

AOBL-IPACO: A Novel and Optimized Algorithm to Mitigate Losses in Electrical Grid Systems

Rahul Gupta^{a,c}, Ashish Khanna^b, Bal Virdee^c

^a*School of Electrical and Electronics Engineering, Maharaja Agrasen Institute of Technology, India,
dr.rahulguptalmu@gmail.com*

^b*School of Computer Science Engineering & Technology, Maharaja Agrasen Institute of Technology, India
ashishkhanna@mait.ac.in*

^c*School of Computing & Digital, London Metropolitan University, UK,
b.virdee@londonmet.ac.uk*

**ashishkhanna@mait.ac.in*

Abstract

This paper shows the framework for solving the economic optimization problem in electrical grid system using Advanced Oppositional Based Learning (AOBL) technique with Invasive Plant Ant Colony Optimization (IPACO) algorithm. The work focuses on application of newly developed algorithm called Advance Oppositional Invasive Plant Ant Colony Optimization (AOIPACO) to solve the various constraints of single objective problem. The artificial algorithm leads to direction of exploration for new space of ant colonies with process of threats elimination from native candidates in energy management. During simulation process, the proposed algorithm reduces the power loss along with improvement of cost factor and computational time. The proposed AOIPACO approach is implemented on standard IEEE-5, 13 and 40 bus systems and generates optimal results as compared to other conventional techniques while solving the complex problem of optimization. Further, this meta heuristic technique help to improve the quality of power market system with minimum computation error at fast convergence rate.

Keywords: Economic and Emission Dispatch (EED); Cost function; Oppositional Base Learning (OBL), Invasive Ant Colony Optimization; Invasive plant Optimization.



Fig 1. Abstract of Invasive Plant Ant Colony Optimization

1. Introduction

In modern electric systems, the power distribution of an area is dependent upon two main significant factors that are economic and emission factors. The economic factor takes the consideration of consumer satisfaction along with all electrical and physical constraints along with reduction in environmental pollution. Therefore, the main focal point of solving economic energy dispatch (EED) is to optimize the cost price for the customer so that generating units of electrical system can utilize the resources efficiently [1-2]. The EED problem involves both differential as well integral computational techniques that support to resolve the issue of power optimization for maximum profit with minimum consumption of possessions. The advancement of artificial techniques leads to further development of new meta heuristic algorithms that can be implemented to solve the complex networks of hybrid power structure. The authors in [3] have formulated an advanced model for solving the economic load dispatch problem in power markets. That is based on demand response of customer's participation. In order to enhance the bidding process for energy trading, the authors in [4] proposed different modelling and frameworks for utility companies. Further, Dayi Li et. al have reviewed the different optimization models for generating stations involved in the bidding process of electrical systems and markets [5]. The authors in [6] presented an advanced 2 step algorithm which is being simulated on IEEE bus systems for solving the economic and emission dispatch problem. The application of fundamental lambda iteration is being incepted with evolutionary algorithm for different sections of power system optimization [7]. Another fundamental differential approach is utilised in [8] for balancing of load in conventional grid systems. Authors in [9] presented the advanced particle swarm optimization as compared to classical approach for 5 and 10 unit systems for finding the losses. Shafei and other author's [10] showed application with particle swarm optimization (PSO) to form Fuzzy Logic Controller (FLC) model for integrated power plant. The classical framework of genetic algorithm called GA is being integrated with Sequential Quadratic Programming (SQP) to find out the optimal solution of two different sets of grid [11].

One of sharp integrated approach called particle swarm optimization oppositional based learning (PSO-OBL) is implemented on testing of standard bus systems [12]. The incorporation of classical particle swarm and ant colony optimization techniques was proposed by Dipankar Santra in [13] to showcase better convergence in economic optimization of power systems. The grey wolf optimizer which is based on hunting and encircling behaviour of wolf for catching the prey is quite useful [14] in solving the economic and emission dispatch problem of different sets of and generating units. Another approach called invasive weed optimization is implemented in [15] for power markets trading units. In conventional power systems, the main consideration is unit commitment which decides the distribution of load. The superlative approach for solving UC problem is krill herd (KH) and Ant Lion Optimization (ALO), which is being presented in [16]. It has been observed that there are some other new existing hybrid algorithms like Predator prey optimization, Krill Herd Algorithm (KHA), Pigeon Inspired Algorithm (PIA), Golden Jackal (GJ) algorithm, Prairie Dog Optimization Algorithm (PDOA) delivers cohesive and optimal outputs in in better way [17-30].

From the literature survey, it has been observed that there is need to integrate the existing optimization techniques in enhanced way in order to develop new hybrid algorithms that gives more accurate results in less computational time for grid optimization process. Further integration with the opposition based learning technique also known as OBL plays pivot role in enhancement to the optimal solution of economic and emission optimization in conventional grid system gives new direction to various sensitive constraints that are difficult to solve by direct application of modern algorithms. Its catalytic property of jumping factor leads to improvement of the overall Response of system. The OBL in biological algorithm leads to generation of mirror image of the both local as well as global parameters in the matrix along with exploration and exploitation conditions.

In this paper, the main consideration is to enhance the performance of grid system by application of the advanced weighted oppositional parameter on accepted phenomenon of invasive plant ant colony optimization technique in solving economic optimization problem of IEEE 5, 13 generators and 40 generators bus system models. The proposed technique developed with advanced Oppositional learning (AOBL) and Invasive Plant Ant Colony Optimization (IPACO) called Advance Oppositional Invasive Plant Ant Colony Optimization (AOIPACO) helps to resolve the error issues in the various considerations of economic energy communication and their cost function. The paper edifice shows that Section II is about energy objective function formulation with position and structural constraints. Section III insights the Meta heuristic algorithms and their framework for solving the EED problem. Section IV discusses the results of proposed technique AOIPCO along with convergence output.

