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Original scientific paper

Dynamic Load Frequency Regulation in Two Area Power Systems via Pelican-Optimized PID Control

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Abstract: This article presents Pelican Optimization Algorithm (POA) for Load Frequency Control (LFC) in two area interconnected power systems. Extensive simulations in MATLAB indicate that the POA surpasses numerous established metaheuristic optimization algorithms, involving the Grey Wolf Optimizer (GWO), Hippopotamus Optimization Algorithm (HOA), Salp Swarm Algorithm (SSA), Particle Swarm Optimization (PSO), Teaching-Learning Optimization Algorithm (TLOA) and Whale Optimization Algorithm (WOA) regarding the mitigation of frequency deviations and improvement of dynamic response. The robustness of the POA based LFC is validated under scenarios of random load disturbances, varying system parameters, typical power system nonlinearities like generation rate constraints (GRC) and governor deadband (GDB), and with renewable energy sources. The studies highlighted in the article demonstrate superior adaptability and effectiveness of POA to optimally tune the gains of PID controller. The statistical analysis demonstrate that the proposed POA achieves convergence to the global optimum with reduced execution time (~ 12% less than the second best HOA) and exhibits lower mean (~15.2% less than the second best SSA) and standard deviation (~3.09% less than the second best HOA) over multiple independent runs. Stability analysis using Bode plots confirms that the proposed control strategy maintains adequate stability margins.

Keywords: Pelican optimization algorithm (POA), Load frequency control (LFC), Frequency stability, Power systems, Renewable energies.

1 Introduction

Load Frequency Control (LFC) is a key component of modern power systems, essential for supporting the stability and better quality of electrical grids.

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In order to meet the load demand, and efficient operation within the standard frequency range, depending on the area, LFC controls the supply frequency, which is either 50 Hz or 60 Hz [1]. In real-time, load frequency control balances the supply and demand of electricity. The drop in frequency indicates a shortage of power supply, while an increase in frequency shows that the generated power is in excess [2]. In the power system, the system may go into unstable mode, damage equipment and widespread blackout if the deviation in frequency is not addressed properly [3]. The primary responsibility of LFC is to mitigate these oscillations by implementing timely and dynamic adjustments in the output of the producing units.

1.1 Literature survey

In load frequency control, there are basically two control loops known as the primary and secondary loops [4]. Here primary control loop is basically a fixed gain control loop in which offset errors occurs and this loop has speed droop characteristics. The secondary loop is responsible for frequency stability and stable power interchange between the neighbouring areas that are interconnected with each other [6]. Due to the simplicity, economic, reliable and efficient operation for mitigating frequency deviations, Proportional integral derivative (PID) controllers are widely used for the secondary control loop. Enhancements in tuning methods and control approaches have increased the efficiency of PID controllers, making them suitable for modern power systems with the integration of renewable energy sources. Improvements in tuning techniques and control strategies have markedly elevated the efficacy of PID controllers, making them satisfactory for modern power systems amidst increasing complexity and the deployment of renewable energy sources. Readers are encouraged to refer to a comprehensive review of modern approaches on AGC/LFC in power systems, along with recent developments and future direction in LFC [7, 8]. In recent years, soft computing, nature-inspired, evolutionary-based, physics-based, human inspired, population-based optimization approaches, including many others, have been identified and reported which makes the tuning of the controller parameters easier. Traditional optimization approaches such as Newton-Raphson, Gradient Descent, and Quadratic Gaussian often exhibit slower convergence rates and a greater propensity to get ensnared in local optima [9 – 11].

Conversely, metaheuristic optimization techniques are particularly useful for scenarios where conventional approaches might not work well because of non-linearity, high-dimensionality, or there are more than one local optima. These techniques, such as Artificial Bee Colony (ABC) [12], Firefly Algorithms (FA) [13], Genetic Algorithms (GA) [14], BAT Algorithms [15], Dragon fly Algorithms (DFA) [16], Particle Swarm Optimization (PSO) [17], Crayfish Optimization Algorithms (COA) [18], Ant Colony Optimization (ACO) [19], Cuckoo Search [20], Grey Wolf Optimization (GWO) [21], Salp Swarm

Algorithms (SSA) [22], Whale Optimization Algorithms (WOA) [23], Teaching Learning Optimization Algorithm (TLOA) [24], Bacteria Foraging Optimization (BFO) [25], Lyrebird optimization [26, 27] including Numerous others are engineered to effectively navigate extensive search regions and identify near-optimal answers with less processing effort. In addition, other robust controls such as sliding mode control (SMC) [28−31], fractional order (FO) control [32-33], linear matrix inequality (LMI) control [34], active disturbance rejection control (ADRC) [35], H_2/H_∞ [36], model predictive control (MPC) [37, 38], μ synthesis [39] among others, are documented in the literature for both conventional and deregulated power systems. **Table 1** summarizes the recent optimization approaches applied in the field of LFC.

1.2 Motivation

According to a review of the literature, several researchers have implemented PI/PID controllers that have been optimized to attain frequency stability in one, two, or multi-area power systems [40−44]. Every optimization method has three key elements: constraints, decision variables and cost function. The basic operating idea is to obey the constraints and quantify the choice variable to minimize/maximize the cost function. Despite of similarity in the working principle of optimization approaches, not all optimization approaches provide similar performance for same problem. This inspiration drives the authors to explore innovative optimization techniques to tackle challenges in interconnected power systems.

1.3 Contribution

This manuscript revisits the load frequency challenges within a networked power system. The primary objective is to regulate frequency and tie-line power exchange between two areas, despite imbalances between generation and demand. These imbalances are balanced by an innovative pelican optimisation-tuned PID controller. Taking inspiration from the hunting behaviour of pelicans, many researchers are interested in the pelican optimisation algorithm (POA) due to its straightforward framework and fast convergence rate. The response we are obtaining with MATLAB simulation is compared with recent optimization algorithms like GWO, PSO, TLOA, WOA, HOA and SSA. From the simulation results it is confirmed that we are getting increased frequency stability with the proposed pelican optimization algorithm. Moreover, the robustness of the proposed approach is tested with variable step load disturbances, variation in system parameters, nonlinearities like GDB, GRC and with renewable energy sources like wind and solar. The Bode plot analysis confirmed the closed-loop stability.

Table 1

Overview of recent reported control strategies and optimization.

