 2018 (2018) 1–9, https://doi.org/10.1155/2018/8042498.

[7] D. Izci, E. Köse, S. Ekinci, Feedforward-compensated PI controller design for air–fuel ratio system control using enhanced weighted mean of vectors algorithm, Arab. J. Sci. Eng. 48 (2023) 12205–12217, https://doi.org/10.1007/s13369-023-07724-w.

[8] N. Shaukat, B. Khan, S.M. Ali, U. Munawar, Z. Ullah, Comparative study of control methods for steam condenser, in: 2017 International Conference on Energy Conservation and Efficiency (ICECE), IEEE, 2017, pp. 32–37, https://doi.org/10.1109/ECE.2017.8248825.

[9] G.F. Franklin, D.J. Powell, A. Emami-Naeini, Feedback Control of Dynamic Systems, Prentice Hall PTR, USA, 2001, 4th ed.

[10] J.G. Ziegler, N.B. Nichols, Optimum settings for automatic controllers, J. Fluids. Eng. 64 (1942) 759–765, https://doi.org/10.1115/1.4019264.

[11] G.H. Cohen, G.A. Coon, Theoretical consideration of retarded control, J. Fluids. Eng. 75 (1953) 827–834, https://doi.org/10.1115/1.4015451.

[12] S. Skogestad, Simple analytic rules for model reduction and PID controller tuning, J. Process. Control 13 (2003) 291–309, https://doi.org/10.1016/S0959-1524(02)00062-8.

[13] K.J. Åström, T. Hägglund, Advanced PID control, ISA - the instrumentation, Syst. Autom. Soc. (2006).

[14] D.E. Rivera, M. Morari, S. Skogestad, Internal model control: PID controller design, Ind. Eng. Chem. Process Des. Dev. 25 (1986) 252–265, https://doi.org/10.1021/i200032a041.

[15] C.Somasundar Reddy, K. Balaji, A Genetic Algorithm (GA)-PID controller for temperature control in shell and tube heat exchanger, IOP. Conf. Ser. Mater. Sci. Eng. 925 (2020) 012020, https://doi.org/10.1088/1757-899X/925/1/012020.

[16] H.A. Suthar, J.J. Gadit, Two degree of freedom controller optimization using GA for shell and tube heat exchanger, in: 2017 11th International Conference on Intelligent Systems and Control (ISCO), IEEE, 2017, pp. 1–7, https://doi.org/10.1109/ISCO.2017.7855651.

[17] J.-S. Wang, S.-X. Li, PID controller of steam condenser based on particle swarm optimization algorithm, J. Comput. Theor. Nanosci. 14 (2017) 3698–3701, https://doi.org/10.1166/jctn.2017.6659.

[18] J.O. Agushaka, A.E. Ezugwu, L. Abualigah, Gazelle optimization algorithm: a novel nature-inspired metaheuristic optimizer, Neural Comput. Appl. (2022), https://doi.org/10.1007/s00521-022-07854-6.

[19] D. Izci, S. Ekinci, E. Eker, M. Kayri, Augmented hunger games search algorithm using logarithmic spiral opposition-based learning for function optimization and controller design, J. King Saud Univ. 36 (2024) 330–338, https://doi.org/10.1016/j.jksues.2022.03.001.

[20] E. Eker, D. Izci, S. Ekinci, M. Shukri Salman, M. Rashdan, Performance evaluation of logarithmic spiral search and selective mechanism based arithmetic optimizer for parameter extraction of different photovoltaic cell models, PLoS. One 19 (2024) e0308110, https://doi.org/10.1371/journal.pone.0308110.

[21] S. Ekinci, D. Izci, Enhancing IIR system identification: harnessing the synergy of gazelle optimization and simulated annealing algorithms, E-Prime - Advances in Electrical Engineering, Electronics Energy 5 (2023) 100225, https://doi.org/10.1016/j.prime.2023.100225.

[22] S. Ekinci, D. Izci, A.G. Hussien, Comparative analysis of the hybrid gazelle-Nelder–Mead algorithm for parameter extraction and optimization of solar photovoltaic systems, IET Renewable Power Gener. 18 (2024) 959–978, https://doi.org/10.1049/rpg2.12974.

[23] S. Ekinci, D. Izci, M. Yilmaz, Efficient speed control for DC motors using novel gazelle simplex optimizer, IEEe Access. 11 (2023) 105830–105842, https://doi.org/10.1109/ACCESS.2023.3319596.

[24] D. Izci, S. Ekinci, Fractional order controller design via gazelle optimizer for efficient speed regulation of micromotors, E-Prime - advances in electrical engineering, Electronics Energy 6 (2023) 100295, https://doi.org/10.1016/j.prime.2023.100295.

[25] S. Ekinci, D. Izci, M.R. Al Nasar, R. Abu Zitar, L. Abualigah, Logarithmic spiral search based arithmetic optimization algorithm with selective mechanism and its application to functional electrical stimulation system control, Soft. Comput. 26 (2022) 12257–12269, https://doi.org/10.1007/s00500-022-07068-x.

[26] S.A. Marzouk, M.M. Abou Al-Sood, E.M.S. El-Said, M.M. Younes, M.K. El-Fakharany, A comprehensive review of methods of heat transfer enhancement in shell and tube heat exchangers, J. Therm. Anal. Calorim. 148 (2023) 7539–7578, https://doi.org/10.1007/s10973-023-12265-3.

[27] S.-X. Li, J.-S. Wang, Dynamic Modeling of Steam Condenser and Design of PI Controller Based on Grey Wolf Optimizer, Math. Probl. Eng. 2015 (2015) 1–9, https://doi.org/10.1155/2015/120975.

[28] D. Izci, Design and application of an optimally tuned PID controller for DC motor speed regulation via a novel hybrid Lévy flight distribution and Nelder–Mead algorithm, Trans. Inst. Meas. Control 43 (2021) 3195–3211, https://doi.org/10.1177/01423312211019633.

[29] D. Izci, S. Ekinci, S. Mirjalili, L. Abualigah, An intelligent tuning scheme with a master/slave approach for efficient control of the automatic voltage regulator, Neural Comput. Appl. 35 (2023) 19099–19115, https://doi.org/10.1007/s00521-023-08740-5.

[30] R.N. Mantegna, Fast, accurate algorithm for numerical simulation of Lévy stable stochastic processes, Phys. Rev. e 49 (1994) 4677–4683, https://doi.org/10.1103/PhysRevE.49.4677.

[31] D. Izci, S. Ekinci, M. Kayri, E. Eker, A novel enhanced metaheuristic algorithm for automobile cruise control system, Electrica 21 (2021) 283–297, https://doi.org/10.5152/electrica.2021.21016.

[32] V. Snášel, R.M. Rizk-Allah, D. Izci, S. Ekinci, Weighted mean of vectors optimization algorithm and its application in designing the power system stabilizer, Appl. Soft. Comput. 136 (2023) 110085, https://doi.org/10.1016/j.asoc.2023.110085.