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Solving the Multi-objective Economic-Emission Load Dispatch Optimization Problem Using Hybrid GWO-PSO Algorithm

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Abstract: Currently, in electrical power systems, economic load dispatch (ELD) combined with reducing the emission of units is a vital issue for allocating power generation through dispatch strategies to minimize fuel costs while also considering environmental issues. Thus, two objective functions, fuel cost and emission level are employed simultaneously in order to meet the requirements of the ELD for power generation. The economic dispatch problem has been solved using a variety of metaheuristic techniques. In this study, the problem has been solved using the modified particle swarm algorithm (MPSO) and hybrid grey wolf-particle swarm optimization (GWO-PSO). The Grey Wolf optimization, based on social and hunting behaviors is applied to achieve the best possible results. This algorithm requires no information about the gradient of the objective function during the optimization search. The work offers efficient cost values with a shorter execution time while meeting all the various constraints of the ELD problem. The three tunable parameters of the original PSO are dynamically adjusted. The GWO algorithm, which has two adjustable parameters, is also used in this study with hybrid PSO. Simulation results for the standard IEEE 30-bus 6-generator test system and Iraqi power grid have been provided in order to demonstrate the effectiveness and practicality of the suggested method. The outcome results are contrasted with results in the latest literature. The obtained results for the ELD problem using GWO-PSO compared with ABC algorithm indicate a promising performance in terms of minimizing fuel cost, emissions effects and power losses which are reduced to 2093.2 $/h, 22.4423 kg/h and 22.7672 MW respectively for the first case system with 700 MW load demand, satisfying all the constraints within their limits. As well as, for the second scenario with 900 MW, compared with NHPSO indicates a reduction in fuel cost which is 3664.25 $/h and when compared with SOS method obtained a promising reduction in terms of minimizing emissions effects and power losses which are reduced to 38.9566 kg/h and 34.1195 MW respectively. Moreover, the results demonstrate that the suggested algorithm offers a reliable, good, and efficient solution to the ELD problem.

Keywords: Economic load dispatch, Grey wolf-particle swarm optimization, Fuel cost, Emission level.

1. Introduction

Power systems plants are vastly connected to transfer power from generators to loads in an economical and reliable way. One of the main targets of these systems is to meet load requirements while reducing total operating costs through the scheduling of different types of generation units with minimum cost [1-2]. Basically, the main source of generation units is based on the fuel consumed in the centralized generation stations, e.g., fossil fuels that produce greenhouse gases (CO2, NOx, SOx, etc.) in the atmosphere [3]. An Economic Load Dispatch (ELD) can be utilized to express a cost minimization problem in power system operation, aiming to obtain the lowest total fuel cost for generating units. In general, the main goal of ELD is to schedule power generation to meet load demand within operational constraints [4, 5].

In this context, to be motivated for a clean and protection of the environment, it is possible to dispatch electric power at minimum possible price with minimum levels of pollution by reducing the emission of units. So, the single objective of ELD for obtaining a minimum total fuel cost can no longer be considered alone. Previously, the ELD problem has been studied and many researchers have presented and proposed various mathematical algorithms to formulate and solve the ELD issue. Algorithms such as the lambda iteration algorithm [6], the dynamics programming method [7], and linear programming were used in [8-10].

However, these algorithms showed a vast shortcoming in solving the problem of ELD because extensive computational requirements were needed to tackle the problem, and they failed in the local area solution when taking into consideration more system constraints. Thus, to overcome these limitations, some optimization techniques have been implemented for the ELD to achieve reasonable and satisfactory results. In this context, the latest metaheuristics optimization algorithms such as simulated annealing (SA) [11], the genetic algorithm (GA) [12], particle swarm optimization (PSO) [13-14], ant colony optimization (ACO) [15], Artificail dance bee colony [1, 16], firefly algorithm [17], bacterial foraging algorithm (BFA) [18], a Symbiotic organisms search algorithm (SOS) [5] and swarm space hopping algorithm (SSHA) [19] have been proposed to obtain an optimizing solution for generation units scheduling in an acceptable way.

Comprehensive reviews of metaheuristic optimization methods for solving economic dispatch ED problems have been proposed by some researchers. According to the studies, PSO and ACO approaches are more often used to solve ELD problems because of their ease of use, simplicity, quick rate of convergence, and increased flexibility in finding the best global points.

Nevertheless, all evolutionary strategies needed to make an appropriate balance between local and global search. Convergence time, tuning optimal parameters, premature convergence, and others have received little research attention. In [20-21], authors have employed different approaches to address these problems, including hybridization of algorithms and modified evolutionary techniques. The PSO technique has been used by [22-23] to address economic load dispatch as well as environmental emission issues. To prevent premature convergence, the authors have adjusted the PSO technique for the overall search. However, nonconvex, multimodal, and discontinuous optimization problems that are unsolvable with conventional methods are increasingly being addressed by the proposed techniques. In order to solve the ED problem, [20] used the Exchange Market Algorithm (EMA) in combination with the PSO approach. [24] employed ant colony optimization (ACO), one of the newest metaheuristic approaches for optimization methods, to solve the ELD. The [25] adapted and applied an efficient variant, called Dance Bee Colony with Dynamic Step Size, to solve the multi-objective environment economic dispatch problem while taking into account generator constraints. The effectiveness and resilience of the suggested technique were confirmed on numerous real- test systems, taking into account the impact of valve points and overall active power losses.

However, the main drawbacks of these metaheuristic approaches still to be their extreme sensitivity to the initial value of the control parameters or for specific points like trapping into local optima and premature convergence. As a result, it is challenging to find workable and acceptable solutions for nonlinear optimization issues with multi-objective functions and constraints.

The main goal of this study is to utilize and apply grey wolf-particle optimization GWO and modified PSO to provide an accurate and workable solution for the ED issue. Falling with local optima and possibly not providing the optimal solution are the main drawbacks of classical approaches. Also, while the practical power system is more complicated, all classical methods operate under the premise that the objective function they must handle is continuous and differentiable. Modern intelligent methods have the benefit of being adaptable when managing qualitative constraints. However, their primary disadvantage remains the exponential growth in computational time with increasing problem size and the unpredictable time to convergence (although convergences are assured).

