International Journal of Advances in Applied Sciences (IJAAS)
Vol. 13, No. 2, June 2024, pp. 249~259
ISSN: 2252-8814, DOI: 10.11591/ijaas.v13.i2.pp249-259

An improved golden jackal optimization algorithm for combined economic emission dispatch problems

Ramamoorthi Ragunathan[1], Balamurugan Ramadoss[2]
[1]Department of Electrical and Electronics Engineering, Government College of Engineering Salem, Salem, India
[2]Department of Electrical and Electronics Engineering, Government College of Engineering Thanjavur, Thanjavur, India

Article Info

Article history:

Received Oct 8, 2023
Revised Dec 14, 2023
Accepted Jan 31, 2024

Keywords:

Combined economic emission dispatch
Golden jackal optimization
Heuristic algorithm
Opposition-based learning
Valve point effect

ABSTRACT

In this research paper, a new improved golden jackal optimization (IGJO) algorithm is applied to address the combined economic emission dispatch (CEED) problem, along with various thermal generator constraints such as valve point loading (VPL) effect, generator limits (GL) in power system. The hunting behavior of the golden jackals is mimicked in the golden jackal optimization (GJO) algorithm. The main aim of the CEED problem is to find the best optimal generation scheduling while minimizing both fuel cost and emission besides meeting the different power system constraints. The original GJO algorithm faces challenges when dealing with high-dimensional optimization problems, as it tends to get trapped in local optima. To address this issue the opposition-based learning (OBL) method was adopted in this GJO algorithm to obtain the global optimal solution and ensure enhanced performance in finding the solution for the CEED problems. To assess the competitiveness of the IGJO algorithm, it is used for various CEED test problems available in the literature, and results are contrasted with other recent heuristic optimization algorithms. Simulation results show that the proposed IGJO performs more effectively than the other compared algorithms in terms of solution quality, and robustness.

Corresponding Author:

Ramamoorthi Ragunathan
Department of Electrical and Electronics Engineering, Government College of Engineering Salem
Salem, Tamil Nadu 636011, India
Email: ram_moorthi2007@yahoo.com

1. INTRODUCTION

Electricity generation using conventional fossil fuels releases large amounts of greenhouse gases such as carbon oxides (CO_X), sulfur oxides (SO_X), and nitrogen oxides (NO_X). These pollutants affect not only humans but also other plants and animals. With increasing concerns over global warming and air pollution, it is increasingly important that electrical power systems reduce their carbon footprint and other harmful emissions. The combined economic emission dispatch (CEED) problem is a critical optimization problem in power system engineering that involves allocating all electricity demand among available thermal generation units to achieve the lowest fuel cost while meeting environmental regulations. This problem is considered challenging because it requires the solution of a nonlinear, non-convex, and multi-centric optimization problem, i.e., the fuel cost and emission constraints. The traditional gradient-based optimization methods such as linear programming [1], Newton-Raphson [2], and goal programming (GP) [3], might not reach the global optimal solutions for such non-differentiable and discontinuous complex functions. On the contrary, population-based heuristic optimization methods like genetic algorithm (GA), ant colony optimization (ACO), and particle swarm optimization (PSO), explore the complex solution space using the population of solution and iteratively improve the obtained solutions towards the best optimal solution. These algorithms do not rely on the type of the optimization problem. These heuristic techniques have advantages over the traditional methods in solving the CEED problem.

Several meta-heuristic optimization techniques have been developed to reduce the drawbacks of conventional approaches. A few such techniques proposed in the literature to solve CEED problems in power systems are as follows, dynamic programming (DP) [4], tabu search algorithm (TSA) [5], artificial bee colony (ABC) [6], differential evaluation (DE) [7], GA [8], modulated particle swarm optimization (MPSO) [9], gravitational search algorithm (GSA) [10], modified shuffle frog leaping algorithm (MSFLA) [11], flower pollination algorithm (FPA) [12], simulated algorithm (SA) [13], competitive swarm optimization (CSO) [14], bacterial foraging algorithm (BFA) [15], hybrid ant colony optimization (HACO) [16], lightening flash algorithm (LFA) [17], cuckoo search based algorithm (CSA) [18]. Various heuristic techniques reported in the literature use two kinds of approaches to solve the CEED problems. In the first approach, Emission from the thermal generator is considered as the constraint but it becomes difficult to find the tradeoff between fuel costs and emission costs. The second method considers price penalty for emission constraints, and because of this bi-objective function becomes a single objective function. In this research, the penalty-factor based CEED problem formulation is considered because of its relevance to the practical situations.

Recently, Chopra and Ansari [19] introduced a swarm-based intelligence algorithm named the golden jackal optimization (GJO) algorithm. It is used in many engineering optimization problems to find the optimal solution. A thorough examination of GJO exposes various drawbacks. Such as, GJO populates initial populations created using random agents. Each agent changes its position based on the previous optimal solutions during further searching steps. The GJO algorithm many times gets trapped in the local optimum points and converges prematurely. To address the above problems, this paper presents an improved variant of GJO known as the opposition-based GJO algorithm. The opposition-based learning (OBL) concept used in addition to the original GJO algorithm improves the global solution searching ability. The proposed improved golden jackal optimization (IGJO) algorithm has better explorations and exploitation capability in finding solutions for optimization problems. IGJO is tested on two CEED problems of 10-unit, and 40-unit thermal generating units and compared with the original GJO and erstwhile algorithms in the literature. The benchmark results prove that IGJO is more efficient than others and has better convergence characteristics.