Ref.	System Type	Controller Type	Optimization	Cost Function	Sources
[12]	Three Area	Decentralized PID	ABC Algorithm	ITSE, ITAE, IAE, ISE	Reheat Thermal Power Plant
[13]	Two Area, Three Area	Decentralized fuzzy PID	Firefly Algorithm and Pattern Search (hFA-PS)	ITAE	Thermal
[14]	Two Area	Decentralized PI	GA	Quadratic	Thermal
[15]	Two Area	Decentralized PI	BAT Algorithm	IAE, ITAE, ISE	Hydrothermal
[16]	Two Area	Decentralized PID	DA	ITAE	Reheat Thermal, Wind, Fuel Cells (FC), Aqua-Electrolyzer, Battery Energy Storage System (BESS), Diesel Engine Generator (DEG)
[17]	Five Area	Decentralized PID	PSO, Fuzzy Logic	IAE, ITAE, ISE, ITSE	Thermal, Hydro, Wind, Diesel
[18]	Two Area	Decentralized fuzzy PID - $TI^{\lambda}D^{\mu}$	Crayfish Optimization Algorithm (COA)	ITAE	Thermal, Hydro, Gas, Wind, Photovoltaic, Controlled Redox Flow Batteries (CRFBs)
[19]	Single Area	Centralized PID	ACO	IAE, ITAE, ISE	Nuclear, SMES, RFB, HAE
[20]	Three Area	Decentralized PI	Cuckoo Search Algorithm	ITSE, ITAE, IAE, ISE	Hydro and Thermal
[21]	Two Area, Three Area	Decentralized PI/PID	GWO	ITAE, ISE, ITSE	Thermal, Hydro, Gas
[22]	Two Area	Decentralized PID	SSA	ITSE, ITAE, IAE, ISE	Thermal, Wind, Photovoltaic
[23]	Two Area	Decentralized PID	WOA	ISE	Thermal, Wind, Photovoltaic, Wave Power Plant
[24]	Two Area	Decentralized Fuzzy-PID	TLBO	ITAE	Thermal
[25]	Two Area	Decentralized PID	Bacterial Foraging Optimization Algorithm (BFOA)	ITAE	Non-reheat thermal power plant
[26]	Three Area	Decentralized PID	Lyrebird Optimization Algorithm (LOA)	ITAE	Thermal, Hydro, Gas, Nuclear, Wind, Solar, Superconducting Magnetic Energy Storage, UPFC

Table 1- Continued
Overview of recent reported control strategies and optimization.

Ref.	System Type	Controller Type	Optimization	Cost Function	Sources
[27]	Two Area	Decentralized PI-(1+ DD)	Hybrid Lyrebird Algorithm and Pattern Search (hLOA-PS)	ITAE	Thermal, Solar, Energy Storage System
[28]	Single Area	SMC Centralized	TLBO	ITAE	Wind, Solar, FC, DEG, BESS, Flywheel Energy Storage System (FESS)
[29]	Single Area	Centralized Event Triggered Sliding Mode Control	-	ITAE	Wind, Solar, FC, DEG, BESS, FESS
[30]	Two-Area	Centralized backstepping SMC	-	No objective function	Thermal Power Plant
[31]	Two Area	SMC Decentralized	POA	ITSE	Thermal, Wind, Solar, EV, Demand Response
[32]	Two Area	Decentralized FOPID	Aquila Optimizer (AO)	ITAE	Thermal, Hydro, Gas, Wind
[33]	Two Area	Decentralized FOPID	TLBO	ITAE	Thermal, FC, DEG, Solar, Wind
[35]	Two Area	Four-Area Interconnected System	TLBO	ISE	Thermal, Hydro
[37]	Single Area, Four Area	Decentralized MPC	Online Optimization	ITAE	Thermal, Wind
[38]	Single Area	Decentralized MPC	Offline Multi-parametric Quadratic Programming (mp-QP)	Quadratic cost function	Thermal, Wind
[49]	Two Area	Decentralized $PI^{\lambda}(1+PDF)$	Zebra Optimization Algorithm (ZOA)	ITAE	Thermal, Wind, PV, Biodiesel Generator, Hydrogen Aqua Electrolyzer Fuel Cell (HAFC)
[50]	Two Area	MPC	Harris Hawks Optimization (HHO)	Discrete-time squared error penalty, +control penalty.	Thermal, Wind, Diesel, and EV aggregator
[51]	Two Area	PID	Tasmanian Devil Optimization (TDO)	ITAE	Thermal, Hydro, Nuclear, EV, Wind, PV, Gas
[52]	Two Area	Cascade Controller	Fuzzy Based	ISE, ITSE, IAE, ITAE	Non-reheat thermal, Hydro, EVs

1.4 Work outline

The next part of our article is as follows: In Section 2, mathematical framework and problem formulation for two area interlinked power system network, the objective function for load frequency control has been discussed. In Section 3, different phases of the pelican optimization algorithm have been discussed, with a flowchart and pseudocode. In Section 4, MATLAB simulation results has been provided. Section 5 concluded with an overview of results and proposes future research directions for exploration and POA's applications for diverse power system conditions.

2 System Modelling and Problem Formulation

A vast power system can be partitioned into subareas, each comprising neighbouring generators that are closely linked and operate as a unified group. These coherent subareas are referred to as control areas, and they collectively respond to changes in load within the system. The key components involved in LFC include sensors, control algorithms, and actuators, which work together to measure frequency variations and adjust the output of generators accordingly. LFC is crucial in linked power systems where multiple generators and loads are involved. It ensures that all parts of the grid operate synchronously and that power is distributed efficiently across the network. Fig. 1 illustrate the block diagram of two-area linked power system.