To deal with these drawbacks, metaheuristic techniques (PSO and GWO) have been cooperated. Some steps of the algorithms are adjusted or new points are added, to improve the algorithms performance in terms of convergence speed, accuracy, and robustness. The main benefit of the proposed GWO-PSO algorithm for dealing with the ELD issue is its capacity to identify superior solutions in contrast to the original algorithms. Where, the PSO algorithm is incorporated into the GWO algorithm in order to improve population diversity and prevent premature convergence. This combination of the two methods is an enhanced method for choosing and updating personal and global best positions for the GWO algorithm with automatic weight adjustment. Additionally, the research compares the outcomes achieved through the modified PSO and GWO-PSO.

The remaining parts of the article are organized as follows: Section 2 describes the mathematical problem formulation with two objective functions: fuel cost and emission effect. Section 3 presents details of the proposed hybrid optimization algorithm. The outcome simulation results and comparison with other results are given in Section 4. Finally, the conclusions are stated in the last section.

2. Problem formulation

The conventional approach to solving the classical economic dispatch problem has been to minimize fuel costs. However, a solution based solely on the reduction of the economic cost is no longer acceptable and must take emissions minimization into consideration due to growing public concerns about the environmental impact of fossil fuel-fuelled electric power plants. In this instance, the economic dispatch problem is restated while accounting for fuel prices and emissions. This leads to the treatment of the problem as a multi-objective optimization assignment with competing goals [1].

A multi-objective making decision (MOMD) is the challenge of determining a vector of decision variables that maximizes or minimizes a vector function whose elements represent the objective functions while satisfying constraints. A MOMD issue is expressed mathematically as the optimization of k distinct objective functions, most of which are at conflict with one another, under the restrictions of the system [26, 27].

$$\text{Minimize} \quad f(x) = \left(f_1(x), f_2(x), \ldots \ldots f_k(x)\right) \quad (1)$$

Subject to $x = (x_1, x_2, \ldots \ldots x_n)$

$$G_j(x) \geq 0 \qquad j = 1,2, \ldots, J$$

where: $f_{1,} f_2, f_3 \ldots \ldots f_k$ indicate the objective functions that need to be minimized.

x is a decision variable and known as the decision space or search space which arrange in an aray vector

Gj , j =1,2,...,J are inequality constraints. Any two solutions, x_1 and x_2, for a problem with more than one objective function, let's say, (f, $j = 1,2, \ldots \ldots J$) can have one of two outcomes: either one dominates the other or the other non-dominates. One solution x1 is said to dominate the other x2 if both of the following conditions hold true:

1.for every $j = 1,2, \ldots J$ objectives, $f_{j(x_1)} < f_{j(x_2)}$ or the solution x1 is not less than to x2 in all objectives.

2. for at least one of $j \in 1,2, \ldots \ldots k$, the $f_{j(x_1)} < f_{j(x_2)}$, or the solution x1 is strictly superior to x2 in at least one objective.

The formulation of the general multi-objective function (MOF) and its conversion into a single objective using the weight (w_i) sum method is given by:

$$\text{Minimize (F)} = \text{Min}(w_1 * f_1 + w_2 * f_2 + w_3 * f_3 + \cdots) \quad (2)$$

where: $\sum_{i=1}^{n} w_i = 1$

In this study, fuel cost and emission objectives are the two competing functions that make up the economic emission load dispatch problem. It is possible to formulate the issue is as follows:

- **Fuel Cost Objective**

Basically, the economic dispatch problem is represented by determining the best mix of power generation to minimize overall fuel costs while meeting all required demand, which can mathematically be represented as follows [26]:

$$F_c = \sum_{i=1}^{N} (a_i + b_i * P_{Gi} + c_i * P_{Gi}^2) \quad (3)$$

where: -
F_c: total fuel cost ($/hr).
a_i, b_i, c_i: fuel cost coefficients of generator.
P_{Gi}: power output by generator.
n: number of generators

- **Emission Objective**

The standard ED problem can be solved by scheduling the power generation units at the lowest possible fuel cost, however, the amount of emissions released during the burning of fossil fuels is not taken into account. The sum of a quadratic function is used to represent the amount of emissions, such as SO_2 or NO_x as a function of generator output as bellows:

$$F_e = \sum_{i=1}^{N} (C_i + B_i * P_{Gi} + A_i * P_{Gi}^2) \quad (4)$$

where: F_e, total emissions. A_i, B_i and C_i are emission coefficients of the G_{ith} generating unit. [28]

- **Combined Economic Emission Dispatch**

The environmental and economic dispatches that separately constitute distinct single problems can be combined to form a multi-objective problem known as combined economic Emission Dispatch (CEED). At this point, it is necessary to transform this multi-objective problem into a single-objective form in order to obtain optimization solution. One way to accomplish the conversion process is by applying the price penalty factor. Nonetheless, the formulation of the single-objective CEED can be demonstrated by following equations [9, 23].

$$min\ F_T = \sum_{i=1}^{N}((a_i + b_i * P_{Gi} + c_i * P_{Gi}^2) + h_i(C_i + B_i * P_{Gi} + A_i * P_{Gi}^2))(\$/h) \quad (5)$$

The following is the formula forh_i, which denoted for the price penalty factor

$$h_i = \frac{a_i+b_i*P_{Gimax}+c_i*P_{Gimax}^2}{C_i+B_i*P_{Gi}max+A_i*P_{Gimax}^2} \quad (6)$$

where: $P_{iG\ max}$ is the ith unit's maximum power generation.

- **Constraints**

It is necessary to satisfy three constraints:

1. **Power balance**

The entire power produced must meet the entire load demand in addition to the transmission losses demonstrated as [22, 29]:

$$\sum_{i=1}^{n} P_{Gi} = P_d + P_{loss} \quad (7)$$

where:
P_d: total load demand
P_{loss}: transmission losses can be formulated as:

$$P_{loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j \quad (8)$$

where: *Bij are* the elements of loss coefficient matrix *B*.

2. **Generator constraint**

Each generator's power output *P* is limited by the following minimum and maximum limits:

$$P_{Gi}^{min} < P_{Gi} < P_{Gi}^{Max} \quad (9)$$

3. **Security constraints**

For safe operation, the transmission line loading is constrained by its maximum limit as follows [24]:

$$S_{Li} < S_{Li}^{Max} \qquad i = 1, \ldots\ldots n_L \quad (10)$$

n: The number of transmission lines.

