
DEVELOPMENT OF AN OPTIMAL CONTROL STRATEGY FOR LOAD FREQUENCY CONTROL OF THE TWO-AREA POWER SYSTEM USING ARITHMETIC OPTIMIZATION ALGORITHM

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ABSTRACT

This study addresses frequency instability and tie-line deviations in interconnected multi-area power systems caused by sudden load perturbations and physical non-linearities such as governor dead band (GDB). To overcome the slow transient recovery and lingering oscillations of conventional particle swarm optimization (PSO) and genetic algorithm (GA) tuned PID controllers, this research implements the Arithmetic Optimization Algorithm (AOA) for optimal decentralized Load Frequency Control (LFC) tuning. A two-area power network incorporating GDB dynamics was modeled in MATLAB/Simulink and subjected to step load perturbations (SLP) of 0.2 p.u. in Area 1 and 0.15 p.u. in Area 2 occurring at $t = 0$ s, utilizing the Integral Time Absolute Error (ITAE) index as the fitness criterion. The proposed AOA-PID controller significantly outpaced traditional methods, achieving a transient settling time of 5.22 s for Area 1 frequency deviation (a 43.68% recovery improvement over PSO) and restricting peak undershoot to -0.0016 Hz (a 82.61% improvement compared to -0.0092 Hz for PSO). Furthermore, the AOA yielded an optimal fitness value of 0.04245, nearly seven times lower than PSO (0.2831) and GA (0.4120). Ultimately, the AOA-PID scheme delivers a robust, highly efficient solution that ensures superior transient stability and rapid equilibrium restoration in interconnected grids.

Keywords: Arithmetic Optimization Algorithm; Load Frequency Control; Multi-area Power System; PID Controller; Tie-line Power; Governor Dead Band

1. INTRODUCTION

Maintaining a continuous balance between electricity generation and dynamic load demand is critical to the operational reliability of modern power systems, yet it remains a substantial challenge due to volatile load variations and the intermittent nature of renewable energy sources (Kothari & Nagrath, 2003; Kunya et al., 2017). In large-scale networks, this operational environment is managed by structuring the grid into a multi-area interconnected power system (MAIPS), where distinct control areas (CAs) are linked via tie-lines or high-voltage direct current (HVDC) connections (Muthana et al., 2011). Because localized load fluctuations propagate across area boundaries and impact neighboring regions, Load Frequency Control (LFC) is essential (Isemin & Onah, 2022). LFC systems fulfill the dual purpose of keeping frequency within strict, pre-designed operational limits and regulating tie-line power exchanges to prevent generator desynchronization and cascading system collapse (Pappachen & Peer Fathima, 2017; Charalampos et al., 2019; Shouran et al., 2021).

Designing effective LFC mechanisms is increasingly complex due to modern factors like market deregulation, decentralized control, and physical non-linearities. A particularly severe physical constraint is the governor dead band (GDB), which represents a strict range of frequency variations where the turbine governor remains unresponsive (Rathnayake et al., 2019). GDB introduces major reaction delays following load adjustments, causing severe overshoots/undershoots and degrading power quality (Alnefaie et al., 2025). To neutralize the adverse effects of GDB, soft-computing and metaheuristic optimization algorithms—such as Bacterial Foraging (Ali & Abdalazim, 2013), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA)—have been utilized to tune controller gains. While these methods improve upon classical Ziegler-Nichols tuning (Ogata, 2011), they often suffer

from premature convergence, high computational burdens, and slow transient damping (Sambariya & Prasad, 2016).

To bridge this gap and optimize power system transient response under GDB non-linearities, this study proposes a decentralized PID control scheme for a two-area interconnected power system tuned via the population-based Arithmetic Optimization Algorithm (AOA). The optimal gain parameters are dynamically computed under operational limits and rate constraints, providing a streamlined and highly effective solution for frequency and tie-line power stabilization.

2. SYSTEM MODELING AND NON-LINEAR DYNAMICS

2.1 LOAD FREQUENCY CONTROL IN MAIPS

In a two-area interconnected power system, separate control areas are linked via tie-lines to maintain mutual power exchanges during disturbances (Wadi et al., 2024; Sun, 2018). The dynamic secondary LFC loop processes the Area Control Error (ACE), which combines local frequency error (Δf) and tie-line power loading deviation ($\Delta P_{tie, i}$) and is given as in (1).

$$ACE = \Delta P_{tie} - \beta \Delta F \quad (1)$$

$$\text{Where: } \Delta P_{tie} = \sum_{i=1}^n P_{tie} - P_{tie \text{ initial}} \quad (2)$$

Where β is the bias parameter, which reflects the contribution of the operating members in the power pool expressed in MW/Hz.