Ref. No.	Optimization Techniques	Inspiration	Applications	Author	Year
[17]	Krill Herd Algorithm (KHA)	Inspired from herding comportment of krill’s found in region of Antarctica that involves diffusion of variable, and scavenging activity.	Modified Krill Herd Algorithm (MKHA) for day ahead scheduling	Weiming Chen et. al	2020
[18]	Improved Particle Swarm Optimization (IPSO)	Inspired from swarm intelligence behavior for best position allocation	UAV optimal tracking from neuro fuzzy technique with improved particle swarm optimization (ANFIS-IPSO)	Boumediene Selma et. al	2020
[19]	Oppositional Based Learning (OBL)	Whale optimization algorithm with oppositional based learning technique for best tracing position	Solving of CHPED problem for Integrated Power System using chaotic quassi-oppositional whale optimization	Chandan Paul et. al	2021
[20]	Advanced Cuckoo search Algorithm	Mut objective evolutionary approach with differential evolution based cuckoo behavior search	Breast Cancer detection	Promod Bp.Bhelaro	2021
[21]	Pigeon Inspired Algorithm (PIA)	High Level Target Navigation with PIO (HTNPIO)	Engineering design problems along with levy flight operators	Hanwing Wang et. al	2022
[22]	Golden Jackal Optimization (GJO)	Three elementary steps integration for prey searching, enclosing and pouncing of algorithm	Beam designing, Pressure Vessel & tension spring weight designing	Nitish Chpra et. Al	2022
[23]	Nizar Optimization Algorithm(NOA)	Mixing mappings integration with transformation mappings	Transform function benchmarks	Saif Eddine et. al	2023
[24]	Harris Hawks Optimization (HHO)	Hawk hunting behavior for prey in different directions	To reduce harmonics in grid with PI controller	Nisha C. Rani et. al	2023
[25]	FD-ADP algorithm	Fully distributed based dynamic programming is based on modification of conventional distributed framework.	Real time PWL applied in ED storage and dispatch.	Xizhen Xue et.al	2023
[26]	Whale Social spider Optimization	Integration of Whale Spider behavior with Convolution Neural Network	Identification of brain tumor cells	Anil Kumar Mandle et. al	2024
[27]	Arithmetic Optimization Algorithm(AOA)	Hybrid algorithm AOA with PSO FORM HAOAPSO with compound opposition based learning(COBL)	Design optimization with conventional benchmark constraint functions.	Xuzhen Deng et. al	2024
[28]	Prairie Dog Optimization Algorithm (PDOA)	Prairie Dog Optimization Algorithm (PDOA) with Dwarf Mongoose Optimization Algorithm (DMOA)	Convergence Characteristics with 23 Standard Functions	Laith Abualigah et. al	2024
[30]	Salp Swarm Optimization	Cooperative guidance by Salp Swarm process of optimization	Enhancement in solar panels energy efficiency	S. Antony Raj et.al	2024

TABLE 1 OVERVIEW OF VARIOUS OPTIMIZATION TECHNIQUES AND APPLICATIONS

2. Formulation of problem

2.1 Objective function

The economic and energy dispatch (EED) problem can be formulated [31].

$$\text{Min Cost } F_T = \sum_G^N F_i(P_i) \quad (1)$$

The equation of objective problem for economic dispatch in EED is

$$F_i(P_i) = \sum_{i=1}^{N_G} \{\alpha_i P_i^2 + \beta_i P_i + \gamma_i\} \quad (2)$$

Where $F_i(P_i)$ is the quadratic energy cost estimation. The economic equation can be modified by adding the emission fuel coefficients as

$$F_i(P_i) = \sum_{i=1}^{N_G} \{\alpha_i P_i^2 + \beta_i P_i + \gamma_i + |\zeta_i \times \sin(\varepsilon_i \times P_i^{min} - P_i)|\} \quad (3)$$

Where N_G shows generating nodes, P_i is energy output, α, β, γ are fuel cost coefficients and ζ_i and ε_i are fuel emission coefficients.

2.2 Energy Emission Constraints

i) Energy constraints are given by

$$P_i^{min} \leq P_i \leq P_i^{max} \quad (4)$$

Where P_i^{min} and P_i^{max} are lower and upper energy generation limit of unit i .

ii) In economic energy dispatch problem, there is main concern of emission parameters that are being released by thermal units. The emission dispatch constraint can be evaluated by equation

$$E_T = \sum_{i=1}^{N_G} \{u_i P_i^2 + v_i P_i + z_i + \zeta_i e^{\tau_i P_i}\} \quad (5)$$

Where u_i, v_i and z_i N_G is total number of generating units, E_T is total pollutant emission, P_i is the power output of generating unit i and α_i, β_i, τ are emission coefficients.