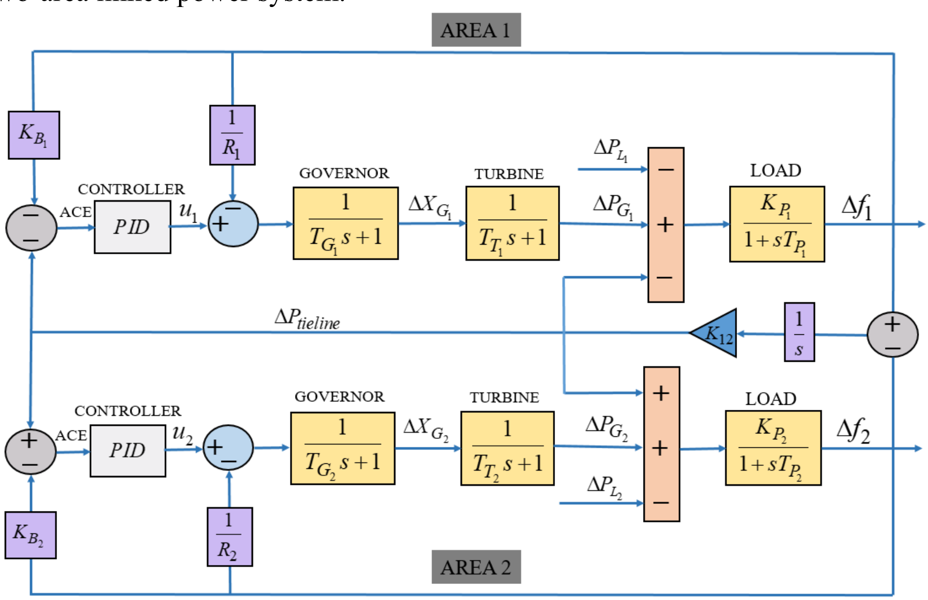


Fig. 1 – *Load frequency control block diagram.*

In system modelling, each block is approximated by a first-order lag, as minor load changes are anticipated during normal operation. The symbols T_{G_i}, T_{T_i} and T_{P_i} represent the time constants of governor, turbine and load respectively. The parameters K_{B_i}, R_i, K_{P_i}, K_{12} represent frequency bias factor, governor speed factor, gain of the load, and synchronizing constant between the areas, respectively. The area control error (ACE) integrates the frequency error and tie-line power deviation into a single value, guiding corrective actions to maintain system balance as shown below, $K_{B_i}\Delta f_i + \Delta P_{tieline_i}$.

$$ACE_i = K_{B_i}\Delta f_i + \Delta P_{tieline}. \tag{1}$$

The PID controller changes the power output of generators to minimize the *ACE*, thus ensuring stable and reliable operation. The optimization method employs the Integral Time Square Error (ITSE) as the objective function, as specified in (2).

$$J_{ITSE} = \int_0^t t\left(\left(ACE_i\right)^2\right)\mathrm{d}t. \tag{2}$$

The suffix i represent the i^{th} area of two area interconnected power network.

3 Pelican Optimization Algorithm

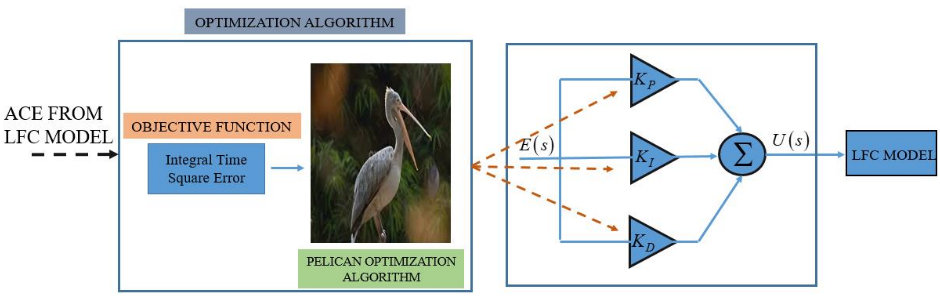


Fig. 2 – *Control Methodology.*

Pelicans dive from 10 to 20 meters high to catch their prey by working together in collaboration. Pelicans spread their wings skillfully on the surface of water to corral fish into shallow regions, which enables them to catch their prey. A good amount of water enters the beak of a pelican when it captures a fish. To expel the additional water, the bird advances its head before ingesting the fish [45, 46]. The POA's efficiency in finding optimal solutions is enhanced by factors such as collective intelligence and adaptive learning, making it useful for a broad

spectrum of applications, involving engineering design, data analysis, and resource management. The control methodology is shown in Fig. 2.
Since the proposed POA is a population based approach, each pelican represents an individual in the population. Based on where they are in the search area, each participant decides what the optimization problem's value should be. As a first step in optimization, we randomly initialize the members according to the problem's upper and lower bounds using (3) [47],

$$x_{i,j} = l_j + rand \cdot (u_j - l_j)\,; \quad i = 1,2,3,\ldots,N\,; \; j = 1,2,3,\ldots,D\,. \tag{3}$$

Here $x_{i,j}$ denotes the amount of the j^{th} design variable for the i^{th} population member, N represents the population size (pelicans), D signifies the cumulative number of design variables, referred to as dimensions, and $rand$ is a random number within the designated range [0, 1], while u_j and l_j are the upper and lower bounds of the j^{th} design variables, respectively. The population matrix X with rows depicting possible solutions and columns identifying issue variables, is demonstrated below.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,D} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,D} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,i} & \cdots & x_{N,j} & \cdots & x_{N,D} \end{bmatrix}_{N \times D} . \tag{4}$$

The objective function F is determined for each possible candidate solution,

$$J = \begin{bmatrix} J_1 \\ \vdots \\ J_i \\ \vdots \\ J_N \end{bmatrix} = \begin{bmatrix} J(X_1) \\ \vdots \\ J(X_i) \\ \vdots \\ J(X_N) \end{bmatrix}_{N \times 1} . \tag{5}$$

3.1 The phase of exploration of pelicans

Here, pelicans locate their prey by seeing its movement, and then they go in that direction. The prey's location is created randomly inside the search area in POA. As a result, POA's potential to accurately navigate the problem-solving area is enhanced. The above discussed concepts and the pelican strategy for prey capture are mathematically simulated in (6) [47],

$$x_{i,j}^{p_1} = \begin{cases} x_{i,j} + rand \cdot (p_j - I \cdot x_{i,j}), & J_p^1 < J_i; \\ x_{i,j} + rand \cdot (x_{i,j} - p_j), & \text{else}; \end{cases} \tag{6}$$

where $x_{i,j}^{p_1}$ denote the updated status of the i^{th} pelican in the j^{th} dimension, I is any random number that is either one or two, p_j signify the prey's position in the j^{th} dimension, and J_p^1 indicate the value of objective function. If the new objective function value is higher than the prior in that location, the new location for a pelican $X_i^{p_1}$ is approved. This procedure is organized as follow,

$$X_i = \begin{cases} X_i^{p_1}, & J_i^{p_1} < J_i; \\ X_i, & \text{else}. \end{cases} \tag{7}$$

3.2 The phase of exploitation

When the pelicans come to the water's surface, they hover and stretch their wings, causing the fish to rise to the surface and be easier to scoop into their neck pouches. This activity increases the pelicans' capacity to capture more fish in their chosen region. By imitating this pelican tactic, the POA gets improved convergence inside the hunting zone, boosting local search efficiency and increasing the POA's exploitation capabilities. This hunting behaviour of pelican is mathematically simulated in (8) [47],

$$x_{i,j}^{p_2} = x_{i,j} + Z\left(1 - \frac{k}{T}\right)\left(2rand - 1\right)x_{i,j} \tag{8}$$

where $x_{i,j}^{p_2}$ denotes the updated state of the i^{th} pelican in the j^{th} dimension during the exploitation phase, Z is a constant valued at 0.2, $Z \cdot \left(1 - k/T\right)$ is the neighbourhood radius of $x_{i,j}$, k is the iteration count while T is the maximum iteration.