2.2 GENERATOR, LOAD, AND TIE-LINE DYNAMICS

The rotational dynamics of synchronous generation and load damping in Control Area i are modeled using the linear swing equation transfer function as in (3).

$$M_{eq} \frac{d\Delta f_i}{dt} = \sum_{l=1}^n \Delta P_{Tli} - \Delta P_{tie, i} - \Delta P_{Di} - D_{eq} \Delta f_i \quad (3)$$

Where: M_{eq} is the equivalent generator inertia constant, D_{eq} is the equivalent load-damping factor, ΔP_{Tli} is turbine power output, $\Delta P_{tie, i}$ is net tie-line power flow, and ΔP_{Di} represents the non-frequency sensitive load variations.

The speed governor and thermal turbine transfer functions are expressed as in (4 and 5).

$$G_{g, i}(s) = \frac{1}{T_{g, i}s + 1} \quad (4)$$

$$T_{t, i}(s) = \frac{1}{T_{t, i}s + 1} \quad (5)$$

where T_g : Governor time constant, T_t : Turbine/engine time constant

The active power transfer variation along the tie-line connecting Area 1 and Area 2 is governed by (6).

$$\Delta P_{Tij} = T_s (\Delta \omega_i - \Delta \omega_j) \quad (6)$$

To evaluate control area deviations, the ACE incorporates both local frequency and tie-line variations as in (7).

$$ACE_i = \beta_i \Delta f_i + \Delta T_{ij} \quad (7)$$

where β_i represents the frequency bias coefficient defined by governor speed regulation (R_i) and damping factor (D_i) as (8).

$$\beta_i = \frac{1}{R_i} + D_i \quad (8)$$

2.3 MODELING OF GOVERNOR DEAD BAND (GDB) NON-LINEARITY

The governor dead band introduces significant non-linearity by delaying governor valve adjustments until frequency deviation exceeds a threshold. Rather than using simple linear approximations, the GDB is represented mathematically via its describing function as given in (9).

$$N(A) = N_r + jN_i \quad (9)$$

The non-linear components are separated and treated mathematically using (10).

$$N_r = \frac{k}{\pi} \left[\frac{\pi}{2} + \arcsin \left(1 - \frac{2D}{A} \right) + 2 \left(1 - \frac{2D}{A} \right) \sqrt{\frac{D}{A} \left(1 - \frac{D}{A} \right)} \right], N_i = \frac{-4kD}{\pi A} \left(1 - \frac{D}{A} \right), (D \geq A) \quad (10)$$

The Simulink schematic of the two-area network is shown in Figure 1.

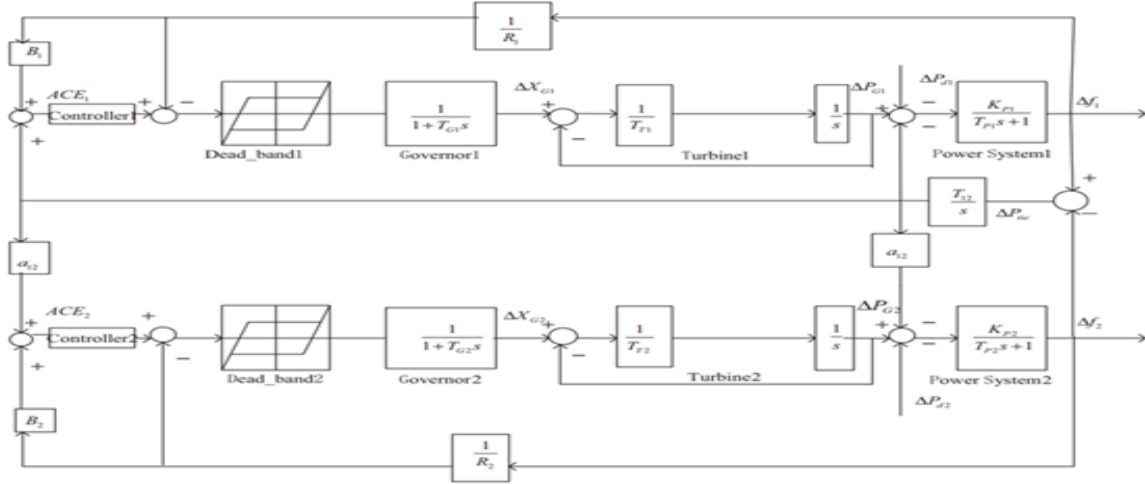


Figure 1: Transfer Function Model of the Investigated Two-area Power System.