2.3 Economic Energy Dispatch (EED) Formulation

The designing of EED problem is being done in such a way that it may generates maximum profit for electricity market [32]. Therefore, there is introduction of a penalty factor and is calculated as

$$p^f = \frac{F_T(P_i^{max})/P_i^{max}}{E_T(P_j^{max})/P_j^{max}} \quad (6)$$

Where p is penalty cost factor, i and j are the highest fuel and emission factors

The EED objective equation for solving economic energy dispatch with penalty factor is given by

$$F_T = \omega_{eco} (\sum_{i=1}^{N_G} \{\alpha_i P_i^2 + \beta_i P_i + \gamma_i + |\zeta_i \times \sin(\varepsilon_i \times P_i^{min} - P_i)|\}) + \omega_{emis} \times p^f \times (\sum_{i=1}^{N_G} \{u_i P_i^2 + v_i P_i + z_i + \zeta_i e^{\tau_i P_i}\}) \quad (7)$$

Where ω_{eco} and ω_{emis} are weighting economic and emission factors having value of 0.5 each

The economic energy dispatch (EED) equation having weighted functions of 0.5 each leads to balancing of load while solving the optimization problem of generating networks. The exponential function used in problem also helps to reduce the noise in costing curves. Therefore, it is essential to calculate and valid at each parameter in optimization process of power system.

3. Outline of Optimization Techniques

3.1 Advanced Opposition Base Learning (AOBL)

The technique of Opposition learning (OBL) is used to converge the response of optimizations. It evaluates both current and opposite parameters of population. Opposition matrix helps to generate the improved results [33-34] for various parameters. The AOBL equation is given as

i) *Weighted Oppositional number (WON)*

It generates the mirror image of solution in opposite direction with weighted stricture in searching region

$$WX^\circ = W[s - X] \quad (8)$$

WX° shows the opposite weighted number with x in solution range of s

ii) *Weighted Oppositional point (WOP)*

WOP search space s is equated as

$$wp_i^\circ = w[s - P_i]; P_i \in [s] \quad (9)$$

Where p_i° show oppositional point having range of $i=1,2,\dots,s$

3.2 Invasive Plant Ant Colony Optimization (IPACO)

The nature and its chain process for sustainable environment gives direction to design the framework of economic energy dispatch (EED) for grid system in such a way that not only it minimizes the cost factor but also reduce the carbon emissions. In order to find the paramount solution for economic development, an algorithm called invasive plant ant colony optimization (IPACO) inspired from invasive ant behaviour for finding the food source is proposed. The technique industrialises the colonization of ants around invasive plants because of their species pheromone like *asclepias syriaca* and *retroflexus*. The uniqueness of invasive plants is labelled by ants in order to fulfil various restraints like fast reproduction, intrusiveness, robustness and self-exploring nature according to changing environmental conditions [35-37].

The most unique association of invasive ants is that they also protect these species from external threat of native ants along with allocation of food resources. The ant colonisation around the invasive plants undergoes into two stages which are low fitter and high fitter plants [38-39]. High fitter usually produce more pheromone and food as compared to native plants for giving more convergence in characteristics but at the same time some less fitter plants carry complementary expedient information than fitter plants. In such conditions, the oppositional algorithm provides the opportunity to less fit plants to reproduce that have better quality and fitness values. The Figure 2 shows the process of IPACO technique in which A signifies the path of invasive ants travelled in search of food, B shows the invasive plant created in the path of ants, C lead to change of route of ants as they try to cover shortest path and form the colony around plant while releasing the chemical pheromone which gives the direction to other ants to follow. Finally, D leads to the final updated position and shortest travelled distance travelled by maximum ants in order to get all food within their colony.

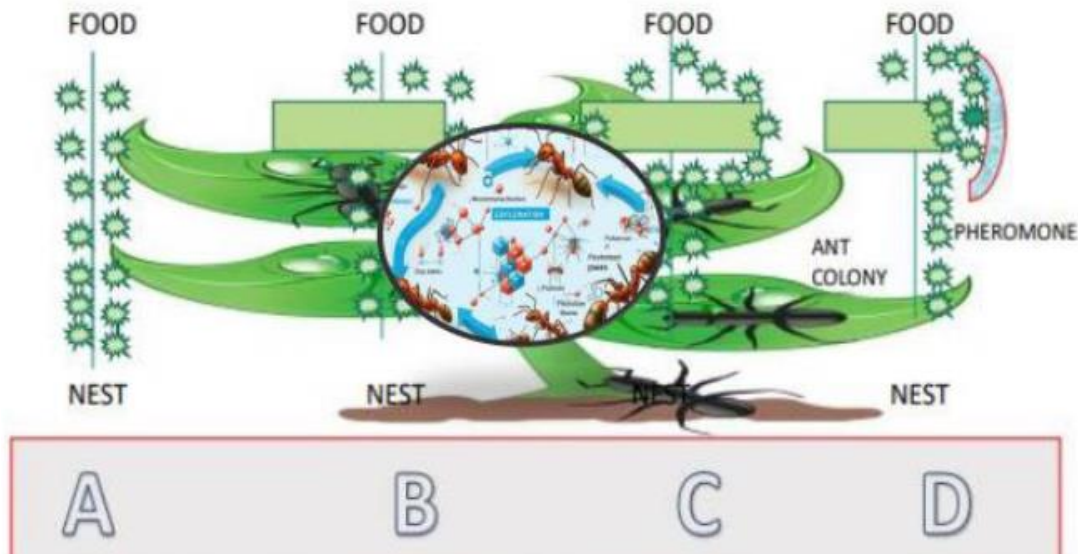


Fig 2. Invasive Plant Ant Colony Optimization (AOIPACO)