This paper is structured into the following sections: CEED formulation is presented in section 2. IGJO algorithm and its implementation for the CEED problem are presented in section 3. The details of the simulation and findings are discussed in section 4, and the conclusion of the research work is presented in section 5.

2. COMBINED ECONOMIC EMISSION DISPATCH PROBLEM FORMULATION

The CEED problem is to find the best way to generate electricity at the lowest cost while also minimizing pollution. This is a difficult problem because the two objectives are often in conflict. For example, using cheaper fuel sources may produce more pollution. The CEED problem is formulated as follows.

2.1. Economic load dispatch

The main aim of the ELD optimization problem is to minimize the fuel cost of the thermal generators. Normally fuel cost curve of the thermal generators is represented by a quadratic function. It is indicated in Figure 1. Consideration of the valve point loading (VPL) effect in thermal generators makes the fuel cost function non-convex and has multiple minimum points.

$$F_T = \sum_{i=1}^{N} F_i(P_i) = \sum_{i=1}^{N}\left(a_i P_i^2 + b_i P_i + c_i + \left|d_i \sin\{\, e_i * (P_i^{min} - P_i)\}\right|\right)\frac{\$}{hr} \tag{1}$$

Here, N indicates the total number of generators and F_T denotes the total fuel cost of the system. a, b, c, d, and e are the fuel cost coefficients, F_i is the fuel cost, Pi is the output of ith unit. The fuel cost function for a typical thermal generator is shown in Figure 1.

2.2. Pollutant emission

The aim of the economic emission dispatch (EED) issue is to reduce overall environmental harm or the collective release of pollutants coming from the combustion of fuels in generating power to fulfill energy demands. The complete emissions resulting from burning fossil fuels in thermal power stations can be expressed as the combination of a quadratic and an exponential function. This expression is depicted in (2).

$$E_T = \sum_{i=1}^{N} E_i(P_i) = \sum_{i=1}^{N}(\alpha_i P_i^2 + \beta_i P_i + \gamma_i) + \zeta_i \exp(\lambda_i P_i) \;\; tons/hr \tag{2}$$

where α, β, γ, ζ, λ are the emission parameters, and the total emission caused by N-generating units is E_T.

2.3. Combined economic emission dispatch

Fuel cost and gas emissions released from the power plant are considered simultaneously for minimization. Here, bi-objective functions are modified into single-objective functions by introducing the price penalty factor. It is represented as (3) and (4).

$$minimize \;\; Z = F + h \times E \tag{3}$$

$$h_i = \frac{F_T(P_i^{max})}{E_T(P_i^{max})} \quad (\frac{\$}{tons}) \tag{4}$$

Where, P_i^{max} is the highest generation limit of the ith generator, h_i is the price penalty factor of the ith generator. Consideration of the price patently factor makes the objective function as (5).

$$Z(P_D) = \sum_{i=1}^{N} \begin{matrix} \left(a_i P_i^2 + b_i P_i + c_i + \left|d_i \sin\{e_i * (P_i^{min} - P_i)\}\right|\right) \\ + \sum_{i=1}^{N} h_i * (\alpha_i P_i^2 + \beta_i P_i + \gamma_i) + \zeta_i \exp(\lambda_i P_i) \end{matrix} \tag{5}$$

2.4. Constraints

Power output generated by the generators must adhere to various operational restrictions. These constraints are broadly classified into equality and inequality constraints. Equality constraints ensure a specific balance, while inequality constraints set permissible limits. The subsequent sections provide a detailed elucidation of these critical operational considerations.

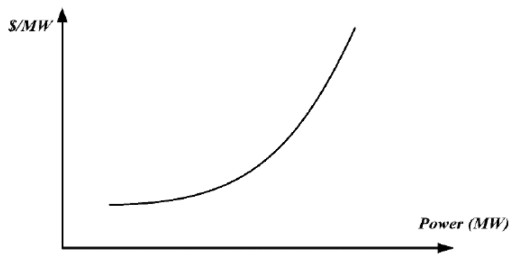

Figure 1. Thermal generators' fuel cost characteristics

2.4.1. Active power balance constraints

This is the equality constraint which models that the thermal power generation should be equal to the power system's electrical load demand in addition to the power transmission losses. This condition mathematically can be conveyed as (6).

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{6}$$

Here P_D, P_L are the total load demand and system loss respectively. The transmission losses are indicated as (7).

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \tag{7}$$

To calculate the system loss, B coefficient is adopted. Loss coefficients of the generators are represented as $B_{ij}, B_{oi}, \; B_{oo}$.

2.4.2. Limits of active power generation

Power generation from thermal generators is restricted by their characteristics. This is known as the limits of active power generation. The minimum possible power generation is represented by P_i^{min} and maximum possible power generation is denoted by P_i^{max}.