During this step, efficient updating is executed to either accept or reject the new pelican position depending on (9),

$$X_i = \begin{cases} X_i^{p_2}, & J_i^{p_2} < J_i; \\ X_i, & \text{else}; \end{cases} \tag{9}$$

where $X_i^{p_2}$ denotes the new updated position of the i^{th} pelican and $J_i^{p_2}$ is its objective function.

After updating all population members through the initial and secondary phases, the optimal candidate solution is revised in accordance with the updated population status and objective function values. The algorithm thereafter advances to the next iteration, repeating the steps of the proposed POA as detailed in (3) – (9) until the completion of the execution. Ultimately, the most suitable candidate solution identified through these iterations is given as a near-best solution to the problem. The procedural phases of the pelican optimization are shown as a flowchart in Fig. 3 and its pseudo-code in **Table 2**.

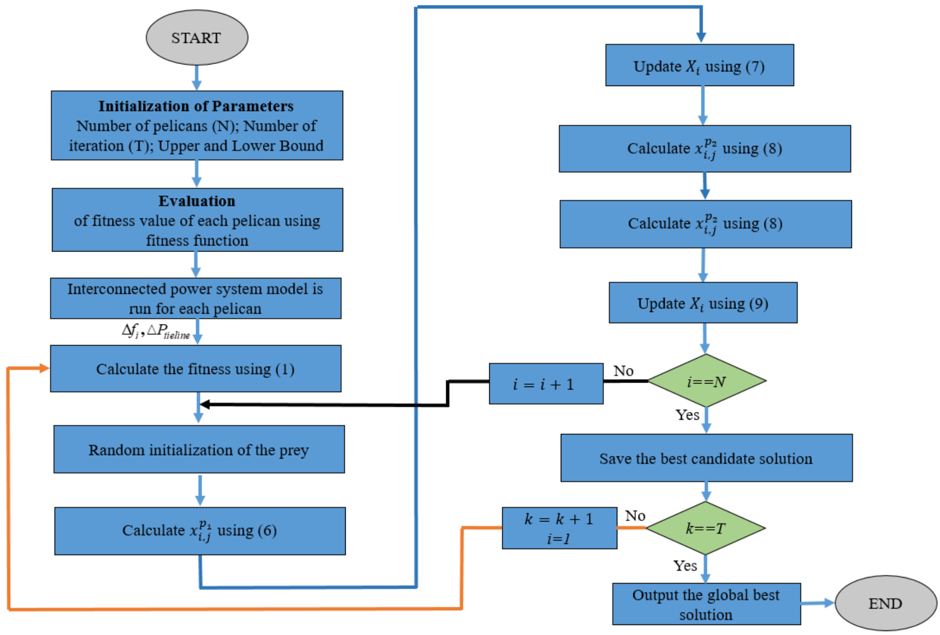


Fig. 3 – *POA Flowchart.*

Table 2
POA Pseudocode.

Steps	Description of Steps:
1	**Start**: Initialize the algorithm.
2	**Initialize Population**: Randomly generate a population of pelicans, each implying a possible solution to the optimization problem.
3	**Evaluate Fitness**: Assess the quality of each solution using a predefined fitness function.
4	**Update Global Best**: Identify the best solution and store it.
5	**Exploration and Exploitation**: ○ **Exploration**: Pelicans search broadly to cover large areas, mimicking their foraging behaviour. ○ **Exploitation**: Pelicans converge towards promising solutions, similar to focused hunting.
6	**Update Positions and Velocities**: Adjust pelican positions based on algorithm-specific rules.
7	**Evaluate and Update**: Continuously assess the new positions and update the global best solution if improvements are found.
8	**End**: Finalize the procedure and provide the optimal result.

3.3 Computational complexity and scalability

The computational complexity of the POA algorithm can be analysed based on four main processes: algorithm initialization, fitness function evaluation, prey generation, and solution updating.

– Initialization stage requires generating initial population which results in computational cost of $O(N)$.

– During each iteration, every population member evaluates the objective function in two phases, leading to a computational complexity of $O(2 \cdot T \cdot N)$.

– Prey generation and its evaluation occur in every iteration, which contributes a complexity of $O(T) + O(T \cdot D)$.

– In each iteration, the positions of N population members with D dimensions are updated in two stages, resulting in a complexity of $O(2 \cdot T \cdot N \cdot D)$ for the solution update process.

The final computational time of POA is $O\big(N + T \cdot (1 + D) \cdot (1 + 2N)\big)$.

As far as scalability of POA for larger multi area system is concerned, the number of decision variables typically increases due to additional generators, controllers, and system constraints. Although this increases the search space, POA maintains good scalability because its population based search strategy efficiently explores and exploits the solution space without requiring gradient information. Moreover, the algorithm's simple update mechanisms help keep computational overhead relatively low.