3. Proposed hybrid optimization algorithm

This section explains the basic ideas behind the particle swarm optimization (PSO) and grey wolf optimizer (GWO) methods, as well as the hybrid GWO-PSO approach that is being suggested, along with the method's flowchart.

Particle swarm algorithm:

The main idea of inspiration for the fundamental judgment was based on social behaviour of organisms, like fish schools and bird flocks [R. Eberhart and J. Kennedy in 1995] [30, 31]. A swarm is a population that is created at random and is made up of individuals known as particles. Each particle within the swarm represents a likely reason for the optimization issue. Every particle changes its position in a D-dimensional search space at a random velocity. Eq. (11) describes the particle ($\boldsymbol{X_i}$) which is the position representation of each individual with an N-dimensional search space [19, 30, 32].

$$\boldsymbol{X_i} = (\boldsymbol{X_{i1}}, \boldsymbol{X_{i2}}, \boldsymbol{X_{i3}} \ldots \boldsymbol{X_{iN}}) \quad (11)$$

Eqs. (12) and (13) are used to update the PSO technique, which finds each partner's position in the crowd for searching the space globally.

$$v_i^{k+1} = \boldsymbol{v_i^k} + \boldsymbol{c_1 r_1}(\boldsymbol{p_i^k} - \boldsymbol{x_i^k}) + \boldsymbol{c_2 r_2}(\boldsymbol{g_{best}} - \boldsymbol{x_i^k}) \quad (12)$$

v_i^k: is the velocity vector of particle
x_i^k: is particle′svector postion
p_i^k: is personal bet postion of particle
g_{best} : is the global best position of particle t is the time of initialization
c1, c2 : are individual and group acceleration coefficients respectively
r1r2: are random values of numbers.

The next positionx_i^{k+1} of the particle is calculated based on the previous particle position x_i^k and its velocity v_i^{k+1}, is as shown in the Eq. (13).

Depending on the particle's previous position x_i^k and its velocity v_i^{k+1}, the next position x_i^{k+1} is determined, as displays in Eq. (13).

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (13)$$

Grey Wolf Optimization technique:

Mirjalili and Lewis [33] suggested GWO technique. Grey wolves are social creatures with a rigid social structure. Within the GWO algorithm's leadership structure, there are four different kinds of grey wolves. The wolves in equation are alpha, delta, beta, and omega. Alpha wolves stand for the best-performing solution in the GWO algorithm. The second and third best options of solution are represented by beta and delta wolves. The finest potential solutions are represented by omega wolves [30, 34].

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Grey wolve's social structure and hunting habits represent as the bases structure of the mathematical modelling of GWO. The hunting strategies employed by grey wolves consist of three primary components as follows:

(1) Following, pursuing, and getting close to the prey.

(2) Challenging, encircling, and irritating the victim until it gives up.

(3) Attacking the prey. The mathematical modelling of the GWO can be based on the following equations:

$$D = \left|C * x_{p(t)} - x(t)\right| \tag{14}$$

$$x(t+1) = x_{p(t)} - A * D \tag{15}$$

where: D is the encircling behaviour of each agent, t is the current iteration, $x_{p(t)}$ is the prey's position vector, x is the location of the grey wolves in vector. A and C are the coefficients for the vectors, the mathematical formulation of the vectors A and C is demonstrated by Eqs. (16) and (17).

$$A = a * (2r_1 - 1) \tag{16}$$

$$C = 2 * r_2 \tag{17}$$

where, as the number of iterations decrease, the number of a decreases linearly from 2 to 0. Uniformly chosen random numbers between [0, 1] are represented by r1 and r2.

Hybrid GWO-PSO approach:

A hybrid low-level co-evolutionary functionality is produced by the hybridization between the GWO and PSO algorithms. The hybrid optimization process reduces performance because it combined the two variants with inferior functionalities. In light of these adjustments, the exploration into PSO is conducted in GWO in order to generate variant strengths that will enhance the mode's benefits [30, 35].

During the hunting task of a grey wolf, beta and delta are supposed to be aware of the potential location of the prey, while alpha is thought to be the best candidate for the task. Consequently, the three good solutions are retained until a particular iteration, at which point other solutions (like omega) are compelled to adjust their locations in the decision space so that they align with the optimal location.

The first three good agent's positions in the search space were used by the proposed Hybrid GWO-PSO. In the search space, inertia constant w governs the grey wolf's exploration and exploitation. Eqs. (18)-(20) are the updated set of controlling equations.

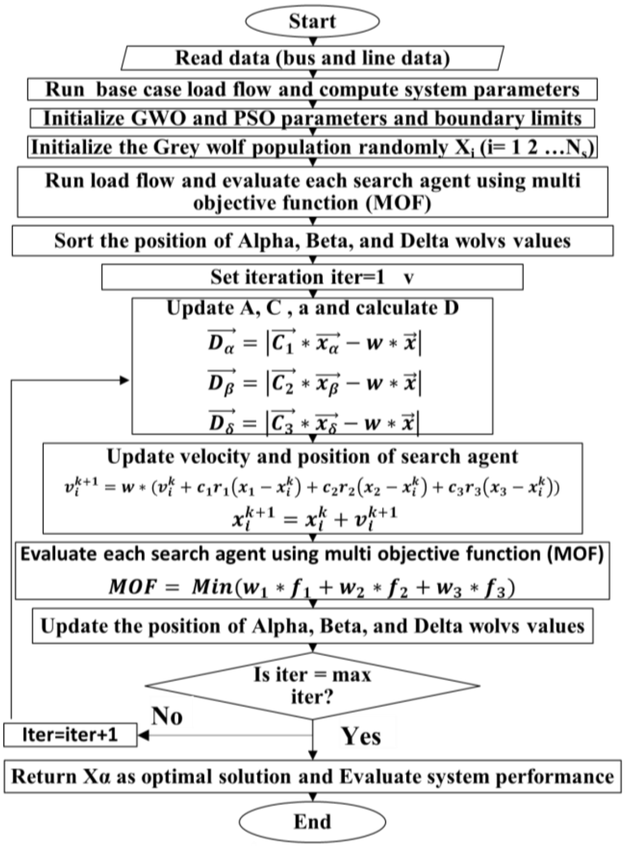

Figure. 1 flowchart of the proposed algorithm GWO-PSO

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} * \overrightarrow{x_\alpha} - w * \vec{x}\right| \tag{18}$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_2} * \overrightarrow{x_\beta} - w * \vec{x}\right| \tag{19}$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_3} * \overrightarrow{x_\delta} - w * \vec{x}\right| \tag{20}$$

where: $\vec{x}$ is the vector position, $\overrightarrow{D_\alpha}$, $\overrightarrow{D_\beta}$, and $\overrightarrow{D_\delta}$ are the three agent positions, C_3 is the positive acceleration constant. Eqs. (21) and (22) propose the velocity and updated equation that can be used to combine the GWO and PSO variants.