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{8}$$

3. PROPOSED OPTIMIZATION ALGORITHM
3.1. Golden jackal optimization algorithm

Chopra and Ansari [19] introduced a swarm-based intelligence algorithm named the GJO algorithm in 2022. It copies the real-time hunting of golden jackals. Typically, male and female golden jackals hunt cooperatively. There are three distinct phases to the golden jackal's hunting behavior: i) locating and approaching the prey, ii) containing and agitating the prey up to its moving cease, and iii) bouncing against the prey. In an initialization phase, a set of random distributions of prey location is created.

$$P_{i.j} = LB_{i,j} + rand(UB_{i,j} - LB_{i,j}) \tag{9}$$

Where *P* denotes prey, *LB*, *UB* denotes the lower and upper boundary of solution space, and the *rand* is the random number between (0, 1). Initialize population size *N*, dimension *D*, and max iteration *T*.

$$P = \begin{bmatrix} P_{1,1} & \cdots & P_{1,j} & \cdots & P_{1,D} \\ P_{2,1} & \cdots & P_{2,j} & \cdots & P_{2,D} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ P_{N-1,1} & \cdots & P_{N-1,j} & \cdots & P_{N-1,D} \\ P_{N,1} & \cdots & P_{N,j} & \cdots & P_{N,D} \end{bmatrix} \tag{10}$$

The escaping energy of prey *E* is calculated as (11),

$$E = E_1 * E_0 \tag{11}$$

where E_1 depicts the declining energy of the prey:

$$E_1 = C_1 * \left(1 - \frac{t}{T}\right) \tag{12}$$

where *T* expresses the maximum iteration, *t* indicates the current iteration, C_1 is a constant with a value of 1.5, and E_0 expresses the actual condition of the energy.

$$E_0 = 2 * r - 1 \tag{13}$$

The (14) and (15) are the mathematical representations of a golden jackal's hunting behavior in the exploration phase and exploitation phase.

$$\begin{aligned} &|\mathrm{E}| \geq 1 \\ &X_1(t) = X_m(t) - E|X_m(t) - rl.prey(t)| \\ &X_2(t) = X_{fm}(t) - E\left|X_{fm}(t) - rl.prey(t)\right| \end{aligned} \tag{14}$$

prey(t) is the prey location at iteration *t*.

$$\begin{aligned} &|E| < 1) \\ &X_1(t) = X_m(t) - E|rl.X_m(t) - prey(t)| \\ &X_2(t) = X_{fm}(t) - E\left|rl.X_{fm}(t) - prey(t)\right| \end{aligned} \tag{15}$$

r represents a random value in [0,1]. *rl* expresses a random vector based on the Levy distribution. $X_{fm}(t)$ denotes the location of the female golden jackal, and $X_m(t)$ indicates the location of the male golden jackal.

$$rl = 0.05 * LF(y) \tag{16}$$

$X_1(t)$ and $X_2(t)$ are the revised positions of golden jackals. The *LF* expresses the levy flight fitness function as (17):

$$LF(y) = 0.01 \times \frac{\mu \times \sigma}{\left|v^{1/\beta}\right|}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times \left(2^{\frac{\beta-1}{2}}\right)} \right)^{\frac{1}{\beta}} \quad (17)$$

where μ and v are given by the random number between (0, 1), β is 1.5.

$$P(t+1) = \frac{X_1(t)+X_2(t)}{2} \quad (18)$$

P(t+1) is the updated prey position based on the location of both male and female golden jackals.

3.2. Opposition-based learning method

Tizhoosh [20] introduced OBL which is based on the concept that the opposite of a good solution has a high probability of being a good solution itself, as it represents the same solution in a different direction. OBL is designed to improve the effectiveness of the search space and speed up the convergence of the optimization algorithm by considering both the original solution and its opposite during the optimization process. The use of OBL leads to the enhancement of the performance in swarm optimization methods, improves their exploration and exploitation capabilities, and helps them escape local optima. Furthermore, OBL can maintain a good balance between exploration and exploitation by guiding the algorithm towards unexplored regions of the search space using the opposites of good solutions, while still utilizing the information from the good solutions. To improve the convergence speed OBL method is combined with the various algorithms as in [21], [22].

3.2.1. Opposition-based initialization

The utilization of contrasting viewpoints can lead to improved initial candidate solutions, known as opposite populations (OP). The initialization of an opposition-based population can be explained as Algorithm 1. Let *N* is the population size and *D* is the number of variables.

Algorithm 1
```
for i = 1: N
    for j = 1: D
        OP_{i,j} = a_j + b_j − P_{i,j}
    end
end
```

3.2.2. Opposition-based generation

New population generation in the GJO algorithm is altered using opposition-based population generation. The jumping rate (Jr) is used for performing the generation. This process of new population generation is explained in the Algorithm 2.

Algorithm 2
```
if rand (0,1) < J_r
    for i = Population no
        for j = 1: D
            OP_{i,j} = a_j + b_j − P_{i,j}
        end
    end
end
```

3.3. Improved golden jackal optimization algorithm

Generally, two main steps are followed in a population-based algorithm namely population initialization and generation of new generations using the algorithm's principle. In this work, the OBL strategy is incorporated into both of these steps. The combination of the OBL method in the original GJO algorithm improves the convergence ability of the IGJO algorithm. The proposed IGJO algorithm is presented as a flowchart in Figure 2. This process continues until the desired coverage area has been achieved, ensuring that each jackal is working towards a common goal.

Implementation of IGJO algorithm to CEED:

Stage 1. An initial population of prey is generated randomly.

Stage 2. Generate an oppositional-based initial population.

Stage 3. The objective value for the current population (*P*) is found and the oppositional population (*OP*) is also calculated.

Stage 4. Sort the N number of fittest individuals from both populations.
Stage 5. Declare the best prey and second-best prey. They are represented by Male jackals and female jackals respectively.
Stage 6. Calculate the escaping energy of the prey E.
Stage 7. Update the prey position using equation (18) and evaluate the fitness values of the position.
Stage 8. Find out the oppositional population for the current population based on the jumping rate J_r.
Stage 9. Calculate the value of an objective function of the opposite population.
Stage 10. Replace the particular population with the opposition population if the fitness value is superior.
Stage 11. Check for maximum iteration. If it is not reached go to stage 5 else go to the next stage.
Stage 12. Output the best prey.