3. OPTIMIZATION METHODOLOGY AND ALGORITHM

3.1 ARITHMETIC OPTIMIZATION ALGORITHM (AOA)

The Arithmetic Optimization Algorithm (AOA) is a population-based metaheuristic developed by

(Abualigah et al. 2021) inspired by elementary arithmetic operations: Division (div), Multiplication (times), Subtraction (-), and Addition (+). AOA uses the Math Optimizer Accelerated (MOA) function to transition between global exploration and local exploitation.

Arithmetic Optimization Algorithm (AOA) is employed to determine optimal PID gains by iteratively improving candidate solutions.

Step 1: Initialization

A population of candidate solutions is randomly generated using (12)

$$X_i = [K_{p1}, K_{i1}, K_{d1}, K_{p2}, K_{i2}, K_{d2}] \quad (12)$$

Step 2: Control Parameters

Math Optimizer Accelerated (MOA) is obtained using (13).

$$MOA(t) = MOA_{min} + \frac{t}{T} (MOA_{max} - MOA_{min}) \quad (13)$$

Math Optimizer Probability (MOP)

Controls step size is expressed as in (14):

$$MOP(t) = 1 - \left(\frac{t}{T} \right)^{1/\alpha} \quad (14)$$

Step 3: Exploration Phase (Global Search)

Used in early iterations to search widely.

Condition as expressed in (15)

$$\text{When } r_1 > MOA \quad (15)$$

Then equation (division operator 16 and multiplication operator 17) is used.

$$X_i^{t+1} = \frac{X_{best}}{MOP + \epsilon} \times ((ub - lb)r_2 + lb) \quad (16)$$

$$X_i^{t+1} = X_{best} \times MOP \times ((ub - lb)r_2 + lb) \quad (17)$$

Step 4: Exploitation Phase (Local Search)

Used in later iterations to refine best solution.

Condition:

$$\text{When } r_1 \leq MOA \quad (18)$$

To achieve exploitation under this condition equation (19 (subtraction) and 20 (addition)) are used.

$$X_i^{t+1} = X_{best} - MOP \times ((ub - lb)r_3 + lb) \quad (19)$$

$$X_i^{t+1} = X_{best} + MOP \times ((ub - lb)r_2 + lb) \quad (20)$$

Where: X_{it} is current solution (PID gains vector), X_{best} is best solution found so far, t is current iteration, T : maximum iterations, r_1, r_2, r_3 are Random numbers in (0,1), ϵ is Small number (to avoid division by zero), α is constant usually 5.

Table 1: Parameters associated with AOA

Parameter	Value
State dimension of the input layer	9
Action dimension of the output layer	3
Reward discount factor	0.995
Minimum batch size	128
Maximum steps per episode	500
Maximum episode	500
Agent sample time	0.02 s
Experience replay buffer	1×10^6
Target smooth factor	1×10^{-3}

Continue steps 2–4 for many episodes until the policy converges or reaches a desired performance level. Table 2 shows the simulation parameters. These parameters were adopted from the work of Qu et al., (2024).

The flowchart of the implementation of AOA is shown in Figure 2.

3.2 DECENTRALIZED PID CONTROLLER OPTIMIZATION

Decentralized PID controllers are deployed in each control area. The time-domain output is expressed as in (21).

$$u(t) = K_p e_p(t) + K_i \int_0^1 e_p(t) dt + K_d \frac{de_p(t)}{dt} \quad (21)$$

where, K_p , K_i , K_d correspondingly indicate the proportional constant, integral constant, and derivative constant.