$$v_i^{k+1} = w * (v_i^k + c_1r_1\left(x_1 - x_i^k\right) + c_2r_2\left(x_2 - x_i^k\right) + c_3r_3\left(x_3 - x_i^k\right)) \tag{21}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{22}$$

The hybrid GWO-PSO technique was introduced to enhance convergence performance. In order to achieve their optimal strengths, it has combined the capabilities of both approaches and explored PSO with the ability to exploit GWO through the use of GWO-PSO. The proposed hybrid GWO-PSO updates the positions of the first three agents in the search space rather than using the conventional mathematical equations, and the inertia constant (w) controls the grey wolf's exploration and and exploitation. Fig. 1 shows the overall flowchart for applying the GWO-PSO method to solve the combined emission and economic dispatch problem.

4. Simulation results

The effectiveness of PSO and GWO-PSO algorithms has been investigated using two power systems (IEEE 30-bus system and the Iraqi power grid).

To validate the usefulness and resilience of the suggested algorithms, three scenarios with various goal functions (fuel cost and emission level) are simulated separately and simultaneously in order to meet the requirements of the ELD for power generation. Comparisons have been made between the PSO and GWO-PSO algorithms' performances and the overall results have been compared with results from other optimization methods, including the Simulated Annealing Algorithm (SA) [11], Symbiotic organisms search algorithm (SOS) [5], multi-objective adaptive real coded quantum-inspired evolutionary algorithm (MO-ARQIEA) [2], artificial bee colony algorithm (ABC) [16], chameleon swarm algorithm (CSA) [23] and New Heuristic particle swarm (NHPSO) [23].

- ***Case study I***

In this case, a standard IEEE 30-bus, 6-generator test system, as shown in Fig. 2 [1], has been tested based on the PSO and GWO-PSO search methods. The accuracy and correctness of these methods are assessed by simulating multiple generator limits and the system's overall operating cost. Table 1 displays the cost coefficient, emission coefficient, and generating limits of the six-generator test system. Tables 2 ,3 and 4 presents the results obtained for the load demand (700 MW), take into consideration the minimum fuel cost, best emission effect and multi-objective function for the ELD problem respectively, and they are compared with results from other optimization methods. Table 2 presents the optimal fuel cost (for 700 MW) obtained from the MPSO and GWO-PSO approaches, which contrasted with other algorithms such as SA [11], SOS [5], and MO-ARQIEA [2].

According to Table 2, the GWO-PSO algorithm offers a lower fuel cost value with 1423.468 \$/h than the MO-ARQIEA [2] approach, as well as a fewer value of emission with 31.259 kg/h than the MO-ARQIEA approach, as indicated in Table 3.

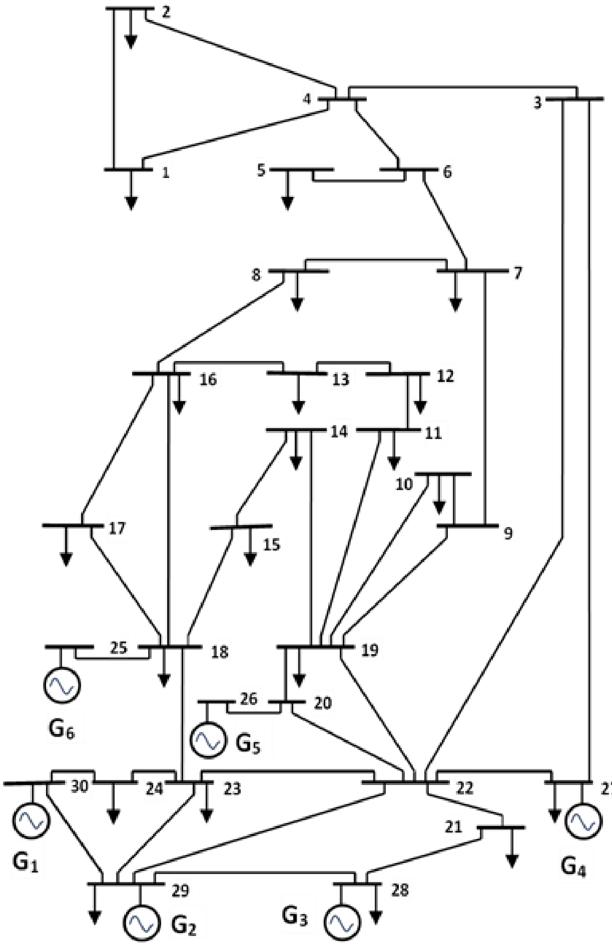

Figure. 2 30-bus system configuration [1]

The outcome results considering the best fitness function solution, including cost and emission effects simultaneously, for the CELD problem with a loading demand of 700 MW are shown in Table 4. The results compared also with other optimization techniques. The obtained results for the ELD problem using GWO-PSO compared with the ABC [16] algorithm indicate a promising performance in terms of minimizing fuel cost, emissions effects, and power losses, which are reduced to 2093.2 \$/h, 22.4423 kg/h, and 22.7672 MW, respectively, satisfying all the constraints within their limits.

For C_1 and C_2, the starting values are 1.8 and 0.2, respectively. After 100 iterations for each algorithm, the results are finalized. It is obvious from the outcomes that all constraints are satisfied within their limits. The outcomes illustrated in Table 2 demonstrate the superiority of the GWO-PSO technique over the PSO and SA techniques. Compared to PSO and SA, GWO-PSO has lower generation costs and less power losses.