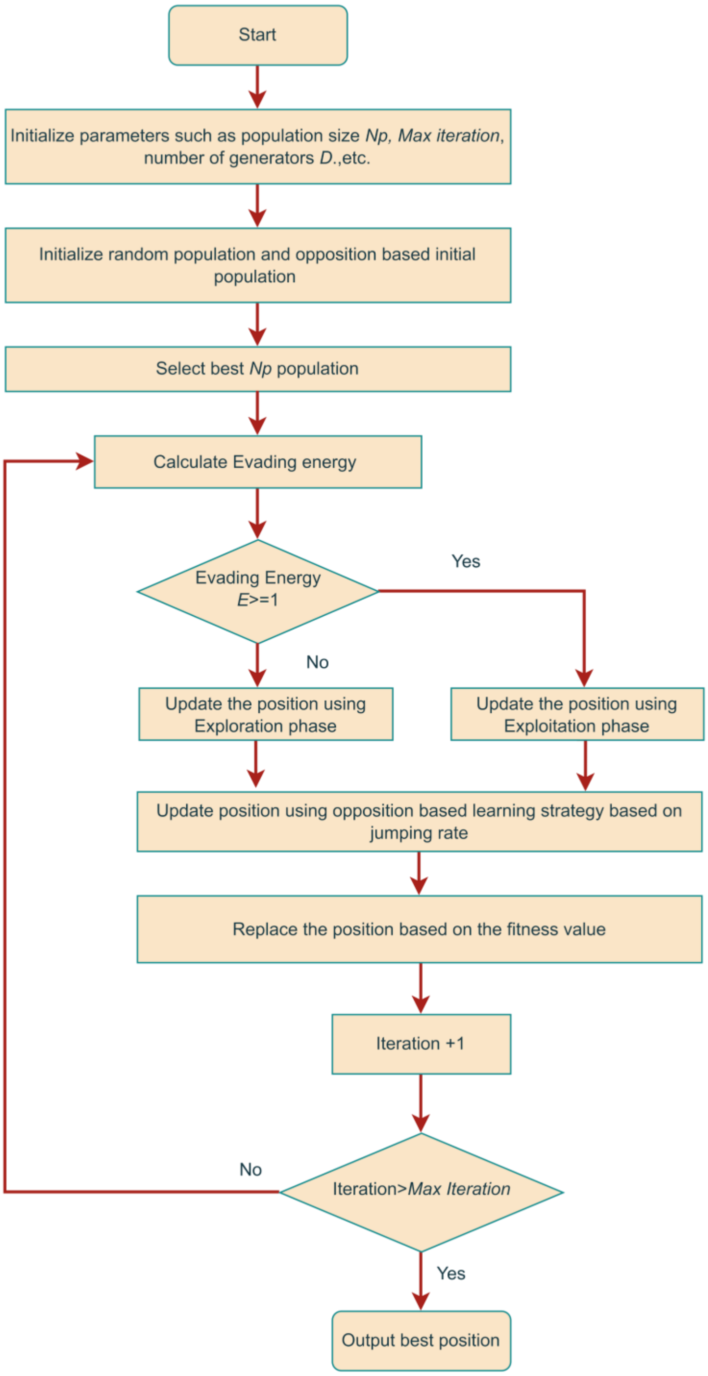

Figure 2. Flowchart for IGJO algorithm

4. NUMERICAL EXAMPLES AND SIMULATION RESULT

The performance and effectiveness of the proposed IGJO method are investigated on 2 different test systems having 10, and 40 thermal generators under non-convex cost functions. Various constraints considered for the test system are specified in Table 1. The IGJO technique was implemented in MATLAB 7.1 and executed on a personal computer equipped with an Intel Core i5 processor and 4 GB of RAM. The outcomes produced by IGJO were compared to those of various other algorithms, including GJO, NSGA-II, GSA, and established algorithms found in the existing literature.

Table 1. Different test systems considered in the analysis

Test case no.	Units	Constraints	Demand
Test system 1	10 units	Transmission loss with valve point effects is considered	2000 MW
Test system 2	40 units	The valve point effect is considered but transmission loss is not considered	10500 MW

4.1. Parameter selection

The IGJO algorithm has three control parameters: N, T, and Jr. The parameter selection in the algorithm is important for the effective operation of the algorithm. The jumping rate controls the diversity of the population, and the optimal values for the control parameters depend on the problem being solved. This involves adjusting the parameters until the best settings are determined. After running several simulations, the parameters were set to the values that produced the best results as presented in Table 2. For the validation of the IGJO algorithm on the test system, the following values were used: N=100, T=500, and Jr=0.4.

4.2. Test system 1

For ascertaining the efficacy of the proposed IGJO algorithm, 10-unit systems having a non-linear fuel cost coefficient with a load demand of 2000 MW are considered. Constraints such as transmission loss, generator power limits, and VPL effects are considered for the test system. The data for the test system was compiled from Basu [23]. Simulation results for the test case using the suggested algorithm are tabulated in Table 2. The combined cost obtained by the IGJO algorithm is 216031.3 $/hr and it is 467.6 $/hr less than the GJO algorithm. The outcome of the simulation is contrasted with the various erstwhile algorithms present in the literature and this proves the effectiveness of the IGJO algorithm. It is quite apparent from Table 3 that the generator output resulting from the IGJO algorithm satisfies all the constraints considered. Figure 3 shows the convergence curve for the IGJO and GJO algorithms. It affirms that the proposed algorithm performs better than the GJO algorithm.