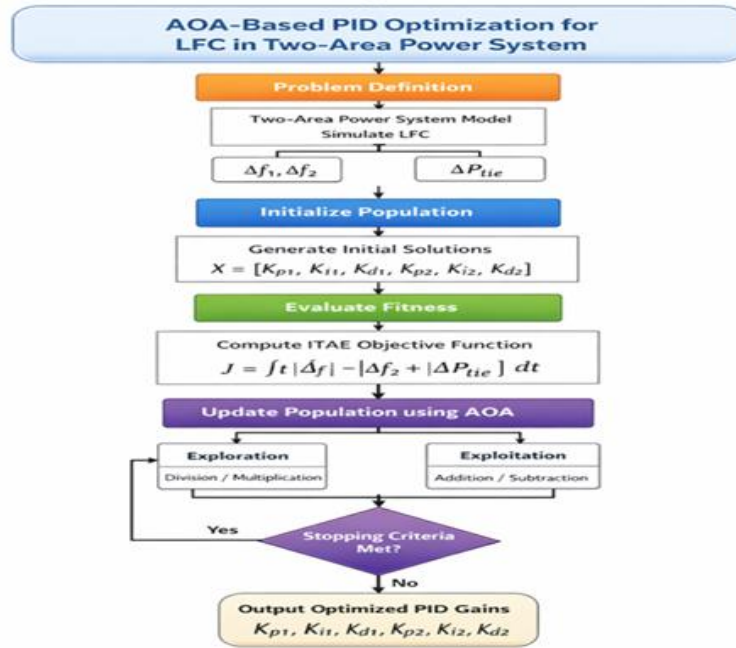


Figure 2: Flowchart of AOA-Based PID Optimization for LFC in Two-Area Power System

$$u(t) = K_p e_p(t) + K_i \int_0^1 e_p(t) dt + K_d \frac{de_p(t)}{dt} \quad (21)$$

where, K_p , K_i , K_d correspondingly indicate the proportional constant, integral constant, and derivative constant.

The optimization will be based on the Integral Square Error (ITAE) criteria as shown in equation (22). $\min (J_{ITAE})$ such that

$$J_{ITAE} = \int_{t=0}^{t_{sim}} t(|\Delta F_1| + |\Delta F_2| + |\Delta P_{tie}|) dt \text{ for } I = 1, 2 \quad (22)$$

It will be carried out subject to the following constraints:

- i. Load-generation balance as equality constraint as expressed in equation (23)

$$\sum P_{Gi} = \sum P_{Di} + P_i^{tie}(t) \quad (23)$$

- ii. Frequency band: the frequency is constrained within the certain upper and lower band as;

$$f_i^{min} \leq f_i \leq f_i^{max} \quad (24)$$

- iii. Controller gains constraints: the controller proportional, integral, and derivate gains are constrained with some upper and lower limits as shown in (25);

$$K_{pi}^{min} \leq K_{pi} \leq K_{pi}^{max}, K_{li}^{min} \leq K_{li} \leq K_{li}^{max}, K_{Di}^{min} \leq K_{Di} \leq K_{Di}^{max} \quad (25)$$

4. RESULTS AND DISCUSSION

The system was simulated under step load perturbations of (0.2 p. u. in area and 0.15 p. u. in area 2 at $t=0$ s), the resulting oscillations exhibited an exponential-sinusoidal decay, as shown in Figures 3–5. Figure 3 shows frequency deviation of area 1 when subjected to SLP of 0.2 p. u.

The Arithmetic Optimization Algorithm (AOA) outperforms GA and PSO in Area 1 frequency deviation control following a load perturbation. AOA minimizes the maximum frequency drop to -5.4×10^{-3} Hz, compared to GA (-8.7×10^{-3} Hz) and PSO (-9.1×10^{-3} Hz). By eliminating secondary oscillations, AOA achieves steady-state equilibrium in 4–5 seconds versus 8–10 seconds for GA and PSO, demonstrating superior grid stability.