Table 5 and 6 displays the best fuel cost and emission level results for the 900-MW loading condition respectively as determined by the proposed

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Table 1. Generator capacity limits, fuel cost and emission coefficients for IEEE 30-bus test system

Unit	P_i^{min} (MW)	P_i^{Max} (MW)	a_i ($/MW^2)	b_i ($/MW)	C_i ($)	A_i ($/MW^2)	B_i ($/MW)	C_i ($)
1	10	125	0.15240	38.53973	756.79886	0.00419	0.32767	13.85932
2	10	160	0.10587	46.15916	451.32513	0.00419	0.32767	13.85932
3	35	225	0.02803	40.39655	1049.9977	0.00683	-0.54551	40.26690
4	35	210	0.03546	38.30553	1243.5311	0.00683	-0.54551	40.26690
5	130	325	0.02111	36.32782	1658.5596	0.00461	-0.51116	42.89553
6	125	315	0.01799	38.27041	1356.6592	0.00461	-0.51116	42.89553

Table 2. Best fuel cost for 6-generator system (PD = 700 MW)

PD (power demand)	700 (MW)				
Method	**SA [11]**	**SOS [5]**	**MO-ARQIEA [2]**	**MPSO**	**GWO-PSO**
P1 (MW)	76.0897	73.9386	74.0686	29.7427	31.7364
P2 (MW)	49.0586	50.3639	50.7264	20.7243	21.5309
P3 (MW)	45.3525	45.8163	46.4357	169.6988	222.9965
P4 (MW)	102.7347	104.023	103.7366	108.8165	171.1479
P5 (MW)	266.3914	270.8317	268.9035	223.5929	130.7094
P6 (MW)	191.3422	189.6709	190.6674	162.7953	133.6086
Fuel Cost ($/h)	38207.591	38364.4273	38359.468	37477	36936
Emissions (Kg/h)	532.6970	543.4094	541.0329	568.2978	496.8566
Power losses (MW)	30.9692	34.6444	34.5382	15.3706	11. 7297
Total Capacity (MW)	730.9692	734.6444	734.5383	715.3706	711.7297

Table 3. Best emission effects for 6-generator system (PD = 700 MW)

PD (power demand)	**700 (MW)**				
Method	**SA [11]**	**SOS[5]**	**MO-ARQIEA [2]**	**MPSO**	**GWO-PSO**
P1 (MW)	105.329	104.3456	103.645	83.3517	79.1520
P2 (MW)	76.408	77.8036	77.4020	89.2773	81.2419
P3 (MW)	92.920	95.5137	93.5958	114.2754	120.2149
P4 (MW)	109.834	110.8788	111.4225	117.7737	113.9356
P5 (MW)	183.192	185.6437	186.0831	171.6605	162.9585
P6 (MW)	170.013	169.8192	169.8602	141.2178	160.2172
Fuel Cost ($/h)	39433.477	39717.4206	39601.7751	38360	38131
Emissions (Kg/h)	462.716	468.5260	466.9628	438.3067	435.7038
Power losses (MW)	37.699	44.0046	42.0087	17.7201	17.5619
Total Capacity (MW)	737.699	744.0046	742.0088	717.5619	717.7201

Table 4. Best fitness function including cost and emission effect for 6-generator system (PD = 700 MW)

PD (power demand)	**700 (MW)**				
Method	**SA [11]**	**SOS[5]**	**ABC[16]**	**MPSO**	**GWO-PSO**
P1 (MW)	84.150	93.0456	94.0712	51.7093	31.3575
P2 (MW)	55.655	66.7444	67.2152	160	20
P3 (MW)	66.005	83.2719	83.1354	98.9206	169.5599
P4 (MW)	107.266	110.7896	110.9599	210	111.6394
P5 (MW)	230.931	205.8610	204.000	138.4984	207.9441
P6 (MW)	187.647	178.7032	179.0000	64.0621	175.1105
Fuel Cost ($/h)	38371.892	38999.351	39028	37685	36934.80
Emissions (Kg/h)	476.537	472.6861	472.1017	468.0695	449.6594
Power losses (MW)	31.656	38.4157	38.3789	23. 1904	15.6117
Total Capacity (MW)	731.656	738.4157	738.3816	723.1904	715.6117

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Table 5. Best fuel cost for 6-generator system (PD = 900 MW)

PD (power demand)	**900 (MW)**				
Method	**SA [11]**	**SOS [5]**	**ABC[16]**	**MPSO**	**GWO-PSO**
P1 (MW)	103.4811	101.5834	125.000	67.5726	34.2326
P2 (MW)	70.1005	72.5721	96.000	36.6160	156.4111
P3 (MW)	60.6818	62.0601	104.1139	225	181.0369
P4 (MW)	139.5618	144.1300	138.000	161.1207	141.1416
P5 (MW)	325.0000	325.0000	273.0068	206.3594	213.2466
P6 (MW)	251.7912	252.1620	225.6305	228.1953	197.7777
Fuel Cost ($/h)	49297.9331	49615.0583	50637	49149	47333
Emissions (Kg/h)	845.6922	857.1338	765.9759	854.1682	727.9466
Power losses (MW)	50.6162	57.4918	61.8483	24.8640	23. 8458
Total Capacity (MW)	950.662	957.4918	961.7512	924.8640	923.8458

Table 6. Best emission effects for 6-generator system (PD = 900 MW)

PD (power demand)	**900 (MW)**			
Method	**SA [11]**	**SOS[5]**	**MPSO**	**GWO-PSO**
P1 (MW)	124.989	125.000	118.1716	115.0131
P2 (MW)	88.322	113.1067	122.7802	127.5254
P3 (MW)	123.954	111.2052	154.1724	138.2461
P4 (MW)	134.833	143.2346	141.8157	160.4175
P5 (MW)	274.647	253.6414	201.1920	206.1876
P6 (MW)	215.480	223.4585	195.1039	171.8401
Fuel Cost ($/h)	50517.633	51368.8812	50059	49817
Emissions (Kg/h)	751.274	759.8674	693.2987	692.4293
Power losses (MW)	62.226	69.6737	33.2358	29. 2298
Total Capacity (MW)	962.226	969.6464	933.2358	929.2298

Table 7. Best fitness function including cost and emission effect for 6-generator system (PD = 900 MW)

