Bulletin of Electrical Engineering and Informatics
Vol. 13, No. 2, April 2024, pp. 781~793
ISSN: 2302-9285, DOI: 10.11591/eei.v13i2.6572

Golden jackal optimization for economic load dispatch problems with complex constraints

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Article Info

Article history:

Received Apr 25, 2023
Revised Aug 19, 2023
Accepted Sep 14, 2023

Keywords:

Economic load dispatch
Golden jackal optimization
Meta-heuristic algorithm
Multi fuel option
Valve point loading effect

ABSTRACT

This research paper uses the golden jackal optimization (GJO), a novel meta-heuristic algorithm, to address power system economic load dispatch (ELD) problems. The GJO emulates the hunting behavior of golden jackals. GJO algorithm uses the cooperative attacking behavior of golden jackals to tackle complicated optimization problems efficaciously. The objective of ELD problem is to distribute power system load requirement to the different generators with a minimum total fuel cost of generation. ELD problems are highly complex, non-linear, and non-convex optimization problems while considering constraints namely valve point loading effect (VPL) and prohibited operating zones (POZs). The proposed GJO algorithm is applied to solve complex, non-linear, and non-convex ELD problems. Six different test systems having 6, 10, 13, 40, and 140 generators with various constraints are used to validate the usefulness of the suggested GJO method. Simulation outcomes of the test system are compared with various algorithms reported in the algorithms such as particle swarm optimization (PSO), ant colony optimization (ACO), and backtracking search algorithm (BSA). Results show that the proposed GJO algorithm produces minimal fuel cost and has good convergence in solving ELD problems of power system engineering.

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1. INTRODUCTION

The design and operation of power systems become more complex day by day. One of the primary key optimization challenges for the efficient and error-free functioning of power systems are economic load dispatch (ELD) problem. A power system's overall load demand is distributed across various generating units using the ELD problem to increase operational efficiency. ELD problem is a non-convex, non-linear complex optimization problem in power engineering. Traditionally, quadratic fuel functions are used in ELD formulation. While considering various real-time constraints such as valve point loading (VPL) effect and prohibited operating zone (POZ) the ELD problem complexity increases. Due to VPL effects and POZ, the search space for the answer will have discontinuities and the number of minimum points. Therefore, the ideal problem for the ELD issue is non-linear with discontinuities and calls for suitable solution methods.

Numerous optimization strategies, including mathematical programming techniques such as lamda iteration method, Lagrange multiplier method, newton method, gradient method, dynamic programming method, and heuristic algorithms such as simulated annealing, artificial bee colony algorithm, have been used to address the issue of economic load dispatch. Due to the problem's extremely non-linear characteristics, the traditional calculus-based approaches fail to provide satisfactory results for solving ELD problems. At the same time, different artificial intelligence-based approaches have been formed and these methods do not depend upon the characteristics of the fuel cost curve so effectively used to tackle the ELD problem to get around challenges raised by conventional methodologies and attain the best results.

Gaing [1] suggested the particle swarm optimization (PSO) algorithm for optimizing the ELD problem. Firefly algorithm (FA), which imitates the social behavior of a firefly, was employed to ELD formulation [2]. Dubey *et al.* [3] used the modified flower pollination algorithm (MFPA), cuckoo search algorithm (CSA) [4] to address the ELD issues. An iterative variant of quick group search optimizer (QGSO) [5] was suggested for implementing ELD problems with VPL impact, POZs, ramp rate restrictions, and losses in power transmission lines. Ghorbani and Babaei [6] used exchange market algorithm [EMA] method to solve the ELD issues under realistic constraints. The stock exchange trading strategies served as the basis for the EMA strategy. Researchers have presented simulated annealing (SA) [7], grey wolf optimization (GWO) [8], crow search algorithm (CSA) [9], to solve the non-convex ELD problem with cost as the objective function. Srivastava and Das [10] advanced class topper optimization [ACTO] and class topper optimization [CTO] were used to solve both combined economic emission dispatch (CEED) and ELD. Rizk-Allah *et al.* [11] suggested a new parallel hurricane optimization algorithm [PHOA] and turbulent flow of water optimization [TFWO] [12] algorithm for resolving CEED and ELD. A unique hybrid algorithm was proposed to solve various ELD problems based on franklin's and coulomb's law [13]. Al-Betar *et al.* [14] hybridized hill climbing with a sine cosine algorithm (SCA) to increase global searching ability and applied it to solve ELD issues. Tariq *et al.* [15] have used an upgraded version of the bat-inspired algorithm (BA) to solve ELD in the existence of renewable energy Sources. Srivastava and Sigh [16] have utilized ant colony optimization (ACO), an enhanced chameleon swarm algorithm (ECSA) [17] to resolve ELD problems. Salp swarm algorithm (SSA) and β-hill climbing optimization technique is hybridized (HSSA) for solving ELD problem with valve point effect [18]. A hybrid sine cosine algorithm (SCA) known as SCA-β hill climbing (SCA-βHC) [14], Harris Hawks optimizer (HHO) with hill-climbing optimization [19] is used solve ELD problems with various constraints. Although numerous heuristic algorithms are available in the literature, these algorithm performances face some difficulties, such as trap in the local optimum and early convergence in solving power system ELD problems many times. The "no free lunch" theorem [20] exhibits that all optimization methods could not find best solution for all kinds of optimization problems. This problem motivates the researchers to explore further to find better solution methods. Recently, a new meta-heuristic algorithm, named golden jackal optimization (GJO) algorithm, was proposed by Chopra *et al.* [21] to solve various optimization problems. The GJO algorithm showcases the forging activities of golden jackals. The cooperative attacking nature of the golden jackals helps to find the optimal global solutions for various optimization problems. The main contribution of the research work is summed up as: i) the ELD problems are formulated by considering various realistic constraints such as VPL, POZ, transmission loss, and multiple fuel options (MFO); ii) a new Meta heuristic method called GJO algorithm is used for obtaining the best optimal generation scheduling by considering the practical ELD problem; and iii) six test cases have been evaluated to show the superiority of the recommended GJO technique, and the findings have been compared to those of the state-of-the-art approach described in the literature.

The paper is organized as follows: the ELD problem formulation is described in section 2. Section 3 elaborates GJO algorithm and its implementation to the ELD problems. Simulation of various test cases and their outcomes are discussed in section 4. The conclusion of the research work is presented in section 5.

2. ELD PROBLEM FORMULATION

The main aim of the ELD problem is to optimize the output of the generators in the power system to meet the system load demand under various system constraints. This section explains the objectives and various system constraints in ELD problem.