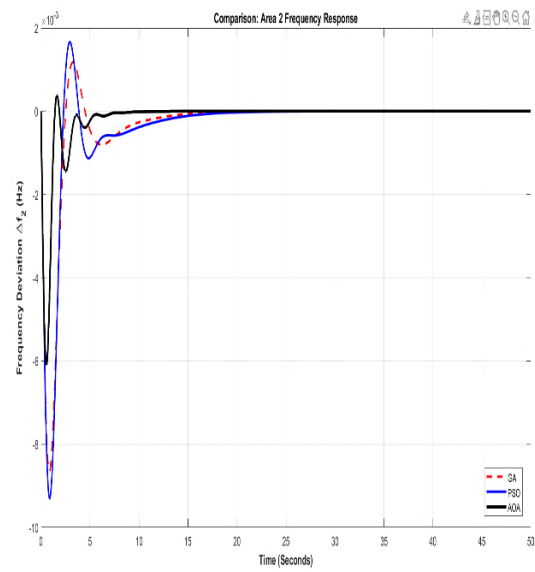
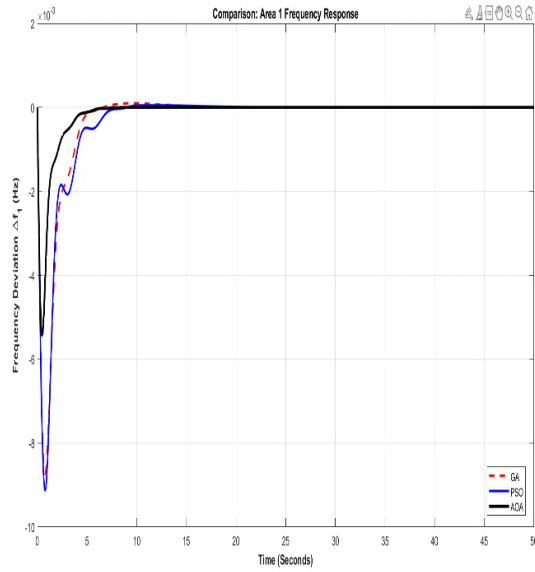


Figure 3: Variation of Area-1 Frequency Due to ΔP_L Figure 4: Variation of Area-2 Frequency Due to ΔP_L

Figure 4 shows frequency deviation of area 2 when subjected to SLP of 0.15 p. u.

From Figure 4, the dynamic performance analysis of Area 2 frequency deviation (Δf_2) shows AOA outperforming GA and PSO. Following a disturbance, AOA limits peak undershoot to -6.1×10^{-3} Hz versus GA (-8.6×10^{-3} Hz) and PSO (-9.3×10^{-3} Hz). By suppressing overshoots and dampening oscillations, AOA restores equilibrium in 6–7 seconds, compared to 15–18 seconds for GA and PSO.

Figure 5 shows the tie-line variation as a result of change in load in area-1 and area-2.

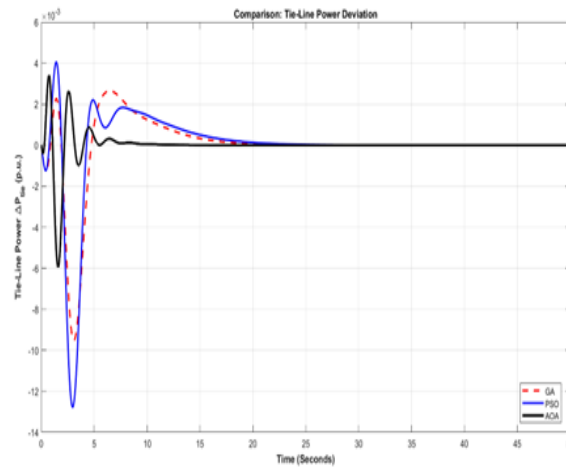


Figure 5: Change in Tie-Line Power due to Load Variation in Area-1 and 2

Table 2: Simulation parameters

component	Parameters	Control Area	
		1	2
Generator	Tg (sec)	0.08	0.08
	Tt (sec)	0.3	0.3
	R (Hz/pu)	2.4	2.4
Power System	Kp (Hz/pu)	120	120
	β_i	0.425	0.425
	T12	0.545	0.545

From Figure 5, the tie-line power deviation response shows AOA outperforming GA and PSO. AOA restricts the peak undershoot to $(-6.0 \times 10^{-3} \text{ p.u.})$, significantly improving upon GA $(-9.5 \times 10^{-3} \text{ p.u.})$ and PSO $(-12.8 \times 10^{-3} \text{ p.u.})$. Furthermore, AOA rapidly dampens inter-area oscillations, restoring steady-state equilibrium in roughly 8.20 seconds compared to over 22.5 and 24.0 seconds for GA and PSO respectively. Comprehensive dynamic performance comparison is shown in Table 3.