PD (power demand)	**900 (MW)**					
Method	**SA [11]**	**SOS [5]**	**CSA [23]**	**NHPSO [23]**	**MPSO**	**GWO-PSO**
P1 (MW)	115.276	125.000	92.315	79.4000	42.9469	42.0228
P2 (MW)	78.809	96.0322	98.3707	99.98	159.4	44.4486
P3 (MW)	81.388	100.4100	150.1997	154.4	224.5	223.301
P4 (MW)	137.345	141.5092	148.5549	145.84	209.3	161.1305
P5 (MW)	298.677	270.6763	220.4051	223.26	195.4601	241.7809
P6 (MW)	238.178	227.6978	218.115	224.14	98.1206	214.5229
Fuel Cost ($/h)	49553.835	50621.817	48108	47889.45	44625	44225.2
Emissions (Kg/h)	772.456	766.257	693.791	669.321	736.6	727.3004
Power losses (MW)	49.676	61.3255	28.004	27.26	29.7377	27.2060
Total Capacity (MW)	949.676	961.3255	928.004	927.26	929.7377	927.2060

algorithms. These findings included comparisons with other techniques like SA [11], SOS [5], and ABC [16]. The Tables show a promising performance in terms of minimizing fuel cost and emissions effects, which are reduced to 1964.9331$/h and 58.85 Kg/h respectively Compared to the values found by SA [11]. While results for best multi-objective function for 900-MW load demand obtained from suggested methods are illustrated in Table 7 and compared with the SA, SOS, ACB, and NHPSO algorithms. For this scenario, compared with NHPSO [23] indicates a reduction in fuel cost which is 3664.25 $/h and when compared with SOS [5] method obtained a promising reduction in terms of minimizing emissions effects

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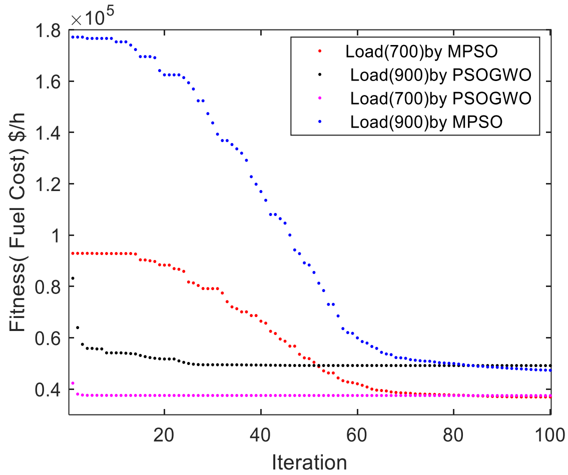

Figure. 3 The convergence characteristic of Fuel cost objective function with load demand (700 MW and 900 MW)

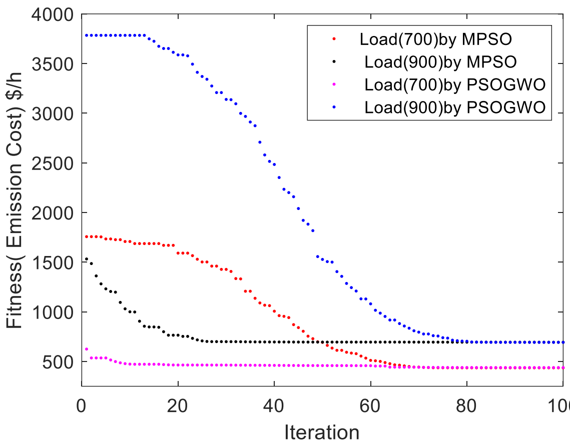

Figure. 4 The convergence characteristic of Emission objective function with load demand (700 MW and 900 MW)

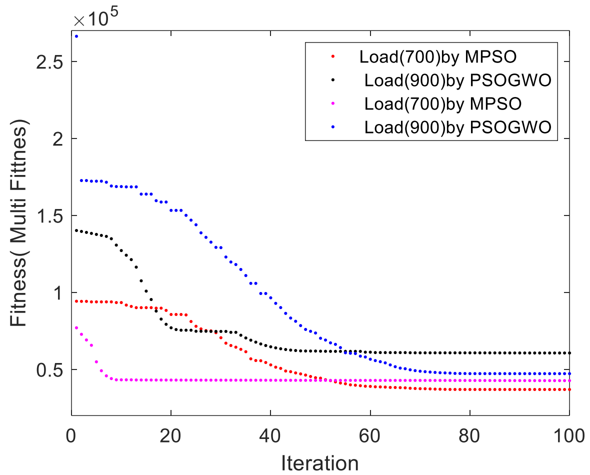

Figure. 5 The convergence characteristic of multi-objective function with load demand (700 MW and 900 MW)

and power losses which are reduced to 38.9566 kg/h and 34.1195 MW respectively. However, from Table 6, the emission effects of the GWO-PSO method are slightly higher than the emission results obtained from MPSO in the case of 900 MW of power demand, conversely, the losses are less. Overall, the results demonstrate that the suggested algorithm offers a reliable, good, and efficient solution to the ELD problem.

Fig. 3 clearly displays the convergence curves that were obtained by applying MPSO and GWO-PSO to the 30-bus test system in term of operating cost minimization objective function with load demand (700 MW and 900 MW). After all iterations, GWO exhibits better results, although the rate of decrease in cost value is initially seen to be significant and then slows down. Also, from the all tables, it is evident that the suggested GWO-PSO algorithm outperforms the other algorithms in terms of fuel cost, emission effects and fitness function including both the operating cost and emission effect.

Figs. (4) and (5) show the convergence curves that were obtained by applying PSO and GWO-PSO to the 30-bus test system in terms of minimization of the emission effect and multioctave fitness function respectively. The GWO-PSO approach converges faster than the PSO approach. Overall, it is determined that the GWO-PSO approach is superior in terms of operating cost, emission effects, power loss, execution time, and higher efficiency, keeping in mind all the constraints so that the power mismatch and violation are zero.

- ***Case study II***

The network being considered in this case is the 400 kV Iraqi super grid (ISG). The network consists of 24 bus bars connected to 14 transmission lines. The system includes twelve generation units that are dispersed throughout the system, two of them are gas units, and the other are a thermal unit. The system's data are taken from [36].