2.1. Objective function

Traditionally, the fuel cost relation for a thermal generator is denoted by the quadratic and represented by (1):

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \quad (1)$$

Where: *a, b, c*: the coefficient of fuel cost functions.
Minimization of the fuel cost is the main objective of the ELD problem, and it is represented as (2):

$$C = minimize \sum_{i=1}^{N} F_i(P_i) \quad (2)$$

Where C is the scheduling cost of the system, $F_i(P_i)$ is the fuel cost function of i^{th} unit, N is the total number of generating units in the system, and P_i is the power output of the i^{th} unit.

The consecutive valve opening in multivalve steam turbines ripples the generator's fuel cost curve. The fuel cost function should take this VPL effect to simulate a real and valuable ELD problem. Figure 1 shows the fuel cost function of a thermal generator for the two different cases.

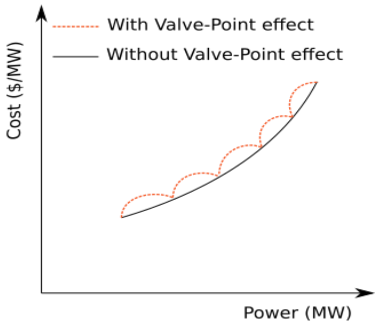

Figure 1. Thermal generator's fuel cost function

Consideration of VPL in thermal generator fuel cost function becomes non-convex, and (3) represents it.

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| d_i * \sin\left(e_i * \left(P_i^{min} - P_i\right)\right) \right| \quad (3)$$

here d and e are the coefficients related to the VPL effects of the thermal generators. In some cases, there are few generating units with different fuel sources. In (4) describes the fuel cost equation for such generating units.

$$F_i(P_i) = \begin{cases} a_{i1}P_i^2 + b_{i1}P_i + c_{i1} & fuel\ 1 & P_i^{min} \leq P_i < P_{i1} \\ a_{i2}P_i^2 + b_{i2}P_i + c_{i2} & fuel\ 2 & P_{i1} \leq P_i < P_{i2} \\ & \vdots & \\ a_{ik}P_i^2 + b_{ik}P_i + c_{ik} & fuel\ k & P_{i\,k-1} \leq P_i < P_i^{max} \end{cases} \quad (4)$$

The cost curve for a generator with k fuel alternatives is segregated into k discrete sections between upper and lower limits. In this, $a_{ik}, b_{ik}, and\ c_{ik}$ are the cost coefficients of the i^{th} unit using fuel type k. Fuel cost function with many fuel alternatives and no VPL impacts and with VPL impacts depicted in Figure 2 and Figure 3 respectively.

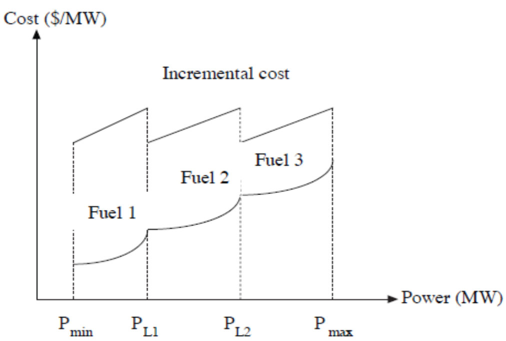

Figure 2. Fuel cost function with multiple fuels

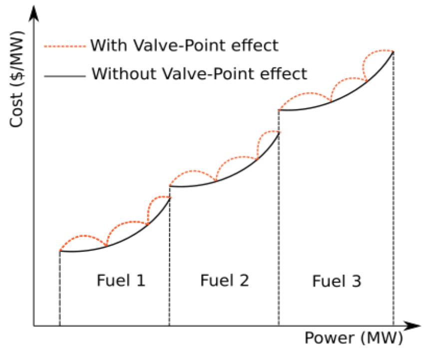

Figure 3. Fuel cost function with multiple fuels and valve point effect

2.2. System constraints

2.2.1. Power balance restriction

The total summation of power output from the generators must be equal to the sum of the power needed and any transmission losses. This condition is given by (5):

$$\sum_{i=1}^{N} P_i = P_D + P_L \quad (5)$$

Here P_L is the system loss and P_D is the total load requirement. The transmission losses are expressed as (6):

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \tag{6}$$

The method-based *B* coefficient formula is adopted to calculate the system loss. B_{ij}, B_{oi}, B_{oo} are the generator's loss coefficients.

2.2.2. Generator capacity constraints

Generators in the power system network can generate power between two extreme capacities. It is an inequality constraint. The limitation is depicted by (7):

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{7}$$

Where P_i^{max} and P_i^{min} are the upper and lower limits of the power generated by the *i*th generator.

2.2.3. Ramp rate limit constraints

Ramp rate constraints limit the operating range of generating units such that they can only operate continuously between two neighboring defined operating regions. The ramp rate limitation regulates all generating units' power output, which appears in (8):

$$P_i - P_i^o \leq UR_i \, ; \; P_i^o - P_i \leq DR_i \tag{8}$$

Where *URi*, and *DRi*, denotes upper and lower end of the generator limits. P_i^o is the initial power output of the *i*th generating unit.

2.3.4. Prohibited operating zone

The prohibited operating zones are caused by the working of the steam valves or vibrations in the shaft bearings. The practically feasible areas of unit *i* can be shown (9):

$$P_i \in \begin{cases} P_i^{min} \leq P_i \leq P_{i.1}^L \\ P_{i,k-1}^U \leq P_i \leq P_{i.k}^L \quad k = 2,3 \ldots nz \\ P_{i,nz}^U \leq P_i \leq P_i^{max} \end{cases} \tag{9}$$

Where $P_{i.}^L$ and $P_{i.}^U$ are the lower and upper limits of prohibited operating zones of *i*th generator, *k* is the number of prohibited zones.

2.3.5. Constraint handling mechanism

Constraint violations are handled using penalty-based approach. Thus, the overall fitness function combines both equality constraints and objective function and it can be defined as (10):

$$fitness = \sum_{i=1}^{N} a_i P_i^2 + b_i P_i + c_i + penalty * abs\left(\sum_{i=1}^{N} P_i - P_L - P_D\right) \tag{10}$$

When objective function includes VPL effect then the overall fitness function can be mentioned as (11):

$$fitness = \sum_{i=1}^{N} a_i P_i^2 + b_i P_i + c_i + \left| d_i * sin\left(e_i * \left(P_i^{min} - P_i\right)\right) \right| + penalty * abs\left(\sum_{i=1}^{N} P_i - P_L - P_D\right) \tag{11}$$

Penalty factor in the above mentioned equations is a constant value and it is taken as 500.