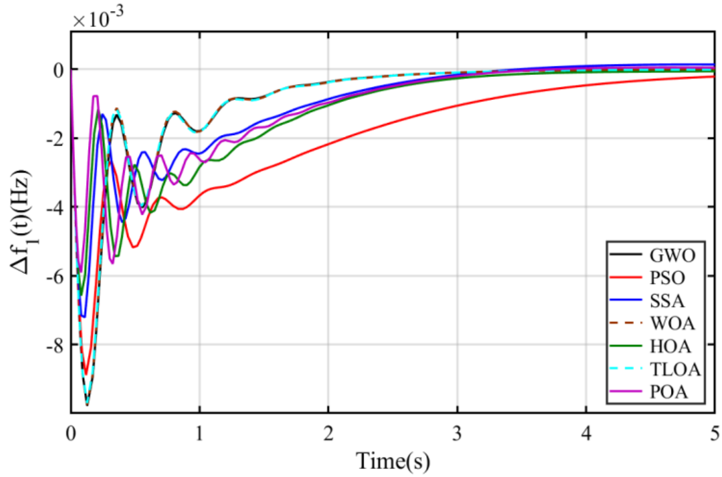
4 Results and Discussion

This research presents simulation findings that explain the tuning process of a PID controller using the POA, conducted inside the MATLAB environment. The optimization method is started with the following settings: population size (number of pelicans) = 30; dimension (number of tunable parameters) = 6; lower and upper bounds of tunable parameters = 0 and 10, respectively; and a maximum iteration limit of 20. The values of the system parameters are shown in **Table 3**.

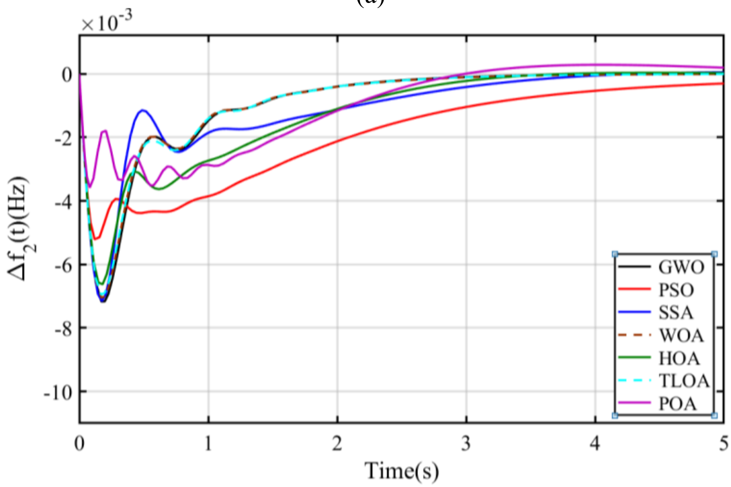
Table 3
System parameter values [21].

Area	T_P	K_P	T_T	T_G	R	K_B	K_{12}
1	20	120	0.3	0.08	2.4	0.41	0.55
2	25	112.5	0.33	0.072	2.7	0.37	

Case 1: In this study, the results obtained in MATLAB simulink environment demonstrate the effectiveness of the proposed design in achieving frequency stability in two-area power system under step load disturbances. The performance of the POA-tuned PID controller is analysed against various extensively accepted and modern metaheuristic optimization methods, including GWO, PSO, SSA, WOA, HOA and TLOA. The comparison study shows that the POA Tuned PID controller offers better frequency stabilisation, with substantially less frequency deviation in response to load changes (see Figs. 4a and 4b). It is evidenced by a faster restoration of the nominal frequency and reduced oscillations, surpassing other metaheuristic techniques.



(a)



(b)

Fig. 4 – *Δf under step change in load demand for* (a) *Area 1* (b) *Area 2.*

Fig. 5 shows the tie line power exchanges between neighboring areas. **Table 4** shows the performance of POA against other optimizations in terms of minimum peaks attained.

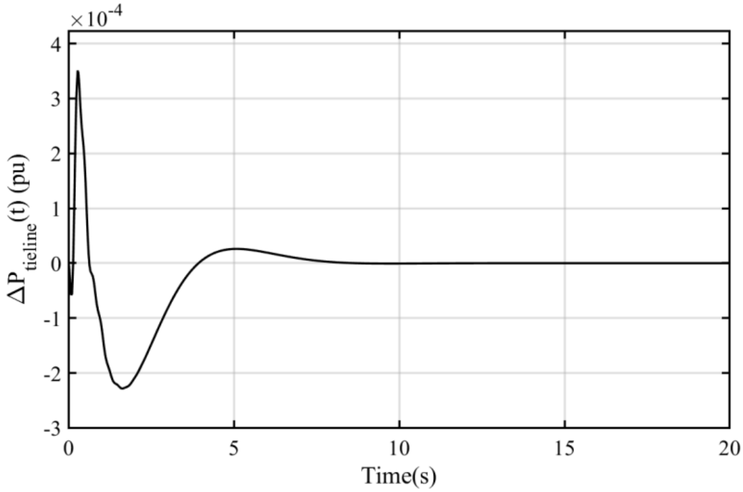


Fig. 5 – *Tie line power deviation.*

Table 4
Performance Analysis.

	Minimum Peak	
Optimization Algorithm	Area 1	Area 2
GWO	-0.009777	-0.007167
PSO	-0.008883	-0.005212
SSA	-0.007205	-0.007159
WOA	-0.009746	-0.007045
HOA	-0.006576	-0.006625
TLOA	-0.009697	-0.006952
POA	**-0.005903**	**-0.003585**

Table 5
Controller parameter values for POA.

	Area 1			Area 2		
Optimization Algorithms	K_P	K_I	K_D	K_P	K_I	K_D
	Filter Coefficient (*N*)=100			Filter Coefficient (*N*)=100		
POA	9.99	8.06	6.83	9.99	8.55	2.21

Fig. 6 shows the convergence plot in which POA surpasses the aforesaid techniques, attaining better cost value in a lesser number of iterations. This exceptional convergence rate of POA not only highlights its effectiveness in faster finding of optimal solutions but also highlights its potential for applications in real time. So POA is a potential choice for optimization of a controller's parameters in large power systems due to its lesser number of iterations required, rapid computational times, and lower consumption of resources. **Table 5** shows the controller's gain obtained using POA. Statistical analysis is also done for different optimization and is shown in **Table 6**. Among all the algorithms, POA achieved the lowest mean value ($1.1701e^{-05}$), indicating the best optimization performance. It also exhibited a relatively low standard deviation ($3.1989e^{-06}$), demonstrating stable results across 10 runs. It can also be inferred from the **Table 6** that the POA algorithm reaches global optima is lesser time.