4.3. Test system 2

A larger test system having 40 thermal generating units is used to ascertain the performance of the IGJO algorithm. The test system considers the VPL effect in addition to the quadratic fuel cost function. Transmission loss for the system is neglected. The expected power demand of 10500 MW was considered. The details of fuel cost factors, Emission factors, and generating limits for each unit are given [23]. The simulation results obtained for this case are compared with the standard GJO, NSGA-II, MODE, SPEA-2, MABC, GSA, and PDE algorithms, and Table 4 shows the results. It exhibits that the proposed IGJO algorithm has a combined cost of 180658.3 $/hr and it is lower than the results obtained by the other algorithms reported in the literature. A convergence characteristic of the IGJO algorithm is contrasted with the GJO algorithm in Figure 4. It is quite apparent that the IGJO algorithm converges better than the GJO algorithm and it proves than better performance of the suggested IGJO method.

4.4. Testing of benchmark functions

In this study, four benchmark functions including two unimodel and two multimodel functions with 30 dimensions are used to validate the robustness of the proposed IGJO approach. Considered benchmark functions and the details of the statistical analysis for the simulation results for 30 trials are tabulated in Table 5. As can be seen from the table the IGJO yields better solutions for all the benchmark functions in terms of minimum, mean, and maximum objective value than the GJO. This proves the effectiveness of the proposed IGJO algorithm.

4.5. Analysis of results

The thermal power outputs and generation cost obtained by the IGJO algorithm for the two test systems are tabulated in Tables 2 and 3. From the results, it is found that the overall costs are reduced compared to the other algorithms and the GJO algorithm. For test system 1 proposed IGJO algorithm gives a combined cost of 467.6 $/hr less than the GJO algorithm, similarly for the second test system obtained cost by the suggested algorithm is 4340.7 $/hr lower than the original GJO algorithm. This result shows that the proposed method provides a better optimal generator schedule than the previously suggested optimization methods. From Figures 3 and 4, it is quite apparent that the proposed IGJO algorithm converges faster than the compared GJO algorithm for test system 1 and test system 2 respectively. It proves the superiority of the IGJO algorithms over other algorithms.

Table 2. Parameter tuning for IGJO algorithm

Population size *(N)*	Jumping rate (J_r)	Mean fuel cost ($/hr) Test system 1	Mean fuel cost ($/hr) Test system 2
50	0.2	216052.6198	180683.359
75	0.2	216048.3729	180685.9488
100	0.2	216053.3433	180682.0031
50	0.4	216035.3602	180676.6491
75	0.4	216039.6728	180674.0521
100	**0.4**	**216034.7245**	**180663.4758**
50	0.6	216037.8094	180684.13
75	0.6	216052.4229	180669.3857
100	0.6	216037.6361	180671.796

Table 3. Combined generation cost comparison for test system 1

Unit	MODE [23]	NSGA-II [23]	PDE [23]	SPEA2 [23]	GSA [10]	EMOCA [24]	LFA [17]	GJO	IGJO
P1	54.9487	51.9515	54.9853	52.9761	54.9992	55	54.992	55	55
P2	74.5821	67.2584	79.3803	72.813	79.9586	80	78.7689	80	80
P3	79.4294	73.6879	83.9842	78.1128	79.4341	83.5594	87.7168	100.4119	120
P4	80.6875	91.3554	86.5942	83.6088	85	84.6031	78.1055	104.057	115.85
P5	136.8551	134.0522	144.4386	137.2432	142.1063	146.5632	140.6272	144.5071	134.4263
P6	172.6393	174.9504	165.7756	172.9188	166.567	169.2481	157.0936	153.5598	151.8141
P7	283.8233	289.435	283.2122	287.2023	292.8749	300	299.9954	294.5121	285.8712
P8	316.3407	314.0556	312.7709	326.4023	313.2387	317.3496	309.2219	302.0438	282.8083
P9	448.5923	455.6978	440.1135	448.8814	441.1775	412.9183	439.3243	427.6489	438.0124
P10	436.4287	431.8054	432.6783	423.9025	428.6306	434.3133	438.6947	421.4264	419.2248
Loss	84.3271	84.2495	83.9331	84.0612	83.9868	83.5571	84.3701	83.1816	83.0016
Fuel cost ($/hr)	113477.6265	113542.9	113506.5	113552.7	113492	113714	113246.4	113410.1	113351.5
Emission (tons/hr)	4124.8642	4150.983	4111.381	4126.854	4111.417	4088.058	4139.895	4159.312	4276.223
Emission cost ($/hr)	105274.2397	105950	104305.3	105498.4	104689.4	104454.5	105018	103080.2	102679.8
Combined cost ($/hr)	218751.8663	219492.9	217811.8	219051.1	218181.4	218168.5	218264.4	216498.9	216031.3