3. GOLDEN JACKAL ALGORITHM

Chopra *et al.* [21], devised the swarm intelligence algorithm known as the golden jackal optimization algorithm; it imitates golden jackals' natural hunting techniques. Usually, male and female golden jackals hunt together. Three steps make up the golden jackal's hunting habit: i) searching and moving toward the prey; ii) getting close to the prey and agitating it until stops moving; and iii) bouncing towards the prey.
A set of prey position matrices with random distributions are constructed during the initialization phase.

$$prey = \begin{bmatrix} Y_{1,1} & \ldots & Y_{1,j} & \ldots & Y_{1,n} \\ Y_{2,1} & \ldots & Y_{2,j} & \ldots & Y_{2,n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ Y_{N-1,1} & \ldots & Y_{N-1,j} & \ldots & Y_{N-1,n} \\ Y_{N,1} & \ldots & Y_{N,j} & \ldots & Y_{N,n} \end{bmatrix} \tag{12}$$

here N indicates the prey population numbers, and n indicates dimension. The following mathematical (13) and (14) give a mathematical illustration of the hunting behavior of golden jackals.
Exploration phase

$$(|E| \geq 1)$$
$$Y_1(t) = Y_m(t) - E|Y_m(t) - rl.prey(t)|$$
$$Y_2(t) = Y_{fm}(t) - E\left|Y_{fm}(t) - rl.prey(t)\right| \tag{13}$$

Exploitation phase

$$(|E| < 1)$$
$$Y_1(t) = Y_m(t) - E|rl.Y_m(t) - prey(t)|$$
$$Y_2(t) = Y_{fm}(t) - E\left|rl.Y_{fm}(t) - prey(t)\right| \tag{14}$$

here t shows the current iteration, $Y_{fm}(t)$ shows the location of the female, $Y_m(t)$ depicts the location of the male golden jackal. $prey(t)$ shows the prey location vector, and $Y_1(t)$ and $Y_2(t)$ are the upgraded locations of both jackals.
The prey escaping energy E is obtained as (15):

$$E = E_1 * E_0 \tag{15}$$

where E_1 expresses the diminishing energy of the prey.

$$E_1 = C_1 * \left(1 - \frac{t}{T}\right) \tag{16}$$

where T represents the maximum iteration, C_1 represents a constant of 1.5, and E_0 represents the starting state of the energy.

$$E_0 = 2 * r - 1 \tag{17}$$

where r represents a random value in [0,1]. rl expresses a random vector based on the levy distribution.

$$rl = 0.05 * LF(y) \tag{18}$$

The LF expresses the levy flight fitness function (19):

$$LF(y) = 0.01 \times \frac{\mu \times \sigma}{\left|v^{1/\beta}\right|} \sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times \left(2^{\frac{\beta-1}{2}}\right)}\right)^{\frac{1}{\beta}} \tag{19}$$

where μ and v represent the random values between (0, 1) and β is 1.5.

$$Y(t+1) = \frac{Y_1(t) + Y_2(t)}{2} \tag{20}$$

where $Y(t+1)$ is the revised location of the prey according to both golden jackals. The element rl used in the algorithm provides random movement and helps to avoid local optimal.

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Implementation steps of the GJO algorithm in ED problems
Initial stage: Max number of iterations T, population size N and dimension n
Final stage: Outputs best prey and its fitness value
Initialize prey population randomly
While (t<T)
   Obtain the objective value for each prey
   Ym= (Male jackal position)indicates best prey
   Yfm= (Female jackal position) indicates Second best prey
   For (every prey)
        Revise prey's evading energy E using the equation. (15)
        If (Exploration Phase) (|E|≥1)
              Revise the location Y1 and Y2 using the equation. (13)
        End if
        If(Exploitation Phase) (|E|<1)
             Revise the location Y1 and Y2 using the equation. (14)
       End if
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      Revise the location using the equation. (20)
   End for
   Increment t by 1
end while
output Y_m
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4. SIMULATION RESULTS AND DISCUSSIONS

The effectiveness of the proposed GJO algorithm is analyzed on six test systems with 6-unit, 13-unit, 10-unit, 40-unit, and 140-unit systems with different complex constraints of power systems such as transmission loss, POZ, VPL effects, ramp rate limit, and MFO. The program is developed on MATLAB 21a software and implemented on a personal computer with an Intel i7 processor and 4GB RAM. The efficacy of GJO on specified cases of ELD is compared with numerous algorithms in literatures. Constraints considered for the test system is shown in Table 1. For the simulation of GJO, the population size of 100 and maximum iterations of 500 are considered.

Table 1. Test cases and considered constraints

Case study	Test system (Unit)	Constraints					Load demand (MW)
		Transmission loss	Valve point effect	Ramp rate limit	Multi fuel option	Prohibited operating zone	
1	6	✓	×	✓	×	✓	1263
2	13	×	✓	×	×	×	2520
3	10	×	×	×	✓	×	2700
4	10	×	✓	×	✓	×	2700
5	40	✓	✓	×	×	×	10500
6	140	×	✓	×	×	×	49342

4.1. Case study 1

In this research case, a test system with six thermal generators with a load demand of 1263 MW is considered. Different power system constraints, such as transmission loss, generator capacity constraints, POZ, and ramp rate limits are considered. Various fuel cost coefficients and generator constraints are taken from [1]. The developed GJO algorithm is applied for this 6-unit test case, and results are tabulated in Table 2. Results show that the proposed algorithm gives better optimal generation scheduling without violating the power system constraints considered.

Table 2. Best generation schedule of different methods for case study 1

Unit power output (MW)	PSO method [1]	CFA [14]	EMA [6]	KHA [20]	BSA [18]	GJO
P_1	447.4970	446.8623	447.3872	447.4150	447.4902	447.057
P_2	173.3221	173.2990	173.2524	173.2917	173.3308	173.171
P_3	263.4745	264.0771	263.3721	263.3559	263.4559	263.912
P_4	139.0594	139.0329	138.9894	138.9646	139.0602	139.41
P_5	165.4761	165.6988	165.3650	165.3759	165.4804	165.566
P_6	87.1280	86.4471	87.0781	87.0417	87.1409	86.6066
Total output	1276.01	1275.4172	1275.4443	1275.4448	1275.9583	1275.36
Loss (MW)	12.9584	12.4172	12.4430	12.4449	12.9583	12.36
Total cost ($/h)	15450	15,442.6553	15443.0749	15443.0752	15449.8995	15441.9

A comparison of obtained results with the other heuristic algorithms such as coulomb-franklin's algorithm (CFA), exchange market algorithm (EMA), krill herd algorithm (KHA), backtracking search algorithm (BSA), is shown in Figure 4. GJO algorithm gives the best optimal cost of 15441.9 ($/hr.), which is lower than the other algorithms. A convergence characteristic of the GJO algorithm for this test case is shown in Figure 5, and it can be seen that the GJO algorithm gives the best optimal solution in the early stage of iteration.