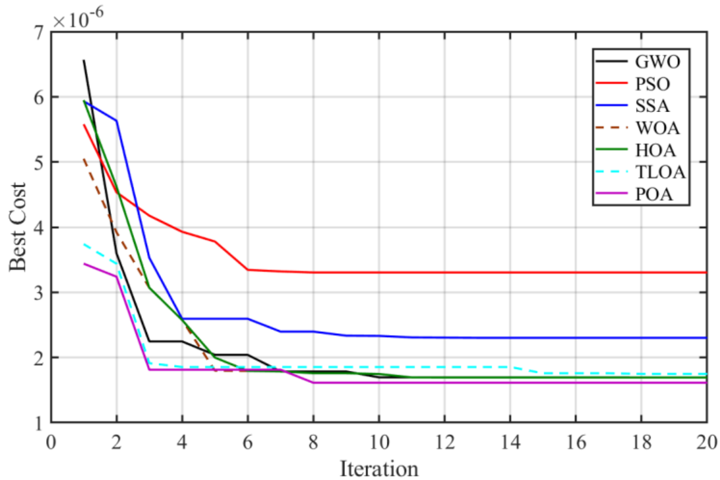


Fig. 6 – *Best cost vs iteration.*

Table 6
Statistical performance comparison.

	Execution Time (sec)	Mean	Standard Deviation
	Across 10 runs		
GWO	857. 43110	3.9338e-05	5.0332e-06
PSO	829.07379	3.2082e-05	6.7609e-06
SSA	737.948	1.3812e-05	3.4798e-06
WOA	819. 55716	1.5565e-05	3.7100e-06
HOA	729.13785	1.4953e-05	3.3009e-06
TLOA	915.87433	1.7288e-05	3.5714e-06
POA	641.96208	1.1701e-05	3.1989e-06

Case 2: The validation of the POA under conditions of random load disturbances demonstrates its robustness and efficacy in maintaining frequency stability within acceptable limits (see Fig. 7). During the simulation, the two-area power system experienced a series of unpredictable load variations, mimicking real-world operational challenges. Despite these fluctuations, the POA-tuned PID controller adeptly managed to keep frequency deviations well within the predefined acceptable range, underscoring the system's resilience. This robust performance highlights the controller's capability to swiftly adapt to sudden changes, thereby ensuring reliable and stable operation in practical scenarios.

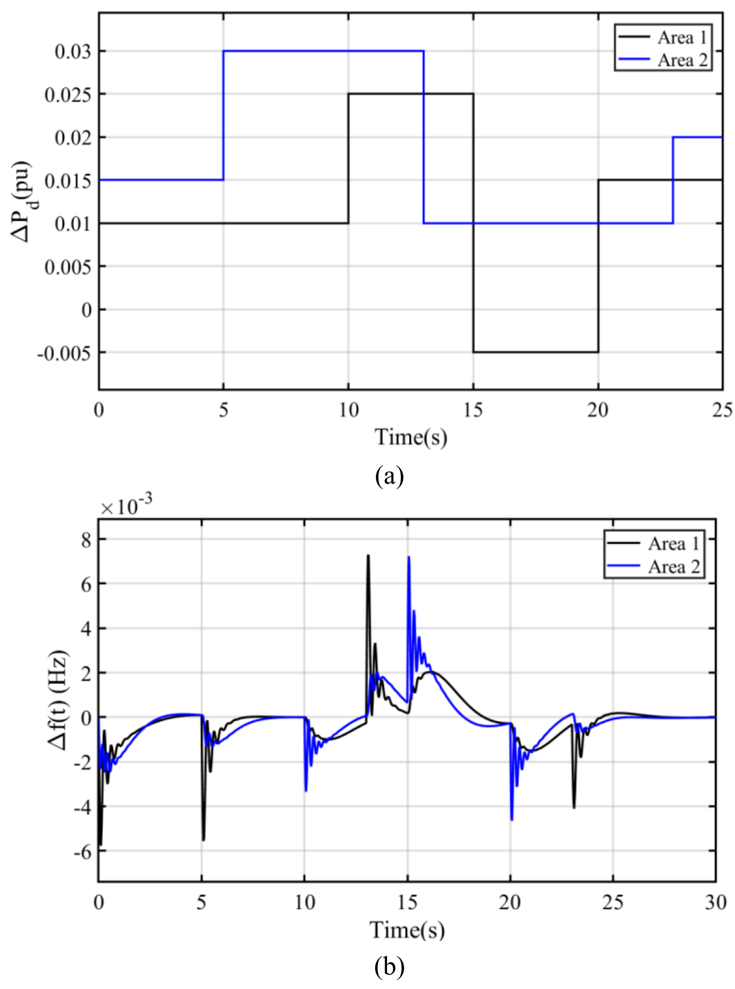


Fig. 7 – (a) *Random step load and* (b) *frequency stabilization using POA.*

Case 3: The variations in system parameters potentially causes deviations from nominal operating conditions. The system parameter K_{B_i}, R_i, T_{T_i} and T_{G_i} are altered by 30% from their standard values for simulation. The potential of the proposed method to effectively handle such changes underscores its adaptability and resilience, ensuring consistent performance and stability under dynamic and random power system scenarios. The results in Fig. 8 demonstrate that the POA-tuned controller maintained excellent frequency stability even in the face of these parameter variations. Such robustness is critical for ensuring reliable operation across different operating conditions and system configurations.