3.3 Solicitation of Advanced Oppositional Invasive Ant Colony Optimization (AOIACO) Algorithm in EED problem

Step 1. Starting and reading of input data

Step 2. Initialize the input data and generation of first node

Step 3. Formation of plant matrix

In this step, there is formation of invasive plant population matrix ($Pop_{max} * d$). Consider $P_j = [P_1, P_2, \dots, P_d]$ be trial vector matrix having random ant colony matrix A is given by

$$A = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1d} \\ P_{21} & P_{22} & \dots & P_{2d} \\ \dots & \dots & \dots & \dots \\ P_{POP_{MAX},1} & \dots & \dots & P_{POP_{MAX},d} \end{bmatrix} \quad (10)$$

$$P_{dd} = P_D + P_{LOSS} - \sum_{i=1}^d P_i \text{ Where element } P_i \text{ is energy output}$$

Step 4. Computation of state transition rule

$$P(r, s) = \frac{[\tau(r, w)] [h(r, w)]^b}{\sum_{k=1} [t(r, x)] [h(r, x)]^b} \quad (11)$$

Where τ is plant pheromone, k is set of nodes travelled by ant

Step 5: Application of local search rule for updating

In this process, the amount of plant pheromone gives direction to ants during building of solution and it is given by equation

$$\tau(r, w) = (1 - \rho) + \rho \Delta \tau(r, w) \quad (12)$$

Where ρ is heuristically defined coefficient and τ is initial pheromone trial value

Step 6: Application of global updating rule

This process upgrades the value of invasive plant pheromone generated by shortest distance travelled by ant. The updated value is given by

$$\tau(r, w) = (1 - \alpha) \tau(r, w) + \alpha \Delta \tau(r, w) \quad (13)$$

Where $\tau(r, w)$ = global pheromone parameter.

Step 7: Updating of iteration

$$iter = iter + 1 \quad (14)$$

Step 8: Generation of oppositional based population

In this step, there is generation of opposite based population from formula given as

$$\tau^o = 1 - \tau(r, w) \\ 1 - \tau(r, w) = 1 - [(1 - \rho) + \rho \Delta \tau(r, w)] \quad (15)$$

Where τ^o is new oppositional invasive plant pheromone parameter

Step 9: Calculation of new generated opposite invasive plant ant population

The program terminates when all the ants completed the shortest paths and new opposite population by taking the inverse value from global updated rule and it is calculated as

$$1 - \tau(r, w) = 1 - [(1 - \alpha) \tau(r, w) + \alpha \Delta \tau(r, w)] \quad (16)$$

Step 10: Calculation of fitness of new invasive ant colony

Generation of new invasive plant ant colony is being calculated by formula given as

$$IPAC = \frac{F_i - F_{worst}}{F_{best} - F_{worst}} (N_{max} - N_{min}) + N_{min} \quad (17)$$

Where F_i is invasive plant ant colony fitness value

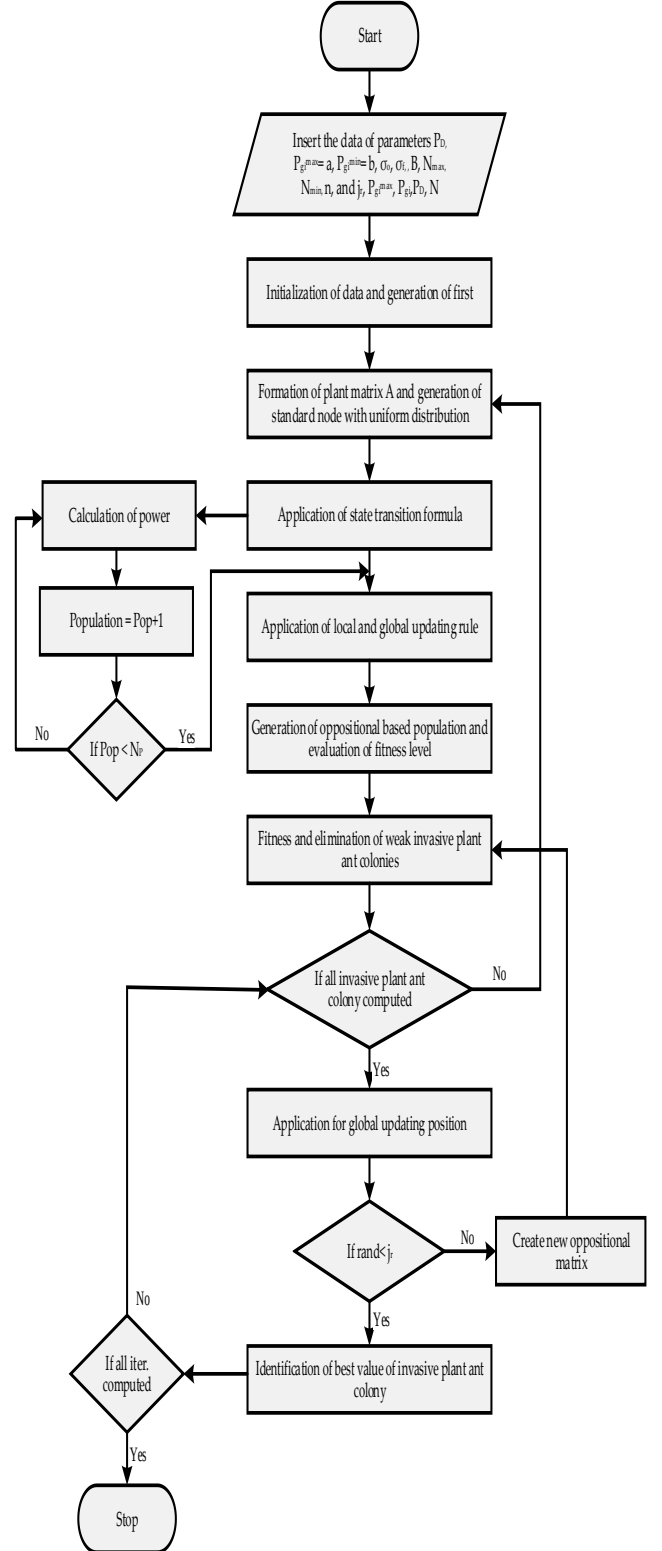
Step 11: New dimension for global position

This step evaluates the fitness and new parameter is taken into account by jumping rate parameter ' j_r ' within range of $\{0, 1\}$ for development of new weighted opposite set (WOS) matrix.