4.2. Case study 2

A case study was conducted on a 13-thermal unit system with valve-point loading effect. The system simulation data were taken from [7]. The required power demand was 2520 MW [7]. Table 3 compares the results obtained using the proposed GJO algorithm and other state-of-the-art algorithms namely hybrid stochastic search (HSS), tabu search algorithm (TSA), hybrid evolutionary programming-sequential programming (EP-SQP), and hybrid particle swarm optimization-sequential programming (PSO-SQP).

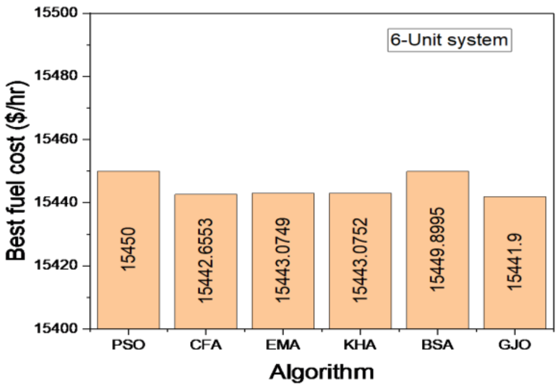

Figure 4. Performance of different heuristic approaches for case study 1

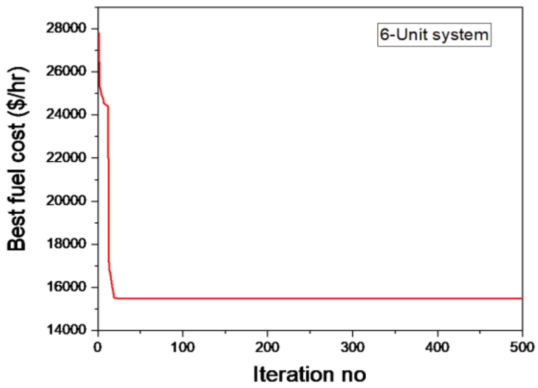

Figure 5. Convergence curve for 6 unit

Table 3. Best generation schedule of various algorithms for case study 2

Unit power output (MW)	HSS [23]	TSA [24]	EP-SQP [25]	PSO-SQP [25]	GJO
P1	628.2300	628.319	628.3136	628.3205	628.3185
P2	299.2200	299.1993	299.1715	299.0524	299.1993
P3	299.1700	331.8975	299.0474	298.9681	294.4639
P4	159.1200	159.7305	159.6399	159.4680	159.7331
P5	159.9500	159.7331	159.6560	159.1429	159.7331
P6	158.8500	159.7306	158.4831	159.2724	159.7331
P7	157.2300	159.7334	159.6749	159.5371	159.7331
P8	159.9300	159.7308	159.7265	158.8522	159.7331
P9	159.8600	159.7316	159.6653	159.7845	159.7331
P10	110.7800	40.0028	114.0334	110.9618	77.3999
P11	75.0000	77.3994	75.0000	75.0000	77.3999
P12	60.0000	92.3932	60.0000	60.0000	92.3999
P13	92.6200	92.3986	87.5884	91.6401	92.3999
Total cost ($/h)	24275.71	24313	24266.44	24261.05	24164.02

From Figure 6, it can be observed that the minimum optimal cost attained by GJO method is lower than that of the other alternative algorithms. The GJO algorithm yielded a minimum fuel cost of 24164.02 ($/hr), next best fuel cost is obtained by the PSO-SQP algorithm which is 24261.05 $/hr. Figure 7 shows the convergence curve for the GJO method in simulation of test case 2 and it shows the robustness of the GJO method.

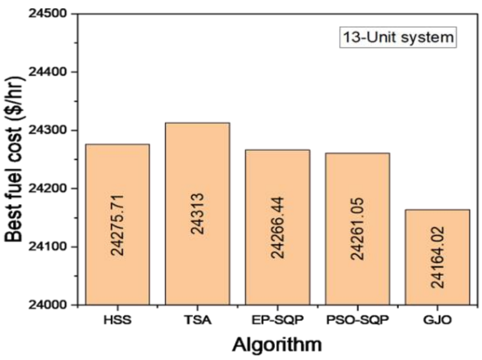

Figure 6. Performance of different heuristic approaches for case study 2

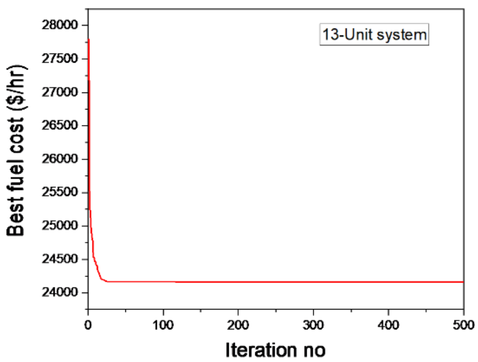

Figure 7. Convergence curve for 13 unit

4.3. Case study 3

In this test case, challenging test system having 10-units along with MFO is considered. Total power system load demand of 2700 MW is considered. Transmission loss, VPL effects and other constraints are not considered in this case. Various parameters and fuel types are considered from [22]. ELD problem for this test case is simulated using GJO algorithm and results are tabulated in Table 4.

Table 4. Best generation schedule of different algorithms for case study 3

Unit	HM [26]		HNN [27]		HGA [28]		CGA-MU [29]		GJO	
	FT	Gen	FT	Gen	FT	Gen	FT	Gen	FT	Gen
P_1	2	218.4	2	224.5	2	218.2559	2	218.4572	2	218.2446
P_2	1	211.8	1	215.0	1	211.6816	1	211.5140	1	211.6633
P_3	1	281.0	1	291.8	1	280.7359	1	280.8987	1	280.7030
P_4	3	239.7	3	242.2	3	239.6298	3	239.6241	3	239.6341
P_5	1	279.0	1	293.3	1	278.4819	1	278.5036	1	278.4998
P_6	3	239.7	3	242.2	3	239.6508	3	239.6390	3	239.63
P_7	1	289.0	1	303.1	1	288.5721	1	288.6201	1	288.5954
P_8	3	239.7	3	242.2	3	239.6280	3	239.6211	3	239.6319
P_9	3	429.2	1	355.7	3	428.5175	3	428.5760	3	428.5214
P_{10}	1	275.2	1	289.5	1	274.8466	1	274.5462	1	274.8755
Total cost ($/hr.)	625.18		626.12		623.8092		623.8095		623.8086	

Obtained best fuel cost by GJO algorithm is contrasted with best results of other algorithms namely hopfield neural network (HNN), hybrid real coded genetic algorithm (HGA), multiplier updating method is combined with conventional genetic algorithm multiplier updating (CCGA-MU) in Figure 8. The fuel cost calculated using the GJO technique is 623.8086 $/hr, with no limitation violations, indicating the suggested approach's excellent accuracy.