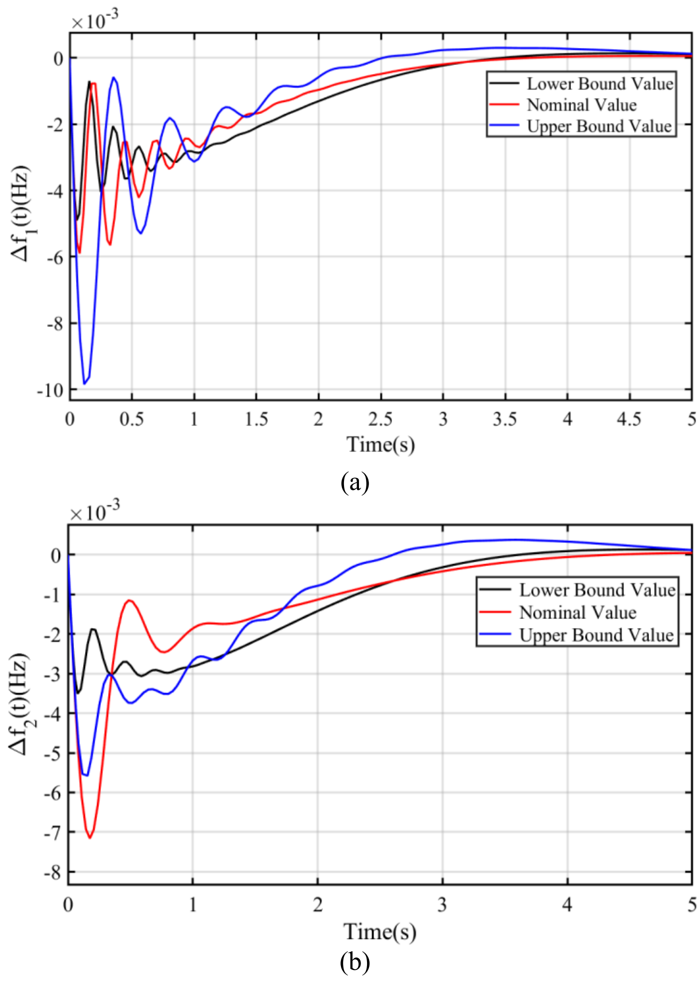


Fig. 8 – *Frequency stabilization using POA under system parameter variation for* (a) *Area 1 and* (b) *Area 2.*

Case 4: Frequency stability in power systems is critical, particularly in the face of uncertainties such as GRC and GDB. GRC, set at 3%/min, limits the rate at which generated power can fluctuate, impacting the system's potential for responding quickly to frequency variations. GDB, with a value of 0.06%, introduces a range within which frequency changes are not detected by the governor, causing delays in the corrective action [48]. These uncertainties contribute to overshoot, where the frequency temporarily exceeds its set point before stabilizing. Considering these problems, the suggested design successfully manages to ensure frequency convergence within acceptable limits, mitigating the detrimental impacts of GRC and GDB while preserving system stability (see Fig. 9).

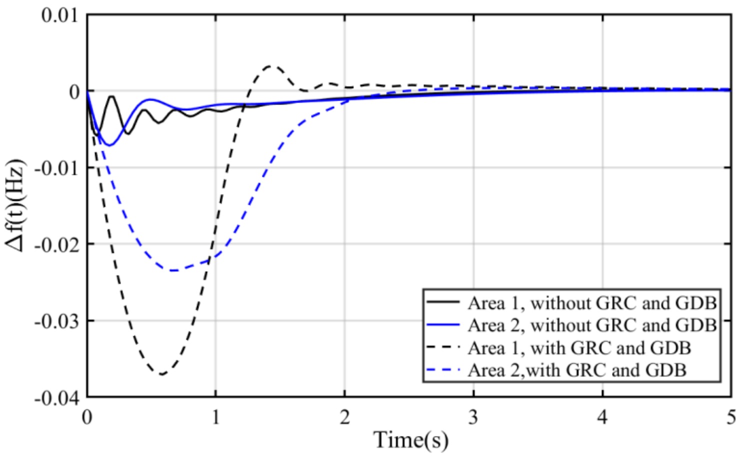
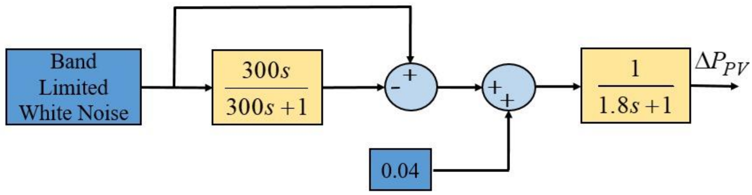


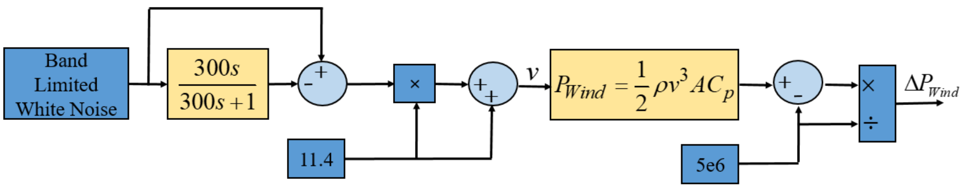
Fig. 9 – *Δf with nonlinearities.*

Case 5: In this case, the claimed control strategy is verified by the inclusion of renewable energy sources, including solar and wind. The increasing global energy demand, with the quest for greener and more reliable energy sources, has instigated a transformation in the energy industry. The change has led to a heightened inclusion of renewable energy inside the traditional energy system. Regulating frequency is challenging with these intermittent energy sources as the output power vary throughout the day. Fig. 10a and 10b illustrate the block diagram of solar and wind system model for the simulink environment. The system parameter and description are well investigated in [49] and hence has not been included in this work.

Fig. 11 depicts the solar and wind energies (p.u.) integrated with the thermal energy unit. The intermittent behavior of this energy can be seen in the frequency regulation shown in Fig. 12. The frequency deviation is impacted by finite amplitude oscillations about the zero line, although it remains within acceptable bounds. This confirms the robustness of the suggested algorithm with intermittent energy sources.



(a)



(b)

Fig. 10 – (a) *PV system model in simulink environment* [49];
(b) *Wind power model in simulink environment* [49].