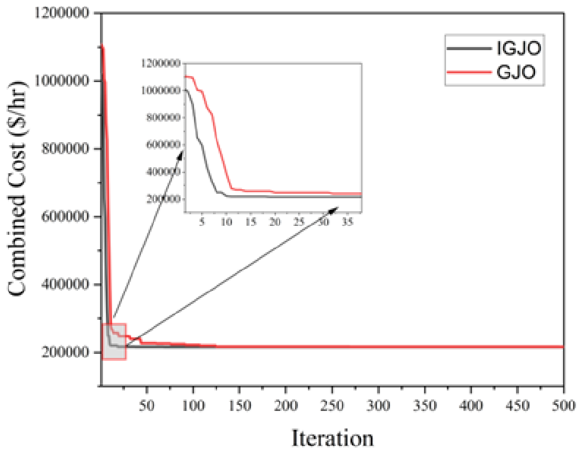

Figure 3. Convergence for test system 1

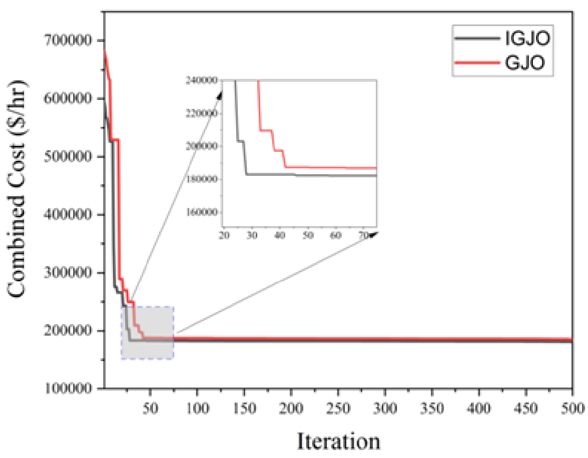

Figure 4. Convergence for test system 2

Table 4. Combined generation cost comparison for test system 2

Unit	MODE [23]	PDE [23]	MABC/D/Cat [25]	MABC/D/Log [25] `	NSGA-II [23]	GSA [10]	SPEA-2 [23]	GJO	IGJO
P1	113.5295	112.1549	110.7998	110.7998	113.8685	113.9989	113.9694	114	110.8137
P2	114	113.9431	110.7998	110.7998	113.6381	113.9896	114	114	110.7772
P3	120	120	97.3999	97.3999	120	119.9995	119.8719	97.79358	98.57637
P4	179.8015	180.2647	174.5504	174.5486	180.7887	179.7857	179.9284	167.6405	173.2594
P5	96.7716	97	87.7999	97	97	97	97	97	87.79572
P6	139.276	140	105.3999	105.3999	140	139.0128	139.2721	140	105.8623
P7	300	299.8829	259.5996	259.5996	300	299.9885	300	300	259.6796
P8	298.9193	300	284.5996	284.5996	299.0084	300	298.2706	282.3489	284.5905
P9	290.7737	289.8915	284.5996	284.5996	288.889	296.2025	290.5228	300	284.6086
P10	130.9025	130.5725	130	130	131.6132	130.385	131.4832	130	130
P11	244.7349	244.1003	318.1921	318.2129	246.5128	245.4775	244.6704	316.721	318.2802
P12	317.8218	318.284	243.5996	243.5996	318.8748	318.2101	317.2003	249.792	245.6664
P13	395.3846	394.7833	394.2793	394.2793	395.7224	394.6257	394.7357	394.4837	394.2569
P14	394.4692	394.2187	394.2793	394.2793	394.1369	395.2016	394.6223	394.3747	394.2756
P15	305.8104	305.9616	394.2793	394.2793	305.5781	306.0014	304.7271	394.2175	394.2846
P16	394.8229	394.1321	394.2793	394.2793	394.6968	395.1005	394.7289	394.2765	394.2399
P17	487.9872	489.304	399.5195	399.5195	489.4234	489.2569	487.9857	461.9292	399.7671
P18	489.1751	489.6419	399.5195	399.5195	488.2701	488.7598	488.5321	461.6597	399.6158
P19	500.5265	499.9835	506.1985	506.1716	500.8	499.232	501.1683	428.2171	505.722
P20	457.0072	455.416	506.1985	506.2206	455.2006	455.2821	456.4324	499.794	506.2062
P21	434.6068	435.2845	514.1472	514.1105	434.6639	433.452	434.7887	447.329	514.111
P22	434.531	433.7311	514.1455	514.1472	434.15	433.8125	434.3937	440.6072	512.9024
P23	444.6732	446.2496	514.5237	514.5664	445.8385	445.5136	445.0772	442.6545	513.0663
P24	452.0332	451.8828	514.5386	514.4868	450.7509	452.0547	451.897	449.1895	513.261
P25	492.7831	493.2259	433.5196	433.5195	491.2745	492.8864	492.3946	443.7763	434.4377
P26	436.3347	434.7492	433.5195	433.5196	436.3418	433.3695	436.9926	442.8143	434.8918
P27	10	11.8064	10	10	11.2457	10.0026	10.7784	10	10
P28	10.3901	10.7536	10	10	10	10.0246	10.2955	12.87356	10
P29	12.3149	10.3053	10	10	12.0714	10.0125	13.7018	10	10
P30	96.905	97	97	87.8042	97	96.9125	96.2431	97	97
P31	189.7727	190	159.733	159.733	189.4826	189.9689	190	190	159.7537
P32	174.2324	175.3065	159.733	159.7331	174.7971	175	174.2163	190	159.7334
P33	190	190	159.733	159.733	189.2845	189.0181	190	190	160.38
P34	199.6506	200	200	200	200	200	200	200	200
P35	199.8662	200	200	200	199.9138	200	200	200	200
P36	200	200	200	200	199.5066	199.9978	200	200	200
P37	110	109.9412	89.1141	89.1141	108.3061	109.9969	110	110	89.19482
P38	109.9454	109.8823	89.1141	89.1141	110	109.0126	109.6912	110	89.11444
P39	108.1786	108.9686	89.1141	89.1141	109.7899	109.456	108.556	110	89.11576
P40	422.0628	421.3778	506.1879	506.1951	421.5609	421.9987	421.8521	465.5088	504.755
Fuel cost ($/hr)	125792.1	125730.9	124447.464	124447.7074	125825.2	125782.4	125807.7	126654.8	124592.5
Emission (tons/hr)	211189.8	211765.5	256567.2483	256551.3207	210949.1	210932.9	211097.8	197990	254245.7
Emission cost ($/hr)	61863.73	62070.61	56332.1486	56330.6821	61864.27	62115.72	61790.76	58344.21	56065.76
Combined cost ($/hr)	187655.8	187801.6	180779.6126	180778.3895	187689.5	187898.1	187598.4	184999	180658.3