4.4. Case study 4

This system considers the test case 3 along with VPL effects. Coefficients of the VPL effects and other data are referred from [22]. The power requirement of 2700 MW is considered. The suggested GJO algorithm's simulated best results are tabulated in Table 5. Results given by the other methods namely improved genetic algorithm with multiplier updating method (IGA-MU), CCGA-MU method, BSA, and coulomb-franklin's algorithm (CFA) are compared with the outcome of GJO method as shown in Figure 9. The GJO algorithm yielded a minimum fuel cost of 623.849 ($/hr), and it is lower than the results of other compared algorithms.

Table 5. Best generation schedule of different algorithms for case study 4

Unit	IGA-MU [30]		BSA [31]		CFA [13]		CGA-MU [30]		GJO	
	FT	Gen	FT	Gen	FT	Gen	FT	Gen	FT	Gen
P_1	2	219.1261	2	218.5777	2	219.1757	2	222.0108	2	219.341
P_2	1	211.1645	1	211.2153	1	213.7436	1	211.6352	1	212.8096
P_3	1	280.6572	1	279.5619	1	280.6243	1	283.9455	1	282.1951
P_4	3	238.4770	3	239.5024	3	238.5002	3	237.8052	3	239.6801
P_5	1	276.4179	1	279.9724	1	278.5722	1	280.4480	1	277.7275
P_6	3	240.4672	3	241.1174	3	238.4946	3	236.0330	3	239.9062
P_7	1	287.7399	1	289.7965	1	288.9525	1	292.0499	1	287.7275
P_8	3	240.7614	3	240.5785	3	238.4906	3	241.9708	3	239.6801
P_9	3	429.3370	3	426.8873	3	428.1783	3	424.2011	3	425.8501
P_{10}	1	275.8518	1	272.7907	1	275.2681	1	269.9005	1	275.0821
Total cost ($/hr.)	624.5178		623.9016		623.9576		624.7193		623.8498	

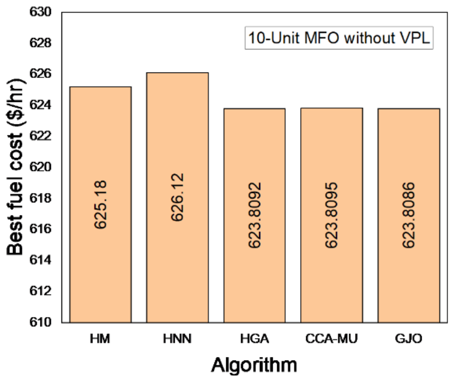

Figure 8. Performance of different heuristic approaches for case study 3

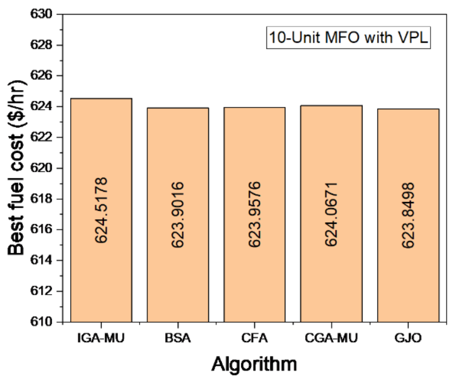

Figure 9. Performance of different heuristic approaches for case study 4

4.5. Case study 5

In this analysis, a 40-unit system with valve-point loading effect and transmission loss is considered. The total load demand for this case study is 10,500 MW. The system's fuel cost, VPL, and loss coefficients are taken from [32]. Table 6 shows the optimal power generation schedule obtained from different algorithms, including the proposed GJO algorithm. The simulation results indicate that the GJO algorithm produces the best feasible solution for this 40-unit test system. To validate the superiority and robustness of the GJO algorithm, its numerical results are compared with those of other algorithms, including GA-API [33], quasi-oppositional teaching learning based optimization (QTLBO) [34], oppositional real coded chemical reaction optimization (ORCCRO) [35], invasive weed optimization (OIWO) [32], teaching learning based optimization (TLBO) [34], shuffled differential evolution (SDE) [36], KHA [37]. The comparison is shown graphically in Figure 10. The results show that the GJO algorithm produces better results than the others. Figure 11 shows the convergence characteristics of the fuel cost graph for the GJO algorithm. The graph shows that the GJO algorithm converges quickly and achieves the best optimal generator scheduling in the early stages of iteration.