Step 13: Identification of best value of invasive plant ant colony

The execution of AOIPACO algorithm is stopped when total number of generations has reached to maximum values and no further up gradation.

Figure 3: Flowchart of proposed ROIACO Algorithm



4. Numerical Results

The proposed AOIPACO algorithm is implemented on the IEEE 5, 13 and IEEE 40 bus system. The simulation along with generation limits was carried out in MATLAB for optimum results of three grid systems.

4.1 Case 1: IEEE 5 Generator System

In the case 1, the AOIPACO is applied on 5-generator system having demand of 1200 MW. Table 2 reflects the energy outputs by implementation of proposed algorithms and that are AOIPACO, IPACO, KHA AND PSO along with power loss factor. The proposed algorithm (AOIPACO) converge the fuel cost as shown in characteristics curves of grid system. Figure 4 shows the optimal results of EED objective function with comparison of conventional and hybrid invasive plant ant optimizer.

Table 2 Power output for 5 generator system for demand of 1200 MW.

Generator Number	AOIPACO(MW)	IPACO(MW)	KHA(MW)	PSO(MW)
1	446.31	446.5	447.1	446.5
2	174.07	175.67	176.77	174.99
3	258.45	257.3	259.4	258.3
4	139.08	138.46	135.46	134.46
5	164.12	163.21	160.21	159.21
Total	1181.39	1179.7	1177.7	1172.5
Loss	19.00	21.53	22.23	22.52
Fuel Cost	15539.65	15542.9	15543.3	15545.4

4.2 Case 2: IEEE 13 Generator System

In the case 2, the Optimisation algorithm AOIPACO is applied on 13 generator system for the demand of 1900 MW. Table 3 shows the power output for 13 bus system. The proposed algorithm is capable of reducing the fuel cost to lower cost as indicated by the results. Figure 5 shows the convergence characteristics of IPACO and AOIPACOO which predicts better convergence.

Table 3 Power output for 13-generator system for demand of 1900 MW.

Generator Number	AOIPACO(MW)	IPACO(MW)	KHA(MW)	PSO (MW)
1	634.13	635.65	633.95	635.65
2	164.65	223.70	225.70	223.70
3	289.35	148.90	149.90	148.90
4	117.07	107.57	112.57	107.57
5	101.65	107.67	105.67	107.67
6	60.50	107.47	106.47	107.47
7	107.75	109.47	108.47	109.47
8	107.45	109.47	110.47	109.47
9	107.45	109.87	106.87	109.87
10	42.00	77.41	65.41	77.41
11	42.00	49.56	52.56	49.56
12	63.00	57.00	52.00	57.00
13	63.00	57.00	65.00	57.00
Total Power	1900.00	1900.74	1900.81	1900.89
Loss	0.00	0.00	0.011	0.023
Fuel cost	18130.45	18132.78	18134.22	18134.99
Error	0.00	0.04	0.05	0.05

4.3 Case 3: IEEE 40 Generator System

In case 3, the performance of the IPACO and AOIPACO is tested by implementing on the 40-generator system. Table 4 shows the power obtained for 40 bus system without loss. It can be observed that the AOIPACO has better capability in optimizing the fuel cost in comparison to IPACO. There is no error in case of AOIPACO in comparison to IPACO. The convergence rate of AOIPACO is also found to be better than IPACO. Figure 6 shows the curve between the fuel cost for generation and number of iterations.