Table 5. Testing of benchmark functions

S no.	Function	Limit	Function value	Algorithm GJO	IGJO
1	$f_1(x)=\sum_{i=1}^{D} x_i^2$	[-100, 100]	Minimum	4.2453e-26	2.8444e-31
			Mean	3.2041e-23	3.2384e-24
			Maximum	2.0356e-22	1.6007e-23
2	$f_2(x)=\sum_{i=1}^{D}\lvert x_i\rvert+\prod_{i=1}^{D}\lvert x_i\rvert$	[-10, 10]	Minimum	1.6853e-20	9.3668e-25
			Mean	1.2256e-17	2.5642e-19
			Maximum	6.9257e-16	2.5372e-17
3	$f_3(x)=\sum_{i=1}^{D}[x_i^2-10cos(2\pi x_i)+10D]$	[-5.12, 5.12]	Minimum	5.6874e-12	2.2064e-15
			Mean	1.6973e-10	4.6197e-12
			Maximum	5.4469e-08	3.8106e-11
4	$f_4(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	[-600, 600]	Minimum	1.1077e-18	3.5506e-21
			Mean	6.3455e-14	1.7911e-17
			Maximum	1.4538e-12	6.1639e-15

5. CONCLUSION

The IGJO algorithm is proposed to handle CEED problems with valve point effects and generator active power constraints. The standard GJO algorithm tends to have challenges in complex optimization objective functions and premature convergence. To address the complexity, the OBL method is integrated into the GJO algorithm, which helps to eliminate premature convergence and improve global search ability. The IGJO algorithm is tested on non-convex CEED problems with different constraints and compared to other meta-heuristic algorithms. After running experiments on two different CEED test cases, findings show that the IGJO algorithm demonstrated superior performance compared to the GJO algorithm and other advanced meta-heuristic algorithms in various aspects, such as achieving a higher potential for solutions, having greater computational efficiency, a better convergence rate, and being more robust. Subsequent efforts will expand the issue's framework to incorporate the assimilation of renewable energy sources and storage mechanisms, amplifying the intricacy involved in solving the problem.

REFERENCES

[1] A. Farag, S. Al-Baiyat, and T. C. Cheng, "Economic load dispatch multiobjective optimization procedures using linear programming techniques," *IEEE Transactions on Power Systems*, vol. 10, no. 2, pp. 731–738, May 1995, doi: 10.1109/59.387910.

[2] S. D. Chen and J. F. Chen, "A direct Newton–Raphson economic emission dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 25, no. 5, pp. 411–417, Jun. 2003, doi: 10.1016/S0142-0615(02)00075-3.

[3] J. Nanda, D. P. Kothari, and K. S. Lingamurthy, "Economic-emission load dispatch through goal programming techniques," *IEEE Transactions on Energy Conversion*, vol. 3, no. 1, pp. 26–32, Mar. 1988, doi: 10.1109/60.4195.

[4] R. Balamurugan and S. Subramanian, "A simplified recursive approach to combined economic emission dispatch," *Electric Power Components and Systems*, vol. 36, no. 1, pp. 17–27, Dec. 2007, doi: 10.1080/15325000701473742.

[5] W. Sa-ngiamvibool, S. Pothiya, and I. Ngamroo, "Multiple tabu search algorithm for economic dispatch problem considering valve-point effects," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 4, pp. 846–854, May 2011, doi: 10.1016/j.ijepes.2010.11.011.

[6] M. R. Adaryani and A. Karami, "Artificial bee colony algorithm for solving multi-objective optimal power flow problem," *International Journal of Electrical Power & Energy Systems*, vol. 53, pp. 219–230, Dec. 2013, doi: 10.1016/j.ijepes.2013.04.021.

[7] R. E. Perez-Guerrero and J. R. Cedefio-Maldonado, "Differential evolution based economic environmental power dispatch," in *Proceedings of the 37th Annual North American Power Symposium, 2005.*, IEEE, pp. 191–197. doi: 10.1109/NAPS.2005.1560523.

[8] L. A. Koridak, M. Rahli, and M. Younes, "Hybrid optimization of the emission and economic dispatch by the genetic algorithm," *Leonardo Journal of Sciences*, no. 14, pp. 193–203, 2008.

[9] V. K. Jadoun, N. Gupta, K. R. Niazi, and A. Swarnkar, "Modulated particle swarm optimization for economic emission dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 73, pp. 80–88, Dec. 2015, doi: 10.1016/j.ijepes.2015.04.004.

[10] U. Güvenç, Y. Sönmez, S. Duman, and N. Yörükeren, "Combined economic and emission dispatch solution using gravitational search algorithm," *Scientia Iranica*, vol. 19, no. 6, pp. 1754–1762, Dec. 2012, doi: 10.1016/j.scient.2012.02.030.