Table 6. Best generation schedule of different algorithms for case study 5

Unit	GA-API	ORCCRO	QOTLBO	TLBO	OIWO	KHA	SDE	GJO
1	114	111.68	114	114	113.9908	114	110.06	114
2	114	112.16	114	114	114	114	112.41	114
3	120	119.98	107.8221	120	119.9977	120	120	120
4	190	182.18	190	182.4448	182.5131	190	188.72	182.4003
5	97	87.28	88.3702	90.6923	88.4227	88.5944	85.91	87.7999
6	140	139.85	140	140	140	105.5166	140	140
7	300	298.15	300	300	299.9999	300	250.19	300
8	300	286.89	300	296.0682	292.0654	300	290.68	300
9	300	293.38	300	288.8518	299.8817	300	300	300
10	205.25	279.34	211.2071	281.952	279.7073	280.6777	282.01	279.5997
11	226.3	162.35	317.2766	238.1293	168.8149	243.5399	180.82	243.5997
12	204.72	94.12	163.7603	251.012	94	168.8017	168.74	94
13	346.48	486.44	481.5709	483.1175	484.0758	484.1198	469.96	484.0392
14	434.32	487.02	480.5462	481.9042	484.0477	484.1662	484.17	484.0392
15	431.34	483.39	483.7683	488.2883	484.0396	485.2375	487.73	484.0392
16	440.22	484.51	480.2998	396.3448	484.0886	485.0698	482.3	484.0392
17	500	494.22	489.2488	494.2577	489.2813	489.4539	499.64	489.2794
18	500	489.48	489.5524	408.3826	489.2966	489.3035	411.32	489.2794
19	550	512.2	512.5482	510.5206	511.3219	510.7127	510.47	511.2794
20	550	513.13	514.2914	521.2217	511.335	511.304	542.04	511.2794
21	550	543.85	527.0877	540.57	549.9412	524.4678	544.81	523.2794
22	550	548	530.1025	522.1852	549.9999	535.5799	550	550
23	550	521.21	524.2912	526.1804	523.2804	523.3795	550	523.2794
24	550	525.01	524.6512	521.1967	523.3213	523.1553	528.16	523.2794
25	550	529.84	525.0586	525.801	523.5804	524.1916	524.16	523.2794
26	550	540.04	524.4654	526.0022	523.5847	523.5453	539.1	523.2794
27	11.44	12.59	10.8929	13.0804	10.0086	10.1245	10	10
28	11.56	10.06	17.4312	11.0397	10.0068	10.1815	10.37	10
29	11.42	10.79	12.7839	12.9373	10.0123	10.0229	10	10
30	97	89.7	88.8119	89.7412	87.8664	87.8154	96.1	87.7999
31	190	189.59	190	190	190	190	185.85	190
32	190	189.96	190	190	189.9983	190	189.54	190
33	190	187.61	190	190	190	190	189.96	190
34	200	198.91	200	200	199.994	200	199.9	200
35	200	199.98	168.0873	200	200	164.9199	196.25	200
36	200	165.68	165.5072	164.7435	164.8283	164.9787	185.85	164.7998
37	110	109.98	110	110	110	110	109.72	110
38	110	109.82	110	110	109.994	110	110	110
39	110	109.88	110	110	110	110	95.71	110
40	550	548.5	511.5313	547.9677	550	512.0678	532.47	511.2794
Cost ($/hr.)	139865	136,855.19	137329.9	137814.2	136,452.68	136670.4	138157.5	136446.5
Loss	1045.06	958.75	1008.96	1002.63	957.2965	978.9251	974.43	972.9496

4.6. Case study 6

To assess the efficacy of the suggested GJO method in solving large-scale power systems, this case study considers a system with 140 power-generating stations. The fuel cost characteristic coefficients and other data for thermal, gas, nuclear, and oil power plants are cited from [38]. In this test case, VPL effects are taken into consideration for the thermal generating units. The total load demand required to be met for the test system is 49342 MW. The best power generation scheduling for the case study with the GJO techbique is shown in Table 7 (in Appendix). It can be noticed that the best total fuel cost obtained using GJO for the large-scale power system is 1559703.40 ($/hr), which is the lowest among the other heuristic approaches compared such as shuffled differential evolution (SDE) [36], improved particle swarm optimization (IPSO) [38], grey wolf optimization (GWO) [39], artificial algae algorithm (AAA) [40], opposition-based krill herd algorithm (OKHA) [41] and KHA [41]. It is graphically compared in the Figure 12. The convergence behaviour for the 140 unit power system is exhibited in Figure 13, and it depicts the robustness of the proposed GJO method.

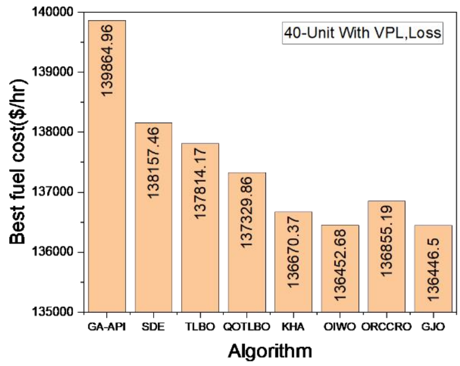

Figure 10. Performance of different heuristic approaches for case study 5

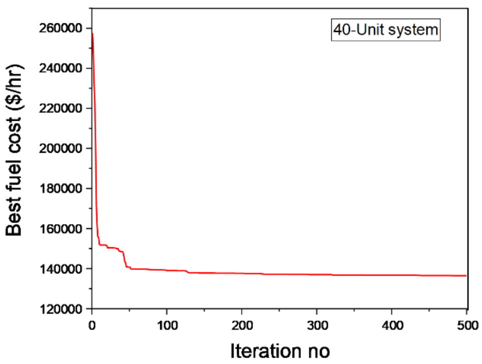

Figure 11. Convergence curve for 40 unit

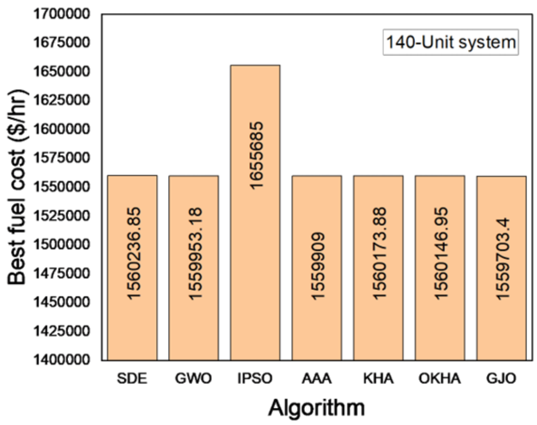

Figure 12. Performance of different heuristic approaches for case study 6

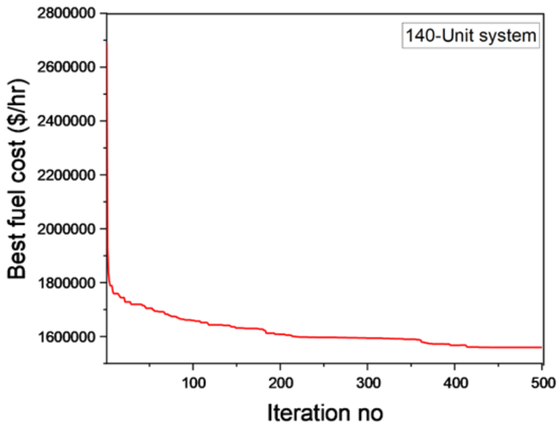

Figure 13. Convergence curve for 140 unit

5. CONCLUSION

In this research work, a comparatively new and an efficient algorithm named GJO which is based on the cooperative hunting nature of golden jackals is developed to solve ELD problems. The developed algorithm is applied to six different ELD problems in the power system with various real time complex constraints, such as VPL, POZs, MFO, and transmission loss. The outcomes show that the suggested GJO can ensure better quality solutions and has good robustness in optimizing generation scheduling of ELD problems while meeting the different constraints rather than the other compared algorithms. The overall research shows that the GJO algorithm is a competing algorithm for finding the best optimal generation scheduling for ELD problems. Further, performance of proposed GJO algorithm for DEED and economic emission dispatch problem, hybridization of GJO along with other algorithms can be explored to further improve the search ability in future works.