G. NO	AOIPACO (MW)	IPACO (MW)	KHA (MW)	PSO (MW)	G. NO	AOIPACO (MW)	IPACO (MW)	KHA (MW)	PSO (MW)
1	111.5600	113.1389	112.3350	114.7600	21	518.7400	523.1900	521.1900	526.7510
2	111.7290	112.4100	113.6290	111.7290	22	518.7400	514.1553	519.3213	519.1553
3	109.2390	120.3426	115.6773	121.0987	23	518.7400	527.0123	525.2131	532.0023
4	178.2300	180.1000	179.7503	178.9700	24	518.7400	548.0786	532.0726	592.3340
5	96.2940	96.950	99.5440	99.9400	25	524.4500	521.2314	523.0094	529.7514
6	135.9000	139.543	137.9000	140.0000	26	524.4500	518.5436	528.9953	529.7564
7	291.9700	299.8913	298.6677	299.8743	27	62.5000	45.1213	53.8656	55.0003
8	297.1900	298.1200	291.8100	292.1900	28	62.5000	58.1220	68.4232	67.1000
9	297.1900	298.1200	299.1000	295.1800	29	13.5000	25.1563	15.5765	18.5431
10	131.5000	147.3700	141.8700	139.9700	30	88.5500	96.1543	85.9754	92.0033
11	95.1000	178.2430	99.3200	94.0000	31	189.0000	179.1452	181.0001	185.9531
12	95.1000	169.9800	195.7600	182.8211	32	189.0000	182.1231	185.0431	189.9122
13	223.5900	198.2400	225.3200	201.5450	33	189.0000	185.5160	184.0060	187.5197
14	415.2300	328.4523	451.2230	445.1300	34	175.8500	174.6800	176.4310	179.3213
15	415.2300	418.3420	419.2100	421.3410	35	196.9600	174.6800	183.2712	197.6512
16	415.2300	418.3420	423.4354	422.4121	36	198.5000	186.6800	196.4510	188.1300
17	512.7400	489.2341	510.5484	514.7120	37	109.4500	98.4300	105.8330	109.4300
18	512.7400	489.2341	522.7889	522.6543	38	109.4500	99.2320	105.4380	103.2380
19	512.3940	514.2100	521.3132	521.5600	39	108.3900	108.6900	108.5980	108.8900
20	512.3940	535.3400	541.4312	541.1231	40	512.9400	520.3400	522.3200	521.1943
Total						10800.0000	10800.8847	10800.8965	10800.9541
Loss						0.0000	0.0000	0.0010	0.0011
Fuel cost						121429.46	121445.34	121446.61	121449.12
Error						0.0000	0.0847	0.0000	0.0847

Table 4 Power output for 40-generator system for demand of 10800 MW

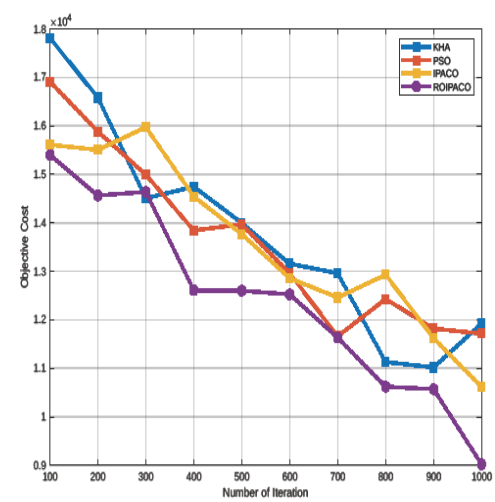


Fig 4. Fuel cost vs iterations for 5-Generator system

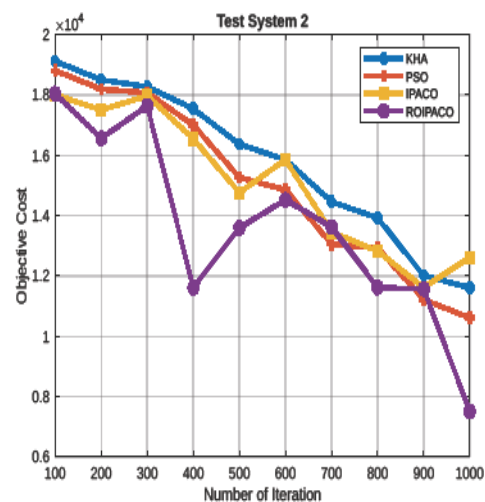


Fig 5. Fuel Cost vs Iterations for 13-generator system

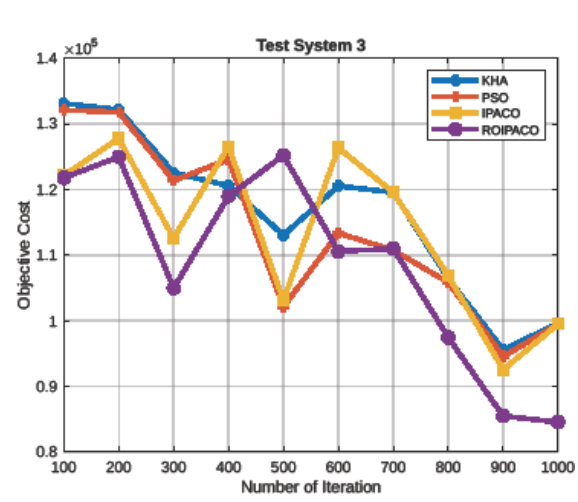


Fig 6. Fuel cost vs iterations for 40-Generator system.

5. Conclusion

This manuscript proposed an advance oppositional approach with invasive plant ant colony optimization (AOIPACO) algorithm to solve the economic energy dispatch (EED) problem of grid system. The projected oppositional technique improves the convergence efficiency rate along with reduction in losses and computational error of invasive ant in hunt space for colonization optimization in comparison to conventional one. The proposed algorithm is efficaciously implemented on three data set of 5, 13 and 40 bus systems. The outcome of planned algorithm is much proficient and shows better convergence for fuel cost characteristics as compared to other optimization techniques in objective problem. Therefore, the biological stimulated AOIPACO algorithm is robust implement that reflects the committed optimal outcome for sustainable economic energy dispatch.

6. Novelty and future scope

The projected artificial algorithm advances oppositional approach with invasive plant ant colony optimization (AOIPACO) gives contribution in escalation of grid system along with reduction in transmission losses and emissions. The implementation of hybrid technique aids the significant assistances like minimizes the CPU evaluation time for large iterations in multi-layered grid arrangement, generates superior results because of weighted parameter in oppositional learning approach. Further, it balances the energy distribution among generating units along with handling of unit constraints in grid system. The proposed algorithm (AOIPACO) can be integrated with advanced quantum AI techniques in future for solving the complex problems of energy management along with other areas.