[11] T. Niknam, M. R. Narimani, M. Jabbari, and A. R. Malekpour, "A modified shuffle frog leaping algorithm for multi-objective optimal power flow," *Energy*, vol. 36, no. 11, pp. 6420–6432, Nov. 2011, doi: 10.1016/j.energy.2011.09.027.

[12] A. Y. Abdelaziz, E. S. Ali, and S. M. Abd-Elazim, "Flower pollination algorithm to solve combined economic and emission dispatch problems," *Engineering Science and Technology, an International Journal*, vol. 19, no. 2, pp. 980–990, Jun. 2016, doi: 10.1016/j.jestch.2015.11.005.

[13] I. Ziane, F. Benhamida, and A. Graa, "Simulated annealing algorithm for combined economic and emission power dispatch using max/max price penalty factor," *Neural Computing and Applications*, vol. 28, no. S1, pp. 197–205, Dec. 2017, doi: 10.1007/s00521-016-2335-3.

[14] P. Mohapatra, "Combined economic emission dispatch in hybrid power systems using competitive swarm optimization," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 10, pp. 8955–8971, Nov. 2022, doi: 10.1016/j.jksuci.2022.08.022.

[15] P. K. Hota, A. K. Barisal, and R. Chakrabarti, "Economic emission load dispatch through fuzzy based bacterial foraging algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 32, no. 7, pp. 794–803, Sep. 2010, doi: 10.1016/j.ijepes.2010.01.016.

[16] I. Karakonstantis and A. Vlachos, "Hybrid ant colony optimization for continuous domains for solving emission and economic dispatch problems," *Journal of Information and Optimization Sciences*, vol. 39, no. 3, pp. 651–671, Apr. 2018, doi: 10.1080/02522667.2017.1385162.

[17] M. Kheshti, X. Kang, J. Li, P. Regulski, and V. Terzija, "Lightning flash algorithm for solving non-convex combined emission economic dispatch with generator constraints," *IET Generation, Transmission & Distribution*, vol. 12, no. 1, pp. 104–116, Jan. 2018, doi: 10.1049/iet-gtd.2017.0257.

[18] T. T. Nguyen and D. N. Vo, "An efficient cuckoo bird inspired meta-heuristic algorithm for short-term combined economic emission hydrothermal scheduling," *Ain Shams Engineering Journal*, vol. 9, no. 4, pp. 483–497, Dec. 2018, doi: 10.1016/j.asej.2016.04.003.

[19] N. Chopra and M. M. Ansari, "Golden jackal optimization: a novel nature-inspired optimizer for engineering applications," *Expert Systems with Applications*, vol. 198, p. 116924, Jul. 2022, doi: 10.1016/j.eswa.2022.116924.

[20] H. R. Tizhoosh, "Opposition-based learning: a new scheme for machine intelligence," in *International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'06)*, IEEE, pp. 695–701. doi: 10.1109/CIMCA.2005.1631345.

[21] P. K. Roy, C. Paul, and S. Sultana, "Oppositional teaching learning based optimization approach for combined heat and power dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 57, pp. 392–403, May 2014, doi: 10.1016/j.ijepes.2013.12.006.

[22] N. F. Alkayem, L. Shen, P. G. Asteris, M. Sokol, Z. Xin, and M. Cao, "A new self-adaptive quasi-oppositional stochastic fractal

search for the inverse problem of structural damage assessment," *Alexandria Engineering Journal*, vol. 61, no. 3, pp. 1922–1936, Mar. 2022, doi: 10.1016/j.aej.2021.06.094.
[23] M. Basu, "Economic environmental dispatch using multi-objective differential evolution," *Applied Soft Computing*, vol. 11, no. 2, pp. 2845–2853, Mar. 2011, doi: 10.1016/j.asoc.2010.11.014.
[24] R. Zhang, J. Zhou, L. Mo, S. Ouyang, and X. Liao, "Economic environmental dispatch using an enhanced multi-objective cultural algorithm," *Electric Power Systems Research*, vol. 99, pp. 18–29, Jun. 2013, doi: 10.1016/j.epsr.2013.01.010.
[25] D. C. Secui, "A new modified artificial bee colony algorithm for the economic dispatch problem," *Energy Conversion and Management*, vol. 89, pp. 43–62, Jan. 2015, doi: 10.1016/j.enconman.2014.09.034.

BIOGRAPHIES OF AUTHORS

Ramamoorthi Ragunathan received his B.E. degree in electrical and electronics engineering, and M.E. degree in power electronics and drives from Anna University, Chennai, Tamilnadu, India in 2010, 2013 respectively. His area of interest includes power system economic load dispatch, power quality improvement devices, and soft computing techniques. applications of computational intelligence techniques in power system engineering. He published 4 research papers in respected national and international journals. He can be contacted at email: ram_moorthi2007@yahoo.com.

Balamurugan Ramadoss received his B.E. degree in electrical and electronics engineering, M.E. degree in power systems, and Ph.D. degree in electrical engineering from Annamalai University, Annamalainagar, Tamilnadu, India in 1994, 1997, 2008 respectively. He guided 4 Ph.D. scholars and 15 M.E. theses and at present three scholars pursuing Ph.D. under his guidance. His area of interest includes digital simulation of power systems and soft computing techniques. Applications of computational intelligence techniques in power system engineering. He published 25 research papers in respected national and international journals. He can be contacted at email: bala_aucdm@yahoo.com.