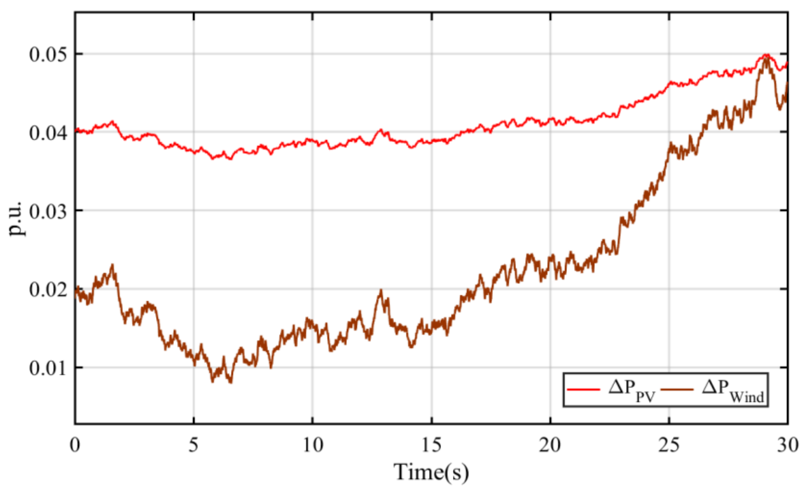


Fig. 11 – *Solar and Wind energies.*

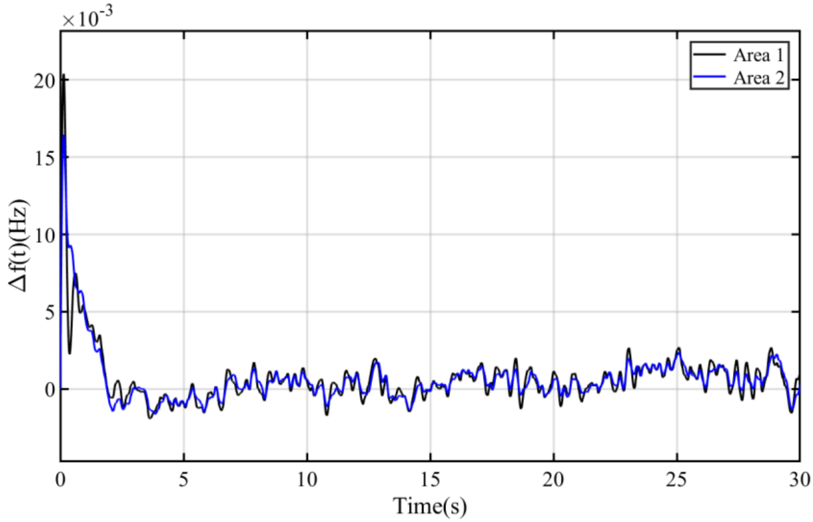
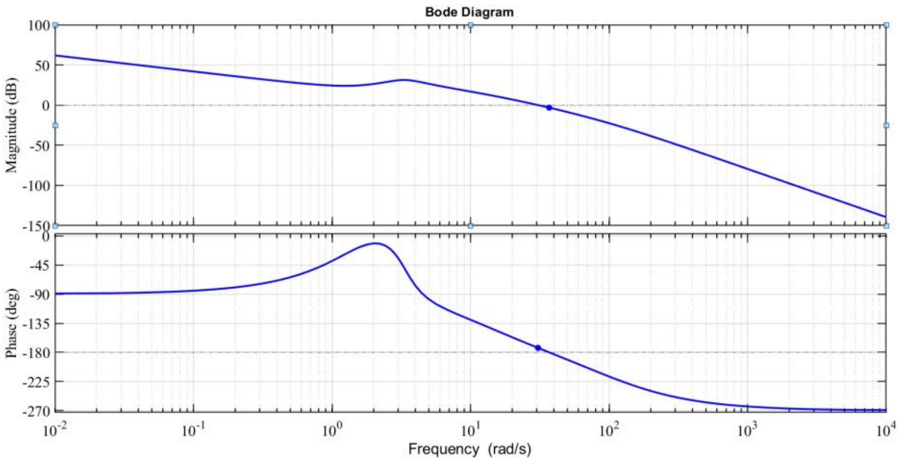


Fig. 12 – *Δf with the incorporation of renewable energy sources.*

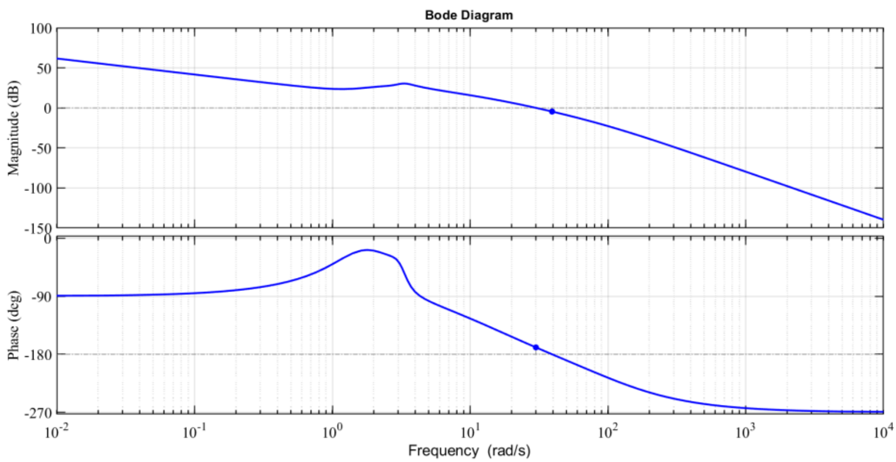
Case 6: The stability analysis of the two-area power system via Bode plot provides a comprehensive understanding of the frequency response and closed-loop stability of the system (see Fig. 13). For Area 1, the Bode plot revealed a gain margin (GM) of 3.19 dB and a phase margin (PM) of 6.95 degrees, indicating adequate buffer before the system reaches instability. Similarly, for Area 2, the GM was observed to be 4.61 dB with a PM of 10.7 degrees, suggesting a more substantial safety margin against potential oscillatory behavior (see **Table 7**). These values confirm that both areas of the power system are closed-loop stable, as they maintain sufficient margins to tolerate perturbations without leading to instability. This Bode plot analysis validates the effectiveness of the suggested PID controller for maintaining secure and stable power system operation.

Table 7
Stability Margins.

Area	GM (dB)	PM (deg)	Closed Loop Stability
1	3.19	6.95	Yes
2	4.61	10.7	Yes



(a)



(b)

Fig. 13 – *Bode Plot for* (a) *Area 1* and (b) *Area 2.*

5 Conclusion

The application of the POA for load frequency regulation has demonstrated significant potential for enhancing power system stability and performance. Through rigorous simulations and comparative analysis, POA has proven to be an effective tool for tuning PID controllers, achieving rapid frequency convergence, and maintaining system reliability under varying load conditions and uncertainties. Its adaptability to manage the complexities of interconnected systems and robustness against nonlinearities such as GRC and GDB, renewable energy integration further underscores its efficacy. Its adaptability to manage the complexities of interconnected systems and robustness against nonlinearities such as GRC and GDB, renewable energy integration further underscores its efficacy. In addition, the proposed design has demonstrated superior performance and stability compared to other recent and popular metaheuristic optimization techniques like GWO, PSO, SSA, WOA, HOA, and TLOA with respect to execution time, mean, and standard deviation.

The successful execution of POA in the LFC framework demonstrates its potential effectiveness and suggests that it may be applied to more complex power system scenarios, contributing to further research in energy system stability and optimization. A hybrid POA can be developed by integrating it with complementary optimization strategies to improve exploration and exploitation capabilities. The global search ability of POA can be improved by incorporating mechanisms such as adaptive parameter tuning, chaotic maps, mutation strategies, or hybridization.

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