5. CONCLUSION

This study presented an optimal decentralized Load Frequency Control (LFC) strategy utilizing the Arithmetic Optimization Algorithm (AOA) to tune PID controllers for an interconnected two-area power system with governor dead band (GDB) non-linearities. Simulation results show that the AOA framework achieved an over 43.68% reduction in settling times and up to an 82.69% improvement in maximum transient undershoot. Concurrently, tie-line power stability was restored up to 79% faster with an ITAE score nearly seven times lower than PSO, validating its robust grid reliability and precise load balancing.

Table 3: Comprehensive Dynamic Performance Comparison

Metric	GA-PID	PSO-PID	AOA-PID	Improvement (%)
Area 1 Peak Drop (Hz)	-0.0087	-0.0092	-0.0016	82.61
Area 1 Settling Time (s)	9.79	9.27	5.22	43.68
Area 2 Peak Drop (Hz)	-0.0088	-0.0093	-0.0060	35.48
Area 2 Settling Time (s)	15.10	14.48	9.14	36.88
Tie-Line Settling Time (s)	34.80	39.15	8.20	79.06
ITAE Fitness Score	0.4120	0.2831	0.04245	85.00

- Abualigah, L., Diabat, A., Mirjalili, S., Abd Elaziz, M., & Gandomi, A. H. (2021). The Arithmetic Optimization Algorithm. *Computer Methods in Applied Mechanics and Engineering*, 376, 113609.
- Ali, T., & Abdalazim, A. (2013). Bacterial foraging optimization algorithm for load frequency control of interconnected power system. *International Journal of Electrical Power & Energy Systems*, 53, 120-128.
- Ali, T., et al. (2022). Load Frequency Control and Automatic Voltage Regulation in a Multi-Area Interconnected Power System. *Sustainability*, 14(19), 11862.
- Alnefaie, F., et al. (2025). Impact of governor deadband non-linearities on multi-area load frequency regulation. *IEEE Access*, 13, 10245-10258.
- Arya, Y. (2018). Automatic generation control of two-area electrical power systems via optimal fuzzy classical controller. *Journal of the Franklin Institute*, 355(5), 2662–2688.
- Charalampos, N., et al. (2019). Robust secondary frequency regulation mechanisms in modern power grids. *IET Generation, Transmission & Distribution*, 13(8), 1420-1430.
- Habib, M., & Cherri, A. (1998). Fuzzy logic control optimization techniques for dynamical power systems. *Energy Conversion and Management*, 39(12), 1251-1262.
- Isemin, U. I., & Onah, A. J. (2022). Load Frequency Control Using Classical Controllers. *Arid Zone Journal of Engineering, Technology & Environment*, 18(2), 145-156.
- Kothari, D. P., & Nagrath, I. J. (2003). *Modern Power System Analysis*. Tata McGraw-Hill Education.
- Kunya, A. B., Jibril, Y., & Okafor, E. (2017). Distributed MPC-Based Load Frequency Control. *Journal of Electrical Engineering, Ahmadu Bello University*, 12(1), 30-39.
- Muthana, T. Alrifai, et al. (2011). Decentralized load frequency controller for a multi-area interconnected power system. *International Journal of Electrical Power & Energy Systems*, 33(2), 198–209.
- Ogata, K. (2011). *Modern Control Engineering* (5th ed.). Prentice Hall.
- Pappachen, A., & Peer Fathima, A. (2017). Critical research areas on load frequency control issues in a deregulated power system. *Renewable and Sustainable Energy Reviews*, 72, 163–177.
- Qu, Z., et al. (2024). A Multi-Source Power System's Load Frequency Control Utilizing Particle Swarm Optimization. *Energies*, 17(2), 517.
- Rathnayake, C., et al. (2019). Analysis of governor deadband effects on primary and secondary frequency response. *IEEE Transactions on Power Systems*, 34(4), 3100-3110.
- Sambariya, D. K., & Prasad, R. (2016). Design of Optimal Proportional Integral Derivative Based Power System Stabilizer Using Bat Algorithm. *Applied Computational Intelligence and Soft Computing*, 2016, 1-12.
- Shouran, M., et al. (2021). Load Frequency Control Based on the Bees Algorithm for the Great Britain Power System. *Energies*, 14(15), 4557.
- Sun, Y. (2018). Robust H-infinity Load Frequency Control of Multi-area Power System. *IEEE/CAA Journal of Automatica Sinica*, 5(2), 610-617.
- Wadi, M., et al. (2024). Load frequency control in smart grids: A review of recent developments. *Renewable and Sustainable Energy Reviews*, 189, 114013.