APPENDIX

Table 7. Best generation schedule of GJO algorithms for case study 6

Unit	Gen	Unit	Gen	Unit	Gen
1	115.2621	48	250	95	978
2	189	49	250	96	682
3	190	50	250	97	720
4	190	51	165	98	718
5	168.5398	52	165	99	720
6	190	53	165	100	964
7	490	54	165	101	958
8	490	55	180	102	1007
9	496	56	180	103	1006
10	496	57	103	104	1013
11	496	58	198	105	1020
12	496	59	312	106	954
13	506	60	281.5004	107	952
14	509	61	163	108	1006
15	506	62	95	109	1013
16	505	63	160	110	1021
17	506	64	160	111	1015
18	506	65	490	112	94
19	505	66	196	113	94
20	505	67	490	114	94
21	505	68	490	115	244
22	505	69	130	116	244
23	505	70	234.7198	117	244
24	505	71	137	118	95
25	537	72	325.4956	119	95
26	537	73	195	120	116
27	549	74	175	121	175
28	549	75	175	122	2
29	501	76	175	123	4
30	501	77	175	124	15
31	506	78	330	125	9
32	506	79	531	126	12
33	506	80	531	127	10
34	506	81	397.5959	128	112
35	500	82	56	129	4
36	500	83	115	130	5
37	241	84	115	131	5
38	241	85	115	132	50
39	774	86	207	133	5
40	769	87	207	134	42
41	3	88	175	135	42
42	3	89	175	136	41
43	248.8904	90	175	137	17
44	246.4609	91	175	138	7
45	250	92	580	139	7
46	250	93	645	140	26
47	241.5353	94	984	Total fuel cost ($/hr)	1559703.4

REFERENCES

[1] Z. L. Gaing, "Particle swarm optimization to solving the economic dispatch considering the generator constraints," *IEEE Transactions on Power Systems*, vol. 18, no. 3, pp. 1187–1195, Aug. 2003, doi: 10.1109/TPWRS.2003.814889.

[2] X. S. Yang, S. S. S. Hosseini, and A. H. Gandomi, "Firefly Algorithm for solving non-convex economic dispatch problems with valve loading effect," *Applied Soft Computing Journal*, vol. 12, no. 3, pp. 1180–1186, Mar. 2012, doi: 10.1016/j.asoc.2011.09.017.

[3] H. M. Dubey, M. Pandit, and B. K. Panigrahi, "A Biologically Inspired Modified Flower Pollination Algorithm for Solving Economic Dispatch Problems in Modern Power Systems," *Cognitive Computation*, vol. 7, no. 5, pp. 594–608, Oct. 2015, doi: 10.1007/s12559-015-9324-1.

[4] M. Basu and A. Chowdhury, "Cuckoo search algorithm for economic dispatch," *Energy*, vol. 60, pp. 99–108, Oct. 2013, doi: 10.1016/j.energy.2013.07.011.

[5] M. Moradi-Dalvand, B. Mohammadi-Ivatloo, A. Najafi, and A. Rabiee, "Continuous quick group search optimizer for solving non-convex economic dispatch problems," *Electric Power Systems Research*, vol. 93, pp. 93–105, Dec. 2012, doi: 10.1016/j.epsr.2012.07.009.

[6] N. Ghorbani and E. Babaei, "Exchange market algorithm for economic load dispatch," *International Journal of Electrical Power and Energy Systems*, vol. 75, pp. 19–27, Feb. 2016, doi: 10.1016/j.ijepes.2015.08.013.

[7] K. P. Wong and Y. W. Wong, "Genetic and genetic/simulated-annealing approaches to economic dispatch," *IEE Proceedings: Generation, Transmission and Distribution*, vol. 141, no. 5, pp. 507–513, 1994, doi: 10.1049/ip-gtd:19941354.

[8] D. Singh and J. S. Dhillon, "Ameliorated grey wolf optimization for economic load dispatch problem," *Energy*, vol. 169, pp. 398–419, Feb. 2019, doi: 10.1016/j.energy.2018.11.034.

[9] F. Mohammadi and H. Abdi, "A modified crow search algorithm (MCSA) for solving economic load dispatch problem," *Applied Soft Computing Journal*, vol. 71, pp. 51–65, Oct. 2018, doi: 10.1016/j.asoc.2018.06.040.

[10] A. Srivastava and D. K. Das, "A New Aggrandized Class Topper Optimization Algorithm to Solve Economic Load Dispatch Problem in a Power System," *IEEE Transactions on Cybernetics*, vol. 52, no. 6, pp. 4187–4197, Jun. 2022, doi: 10.1109/TCYB.2020.3024607.

[11] R. M. Rizk-Allah, R. A. El-Sehiemy, and G. G. Wang, "A novel parallel hurricane optimization algorithm for secure emission/economic load dispatch solution," *Applied Soft Computing Journal*, vol. 63, pp. 206–222, Feb. 2018, doi: 10.1016/j.asoc.2017.12.002.

[12] S. Deb, E. H. Houssein, M. Said, and Di. S. Abdelminaam, "Performance of Turbulent Flow of Water Optimization on Economic Load Dispatch Problem," *IEEE Access*, vol. 9, pp. 77882–77893, 2021, doi: 10.1109/ACCESS.2021.3083531.

[13] M. Ghasemi, S. Ghavidel, J. Aghaei, E. Akbari, and L. Li, "CFA optimizer: A new and powerful algorithm inspired by Franklin's and Coulomb's laws theory for solving the economic load dispatch problems," *International Transactions on Electrical Energy Systems*, vol. 28, no. 5, p. e2536, May 2018, doi: 10.1002/etep.2536.

[14] M. A. Al-Betar, M. A. Awadallah, R. A. Zitar, and K. Assaleh, "Economic load dispatch using memetic sine cosine algorithm," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 9, pp. 11685–11713, Sep. 2023, doi: 10.1007/s12652-022-03731-1.

[15] F. Tariq, S. Alelyani, G. Abbas, A. Qahmash, and M. R. Hussain, "Solving renewables-integrated economic load dispatch problem by variant of metaheuristic bat-inspired algorithm," *Energies*, vol. 13, no. 23, p. 6225, Nov. 2020, doi: 10.3390/en13236225.

[16] A. Srivastava and S. Singh, "Implementation of ant colony optimization in economic load dispatch problem," in *2020 7th International Conference on Signal Processing and Integrated Networks, SPIN 2020*, IEEE, Feb. 2020, pp. 1018–1024, doi: 10.1109/SPIN48934.2020.9071407.

[17] M. S. Braik, M. A. Awadallah, M. A. Al-Betar, A. I. Hammouri, and R. A. Zitar, "A non-convex economic load dispatch problem using chameleon swarm algorithm with roulette wheel and Levy flight methods," *Applied Intelligence*, vol. 53, no. 14, pp. 17508–17547, Jul. 2023, doi: 10.1007/s10489-022-04363-w.