7. Conflict of interest statement

On behalf of all authors, I state that there is no conflict of interest.

8. Data availability statement

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

References

- [1] Akbari-Dibavar, A., Mohammadi-Ivatloo, B., Zare, K., Khalili, T., & Bidram, A. (2021). Economic-emission dispatch problem in power systems with carbon capture power plants. *IEEE Transactions on Industry Applications*, 57(4), 3341-3351, 10.1109/TIA.2021.3079329
- [2] Zaoui, S., & Belmadani, A. (2022). Solution of combined economic and emission dispatch problems of power systems without penalty. *Applied Artificial Intelligence*, 36(1), 1976092, <https://doi.org/10.1080/08839514.2021.1976092>
- [3] Sutar, M., & Jadhav, H. T. (2022). An economic/emission dispatch based on a new multi-objective artificial bee colony optimization algorithm and NSGA-II. *Evolutionary Intelligence*, 1-36. <https://doi.org/10.1007/s12065-022-00796-x>
- [4] Chen, X., & Tang, G. (2022). Solving static and dynamic multi-area economic dispatch problems using an improved competitive warm optimization algorithm. *Energy*, 238, 122035.
- [5] Li, D., Wang, T., Pan, W., Ding, X., & Gong, J. (2021). A comprehensive review of improving power quality using active power filters. *Electric Power Systems Research*, 199, 107389. <https://doi.org/10.1016/j.epsr.2021.107389>
- [6] Mahdi, F. P., Vasant, P., Kallimani, V., Watada, J., Fai, P. Y. S., & Abdullah-Al-Wadud, M. (2018). A holistic review on optimization strategies for combined economic emission dispatch problem. *Renewable and Sustainable Energy Reviews*, 81, 3006-3020.
- [7] Hao, W. K., Wang, J. S., Li, X. D., Wang, M., & Zhang, M. (2022). Arithmetic optimization algorithm based on elementary function disturbance for solving economic load dispatch problem in power system. *Applied Intelligence*, 52(10), 11846-11872.
- [8] Li, S., Gong, W., Wang, L., Yan, X., & Hu, C. (2020). Optimal power flow by means of improved adaptive differential evolution. *Energy*, 198, 117314. <https://doi.org/10.1016/j.energy.2020.117314>
- [9] Verdejo, H., Pino, V., Kliemann, W., Becker, C., & Delpiano, J. (2020). Implementation of particle swarm optimization (PSO) algorithm for tuning of power system stabilizers in multimachine electric power systems. *Energies*, 13(8), 2093.
- [10] Shafei, M. A. R., Ibrahim, D. K., & Bahaa, M. (2022). Application of PSO tuned fuzzy logic controller for LFC of two-area power system with redox flow battery and PV solar park. *Ain Shams Engineering Journal*, 13(5), 101710. <https://doi.org/10.1016/j.asej.2022.101710>
- [11] Mehmood, A., Zameer, A., Ling, S. H., Rehman, A. U., & Raja, M. A. Z. (2020). Integrated computational intelligent paradigm for nonlinear electric circuit models using neural networks, genetic algorithms and sequential quadratic programming. *Neural Computing and Applications*, 32, 10337-10357.
- [12] Saeed, H., Mehmood, T., Shah, M. S., Ali, H., Khan, F. A., & Ullah, M. F. (2022). An improved search ability of particle swarm optimization algorithm for tracking maximum power point under shading conditions. *Электротехника и электромеханика*, (2 (eng)), 23-28.
- [13] Santra, D., Mukherjee, A., Sarker, K., & Mondal, S. (2020). Dynamic economic dispatch using hybrid metaheuristics. *Journal of Electrical Systems and Information Technology*, 7(1), 1-30. <https://doi.org/10.1186/s43067-020-0011-2>
- [14] Paliwal, N., Srivastava, L., & Pandit, M. (2022). Application of grey wolf optimization algorithm for load frequency control in multi-source single area power system. *Evolutionary Intelligence*, 1-22.
- [15] Wang, J., Zhang, S., Huo, J., Zhou, Y., Li, L., & Han, T. (2021). Dispatch optimization of thermal power unit flexibility transformation under the deep peak shaving demand based on invasive weed optimization. *Journal of Cleaner Production*, 315, 128047. <https://doi.org/10.1016/j.jclepro.2021.128047>