Three scenarios with two objective functions (fuel cost and emission level) are simulated separately and simultaneously, in order to demonstrate the efficacy of the suggested method. The load demand of the system is 5297.855 MW. The BAJG station is considered a slack bus in the load flow calculation. Table 8 displays the comparative simulation results of the suggested algorithm. As shown in Table (8), the set of optimal solutions for the generation units achieved by the suggested algorithms clarifies the relevance between the overall fuel cost of the units and the emissions effects with total power losses, which have been minimized both separately and simultaneously. For total fuel cost,

Table 8. Best fitness function including cost and emission effect for Iraqi Super Grid

fitness function	**fitness function (Cost)**		**fitness function (Emission)**		**fitness function (cost and emission)**	
Method / Generation units	**MPSO**	**GWO-PSO**	**MPSO**	**GWO-PSO**	**MPSO**	**GWO-PSO**
slack BAJG(MW)	**567.3852**	**351.6170**	**723.2543**	**601.2627**	**751.7259**	**467.8342**
MMDH (MW)	**649.7743**	**512.3344**	**730.4401**	**613.5307**	**753.0076**	**544.7537**
BAJP (MW)	**359.8621**	**468.3145**	**610.5455**	**617.0647**	**422.0707**	**514.7259**
MUSP (MW)	**826.9856**	**520.2028**	**792.3000**	**654.8963**	**891.3627**	**475.4606**
KRK4 (MW)	**372.6591**	**462.3147**	**172.3276**	**421.7645**	**313.3868**	**504.8008**
MUSG (MW)	**499.8415**	**544.9438**	**409.5074**	**535.0224**	**385.6943**	**464.9053**
HDTH (MW)	**556.1816**	**526.7626**	**124.7605**	**91.1126**	**184.8548**	**532.8426**
QDSG (MW)	**555.5635**	**478.1175**	**770.0887**	**690.1820**	**801.6876**	**547.7876**
KAZG (MW)	**389.6243**	**505.2566**	**242.2371**	**332.3823**	**260.1118**	**402.7999**
HRTP (MW)	**329.7803**	**462.2877**	**620.5110**	**536.6770**	**335.5176**	**326.2302**
NSRP (MW)	**678**	**540.4509**	**421**	**655.8832**	**394**	**429**
AMN4 (MW)	**167**	**543.4255**	**171**	**150.2763**	**159**	**187**
Fuel Cost ($/h)	**6.9094e+04**	**6.0351e+04**	**7.9044e+04**	**7.0801e+04**	**7.9787 e+04**	**6.1812e+04**
Emissions (Kg/h)	**3.9976e+04**	**5.3541e+04**	**2.2318e+04**	**2.0202e+04**	**2.4298 e+04**	**2.6017e+04**
Power losses (MW)	**654.8025**	**618.173**	**490.1172**	**422.1997**	**374.5648**	**317.5648**
Total Capacity (MW)	**5952.6575**	**5916.028**	**5787.9722**	**5720.0547**	**5672.4198**	**5615.4198**

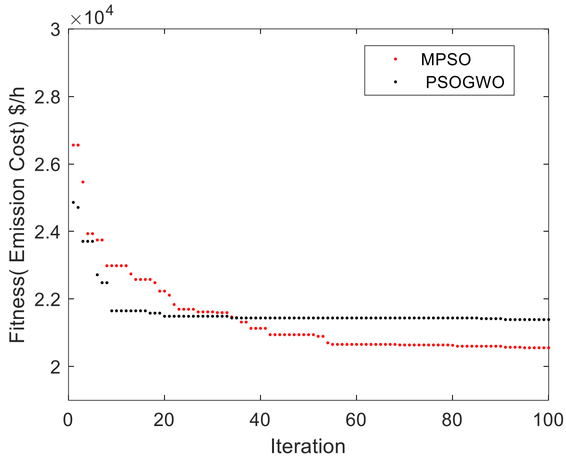

Figure. 6 The convergence characteristic of Emission objective function of Iraqi Grid

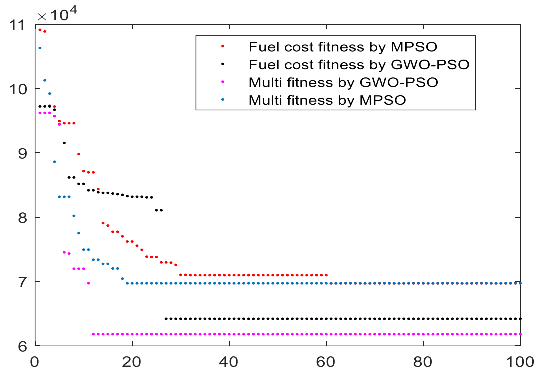

Figure. 7 The convergence characteristic of Fuel cost and Multi objective functions of Iraqi Grid

emissions effects, and real power loss, the best compromise solutions are found by the GWO-PSO algorithm with multi-objective function, which are 6.1812e+04 [$/h], 2.6017e+04 (Kg/h), and 317.5648 [MW], respectively.

Figs. (6) and (7) show the convergence curves that were obtained by applying PSO and GWO-PSO to the Iraq test system in terms of minimization of the emission effect, Fuel cost and multi-objective fitness function. The GWO-PSO approach converges faster than the PSO approach.

5. Conclusion

A large amount of the primary energy (total energy content) of fossil fuels that are burned in power plants is wasted during production and delivery to end users. In addition to its effects on the environment. So, it is necessary that there are chances to enhance the energy efficiency of power plants and locate units that generate electricity in a way that minimizes fuel costs and power losses during economic load dispatch. In this way, the electrical grid will ensure low emissions of carbon gases and become even more reliable and secure.

In this work, multi-objective functions (fuel cost and emission level) are employed separately and simultaneously in order to meet the requirements of the ELD for power generation.

This study presents modified PSO and GWO-PSO algorithms to solve the CELD problem. The implementation results obtained from the simulation demonstrate successfully implementing algorithms, and the GWO-PSO approach offers a reliable, good, and high-quality solution. Furthermore, the simulation results are either superior or comparable (approximate) to those produced by other methods documented in the literature.

Notation	Description
a_i, b_i, c_i	fuel cost coefficients of generator.
A_i, B_i and C_i	Emission coefficients of the G_{ith} generating unit.
Bij	Elements of loss coefficient matrix *B*.
$c1, c2$	Acceleration coefficients.
F_c	Total fuel cost ($/hr).
F_e	Total emissions.
f_k	Objective functions that need to be minimized.
g_{best}	Global best position of particle t is the time of initialization.
Gj	Inequality constraints.
h_i	Price penalty factor
n	Number of generators
P_d	Total load demand
p_i^k	Personal bet postion of particle
P_{Gi}	Power output by generator j.
P_{loss}	Transmission losses
$r1, r2$	Random values.
S_{Li}	Transmission line loading
v_i^k	Velocity vector of particle
W_i	Weight factor
X	Swarm
x_i^k	Particle′s vector postion
$X_i(t)$	Position vector of ith grey wolf in the current iteration
x_α, D_α	Position and coefficient vectors of the alpha wolf.
x_β, xD_β	Position and coefficient vectors of the beta wolf.
x_δ, D_δ	Position and coefficient vectors of the delta wolf

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The first and second authors carried out the background work for the paper, collected the data set, edited the manuscript, and analyzed and compared the results. While the programs were implemented by the three authors.