[18] M. S. Alkoffash, M. A. Awadallah, M. Alweshah, R. A. Zitar, K. Assaleh, and M. A. Al-Betar, "A Non-convex Economic Load Dispatch Using Hybrid Salp Swarm Algorithm," *Arabian Journal for Science and Engineering*, vol. 46, no. 9, pp. 8721–8740, Sep. 2021, doi: 10.1007/s13369-021-05646-z.

[19] M. A. Al-Betar *et al.*, "A hybrid Harris Hawks optimizer for economic load dispatch problems," *Alexandria Engineering Journal*, vol. 64, pp. 365–389, Feb. 2023, doi: 10.1016/j.aej.2022.09.010.

[20] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 67–82, Apr. 1997, doi: 10.1109/4235.585893.

[21] N. Chopra and M. Mohsin 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.

[22] M. Pandit, L. Srivastava, M. Sharma, H. M. Dubey, and B. K. Panigrahi, "Large-scale multi-zone optimal power dispatch using hybrid hierarchical evolution technique," *The Journal of Engineering*, vol. 2014, no. 3, pp. 71–80, Mar. 2014, doi: 10.1049/joe.2013.0262.

[23] D. B. Das and C. Patvardhan, "Solution of Economic Load Dispatch using real coded Hybrid Stochastic Search," *International Journal of Electrical Power and Energy Systems*, vol. 21, no. 3, pp. 165–170, Mar. 1999, doi: 10.1016/s0142-0615(98)00036-2.

[24] S. Khamsawang, C. Boonseng, and S. Pothiya, "Solving the economic dispatch problem with tabu search algorithm," in *Proceedings of the IEEE International Conference on Industrial Technology*, IEEE, 2002, pp. 274–278, doi: 10.1109/ICIT.2002.1189906.

[25] T. A. A. Victoire and A. E. Jeyakumar, "Hybrid PSO-SQP for economic dispatch with valve-point effect," *Electric Power Systems Research*, vol. 71, no. 1, pp. 51–59, Sep. 2004, doi: 10.1016/j.epsr.2003.12.017.

[26] C. E. Lin and G. L. Viviani, "Hierarchical Economic Dispatch for Piecewise Quadratic Cost Functions," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-103, no. 6, pp. 1170–1175, Jun. 1984, doi: 10.1109/TPAS.1984.318445.

[27] J. H. Park, Y. S. Kim, I. K. Eom, and K. Y. Lee, "Economic load dispatch for piecewise quadratic cost function using hopfield neural network," *IEEE Transactions on Power Systems*, vol. 8, no. 3, pp. 1030–1038, 1993, doi: 10.1109/59.260897.

[28] S. Baskar, P. Subbaraj, and M. V. C. Rao, "Hybrid real coded genetic algorithm solution to economic dispatch problem," *Computers and Electrical Engineering*, vol. 29, no. 3, pp. 407–419, May 2003, doi: 10.1016/S0045-7906(01)00039-8.

[29] N. Amjady and H. Nasiri-Rad, "Economic dispatch using an efficient real-coded genetic algorithm," *IET Generation, Transmission and Distribution*, vol. 3, no. 3, pp. 266–278, Mar. 2009, doi: 10.1049/iet-gtd:20080469.

[30] C. L. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels," *IEEE Transactions on Power Systems*, vol. 20, no. 4, pp. 1690–1699, Nov. 2005, doi: 10.1109/TPWRS.2005.857924.

[31] M. Modiri-Delshad, S. H. A. Kaboli, E. Taslimi-Renani, and N. A. Rahim, "Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options," *Energy*, vol. 116, pp. 637–649, Dec. 2016, doi: 10.1016/j.energy.2016.09.140.

[32] A. K. Barisal and R. C. Prusty, "Large scale economic dispatch of power systems using oppositional invasive weed optimization," *Applied Soft Computing Journal*, vol. 29, pp. 122–137, Apr. 2015, doi: 10.1016/j.asoc.2014.12.014.

[33] I. Ciornei and E. Kyriakides, "A GA-API solution for the economic dispatch of generation in power system operation," *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 233–242, Feb. 2012, doi: 10.1109/TPWRS.2011.2168833.

[34] P. K. Roy and S. Bhui, "Multi-objective quasi-oppositional teaching learning based optimization for economic emission load dispatch problem," *International Journal of Electrical Power and Energy Systems*, vol. 53, pp. 937–948, Dec. 2013, doi: 10.1016/j.ijepes.2013.06.015.

[35] K. Bhattacharjee, A. Bhattacharya, and S. H. N. Dey, "Oppositional Real Coded Chemical Reaction Optimization for different economic dispatch problems," *International Journal of Electrical Power and Energy Systems*, vol. 55, pp. 378–391, Feb. 2014, doi: 10.1016/j.ijepes.2013.09.033.

[36] A. S. Reddy and K. Vaisakh, "Shuffled differential evolution for large scale economic dispatch," *Electric Power Systems Research*, vol. 96, pp. 237–245, Mar. 2013, doi: 10.1016/j.epsr.2012.11.010.

[37] B. Mandal, P. K. Roy, and S. Mandal, "Economic load dispatch using krill herd algorithm," *International Journal of Electrical Power and Energy Systems*, vol. 57, pp. 1–10, May 2014, doi: 10.1016/j.ijepes.2013.11.016.

[38] J. B. Park, Y. W. Jeong, J. R. Shin, and K. Y. Lee, "An improved particle swarm optimization for nonconvex economic dispatch problems," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 156–166, Feb. 2010, doi: 10.1109/TPWRS.2009.2030293.

[39] M. Pradhan, P. K. Roy, and T. Pal, "Grey wolf optimization applied to economic load dispatch problems," *International Journal

of Electrical Power and Energy Systems*, vol. 83, pp. 325–334, Dec. 2016, doi: 10.1016/j.ijepes.2016.04.034.
[40] M. Kumar and J. S. Dhillon, "Hybrid artificial algae algorithm for economic load dispatch," *Applied Soft Computing Journal*, vol. 71, pp. 89–109, Oct. 2018, doi: 10.1016/j.asoc.2018.06.035.
[41] S. M. A. Bulbul, M. Pradhan, P. K. Roy, and T. Pal, "Opposition-based krill herd algorithm applied to economic load dispatch problem," *Ain Shams Engineering Journal*, vol. 9, no. 3, pp. 423–440, Sep. 2018, doi: 10.1016/j.asej.2016.02.003.

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