- [16] Guo, Y., Dai, X., Jernsittiparsert, K., & Razmjoo, N. (2020). An optimal configuration for a battery and PEM fuel cell-based hybrid energy system using developed Krill herd optimization algorithm for locomotive application. *Energy Reports*, 6, 885-894. <https://doi.org/10.1016/j.egy.2020.04.012>
- [17] Chen, Weiming & Shao, Zehui & Wakil, Karzan & Aljojo, Nahla & Samad, Sarminah & Rezvani, Alireza. (2020). An efficient day-ahead cost-based generation scheduling of a multi-supply microgrid using a modified krill herd algorithm. *Journal of Cleaner Production*, 272, 122364. [10.1016/j.jclepro.2020.122364](https://doi.org/10.1016/j.jclepro.2020.122364).
- [18] Selma, B., Chouraqui, S. & Abouaïssa, H. Optimal trajectory tracking control of unmanned aerial vehicle using ANFIS-IPSO system. *Int. j. inf. tecnol.* 12, 383–395 (2020). <https://doi.org/10.1007/s41870-020-00436-6>
- [19] Chandan Paul, Provas Kumar Roy, V. Mukherjee, Chaotic-quasi-opposition based whale optimization technique applied to multi-objective complementary scheduling of grid connected hydro-thermal–wind–solar-electric vehicle system, *Optimal Control Applications and Methods*, 10.1002/oca.3113.
- [20] Bhalerao, P.B., Bonde, S.V. Cuckoo search based multi-objective algorithm with decomposition for detection of masses in mammogram images. *Int. j. inf. tecnol.* 13, 2215–2226 (2021). <https://doi.org/10.1007/s41870-021-00805-9>.
- [21] Wang, H., & Zhao, J. (2023). A novel high-level target navigation pigeon-inspired optimization for global optimization problems. *Applied Intelligence*, 53(12), 14918-14960.
- [22] Chopra, N., & Ansari, M. M. (2022). Golden jackal optimization: A novel nature-inspired optimizer for engineering applications. *Expert Systems with Applications*, 198, 116924..
- [23] Khouni, S.E., Menacer, T. Nizar optimization algorithm: a novel metaheuristic algorithm for global optimization and engineering applications. *J Supercomput* 80, 3229–3281 (2024). <https://doi.org/10.1007/s11227-023-05579-4>
- [24] Rani, N.C., Amuthan, N. Grid connected PV based on quasi resonant zeta converter with Harris Hawk optimization algorithm for the implementation of PI controller. *Int. j. inf. tecnol.* 16, 321–327 (2024)..
- [25] Xue, X., Fang, J., Ai, X., Cui, S., Jiang, Y., Yao, W., & Wen, J. (2023). A fully distributed ADP algorithm for real-time economic dispatch of microgrid. *IEEE Transactions on Smart Grid*, 15(1), 513-528.
- [26] Mandle, A.K., Sahu, S.P. & Gupta, G.P. WSSOA: whale social spider optimization algorithm for brain tumor classification using deep learning technique. *Int. j. inf. tecnol.* (2024). <https://doi.org/10.1007/s41870-024-01782-5>
- [27] Deng, X., He, D., & Qu, L. (2024). A novel hybrid algorithm based on arithmetic optimization algorithm and particle swarm optimization for global optimization problems. *The Journal of Supercomputing*, 80(7), 8857-8897..
- [28] Abualigah, L., Oliva, D., Jia, H. et al. Improved prairie dog optimization algorithm by dwarf mongoose optimization algorithm for optimization problems. *Multimed Tools Appl* 83, 32613–32653 (2024). <https://doi.org/10.1007/s11042-023-16890-w>
- [29] Behera, S., Kumar, A. P., & Nayak, S. C. (2024). Analyzing the performance of geometric mean optimization-based artificial neural networks for cryptocurrency forecasting. *International Journal of Information Technology*, 1-13..
- [30] Raj, S.A., Elakkiya, E., Rajmohan, S. et al. CGFSSO: the co-operative guidance factor based Salp Swarm Optimization algorithm for MPPT under partial shading conditions in photovoltaic systems. *Int. j. inf. tecnol.* (2024) Zaman, M. F., Elsayed, S. M., Ray, T., & Sarker, R. A. (2015). Evolutionary algorithms for dynamic economic dispatch problems. *IEEE Transactions on Power Systems*, 31(2), 1486-1495.
- [31] Zhou, S., Hu, Z., Gu, W., Jiang, M., Chen, M., Hong, Q., & Booth, C. (2020). Combined heat and power system intelligent economic dispatch: A deep reinforcement learning approach. *International journal of electrical power & energy systems*, 120, 106016. <https://doi.org/10.1016/j.ijepes.2020.106016>
- [32] Dey, B., Basak, S., & Bhattacharyya, B. (2021). A comparative analysis between price-penalty factor method and fractional programming method for combined economic emission dispatch problem using novel hybrid CSA-JAYA algorithm. *IET Smart Grid*, 4(4), 367-380.
- [33] Choudhary, P. K., & Das, D. K. (2021). Optimal coordination of over-current relay in a power distribution network using opposition based learning fractional order class topper optimization (OBL-FOCTO) algorithm. *Applied Soft Computing*, 113, 107916 <https://doi.org/10.1016/j.asoc.2021.107916>.
- [34] Liu, T., Xiong, G., Mohamed, A. W., & Suganthan, P. N. (2022). Opposition-mutual learning differential evolution with hybrid mutation strategy for large-scale economic load dispatch problems with valve-point effects and multi-fuel options. *Information Sciences*, 609, 1721-1745.
- [35] Zheng, Z. X., Li, J. Q., and Sang, H. Y. (2019). A hybrid invasive weed optimization algorithm for the economic load dispatch problem in power systems. *Mathematical biosciences and engineering: MBE*, 16(4), 2775- 2794
- [36] Mishra, S., Barisal, A. K., and Babu, B. C. (2019). Invasive weed optimization-based automatic generation control for multi-area power systems. *International Journal of Modelling and Simulation*, 39(3), 190-
- [37] Dorigo, M., & Stützle, T. (2019). *Ant colony optimization: overview and recent advances* (pp. 311-351). Springer International Publishing
- [38] Karakonstantis, I., and Vlachos, A. (2015). Ant colony optimization for continuous domains applied to emission and economic dispatch problems. *Journal of Information and Optimization Sciences*, 36(1-2), 23- 42
- [39] Kumar, A., Thakur, M., & Mittal, G. (2022). Planning optimal power dispatch schedule using constrained ant colony optimization. *Applied Soft Computing*, 115, 108132. <https://doi.org/10.1016/j.asoc.2021.108132>