References

[1] G. Mehta1, R. P. Singh, and V. K. Yadav "Optimization of Combined Economic Emission Dispatch Problem Using Artificial Bee Colony Method", *International Journal on Cybernetics and Informatics s (IJCI)*, Vol. 6, No. 1/2, pp.107-118, 2017.

[2] J. Singh, A. Mani, H. P. Singh, and D. S. Rana "Solution of the Multi-objective Economic and Emission Load Dispatch Problem Using Adaptive Real Quantum Inspired Evolutionary Algorithm", *International Journal on Recent and Innovation Trends in Computing and Communication*, Vol. 11, No. 1, pp. 1-12, 2023.

[3] A. M. Abed, A. A. Alkhazraji, and S. A. Al-Kubragyi, "Modelling and Simulation of an on Grid 100-kw Photovoltaic system", *International Journal of Power Electronics and Drive System (IJPEDS)*, Vol. 14, No. 3, pp. 1651-1659, 2023.

[4] Ch. Fu, S. Zhang, and K. Chao, "Energy Management of a Power System for Economic Load Dispatch Using the Artificial Intelligent Algorithm", *Electronics*, Vol. 9, No. 1, pp 1-19, 2020.

[5] M. K. Dosoglu, U. Guvenc, S. Duman, Y. Sonmez, and H. T. Kahraman, "Symbiotic organisms search optimization algorithm for economic/ emission dispatch problem in power systems", *Neural Computing and Applications*, Vol. 29, pp. 721-737, 2018.

[6] M. Suman, M. V. G. Rao, A. Hanumaiah, and K. Rajesh, "Solution of Economic Load Dispatch problem in Power System using Lambda Iteration and Back Propagation Neural Network Methods", *International Journal on Electrical Engineering and Informatics*, Vol. 8, No. 2, pp.347-355, 2016.

[7] X. Xia, and A. M. Elaiw, "Optimal dynamic economic dispatch of generation: A review:", *Electric Power Systems Research*, Vol. 80, No. 8, pp. 975-986, 2010

[8] B. M. S. Muhammad Ramadan, T. Logenthiran, R. T. Naayagi, and C. Su, "Accelerated Lambda Iteration Method for solving economic dispatch with transmission line losses management", In: *Proc. of Conference IEEE PES Innovative Smart Grid Technologies (ISGT Asia)*, Melbourne, VIC, Australia, pp. 138-143, 2016.

[9] D. O. Dike, M. I. Adinfono, and G. Ogu, "Economic Dispatch of Generated Power Using Modified Lambda Iteration Method", *IOSR Journal of Electrical and Electronics*

Engineering (IOSR-JEEE), Vol. 7, Issue 1, pp. 49-54, 2013.

[10] J. Kim, and K. K. Kim, "Dynamic programming for scalable just-in-time economic dispatch with non-convex constraints and anytime participation", *International Journal of Electrical Power & Energy Systems*, Vol. 123, 2020.

[11] Hardiansyah, Junaidi, and Yandri, "Combined Economic Emission Dispatch Solution using Simulated Annealing Algorithm", *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, Vol. 11, No. 5, PP 141-148, 2016.

[12] A. Haghrah, M. Nazari-Heris, and B. Mohammadi-ivatloo, "Solving combined heat and power economic dispatch problem using real coded genetic algorithm with improved Mühlenbein mutation", *Applied Thermal Engineering*, Vol. 99, pp. 465-475 2016.

[13] A. Lakshmi Devi, and O. Vamsi Krishna, "Combined Economic and Emission Dispatch Using Evolutionary Algorithms-A Case Study", *Arpn Journal of Engineering and Applied Sciences*, Vol. 3, No. 6, pp. 28-35, 2008.

[14] J. K. Pattanaik, M. Basu, and D. P. Dash, "Dynamic economic dispatch: a comparative study for differential evolution, particle swarm optimization, evolutionary programming, genetic algorithm, and simulated annealing", *Journal of Electrical Systems and Information Technology*, Vol. 6, No. 1, pp. 1-18, 2019.

[15] J. Zhou, C. Wang, Y. Li, P. Wang, C. Li, P. Lu, and L. Mo, "A multi-objective multi-population ant colony optimization for economic emission dispatch considering power system security", *Applied Mathematical Modelling*, Vol. 45, pp. 684-704, 2017.

[16] Ö. P. Akkaş, E. Çam, I. Eke, and Y. Arıkan "New Optimization Algorithms for Application to Environmental Economic Load Dispatch in Power Systems", *Electrica*, Vol. 18, No. 2, pp. 133-142, 2018.

[17] S. Gajbhiye, "Multiobjective Deterministic Economic-Emission Load Dispatch Optimization Problem using Firefly Algorithm", *International Journal of Latest Trends in Engineering and Technology (IJLTET)*, Vol. 6, No. 3, pp. 75-82, 2016.

[18] N. Pandit, A. Tripathi, S. Tapaswi, and M. Pandit, "An improved bacterial foraging algorithm for combined static/dynamic environmental economic dispatch", *Applied Soft Computing*, Vol. 12, No. 11, pp. 3500-3513, 2012.

[19] P. D. Kusuma, and M. Kallista, "Swarm Space Hopping Algorithm: A Swarm-based Stochastic Optimizer Enriched with Half Space Hopping Search", *International Journal of Intelligent Engineering and Systems*, Vol. 17, No. 2, pp. 670-682, 2024, doi: 10.22266/ijies2024.0430.54.

[20] H. Nourianfar, and H. Abdi, "Environmental/Economic Dispatch Using a New Hybridizing Algorithm Integrated with an Effective Constraint Handling Technique", *Sustainability*, Vol. 14, No. 6, 2022.

[21] R. L. Rose, B. D. A. Selvi, and R. L. R. Singh, "Development of hybrid algorithm based on PSO and NN to solve economic emission dispatch problem", *Circuits and Systems*, Vol. 7, No. 9, pp. 2323-2331, 2016.

[22] N. Singh, and Y. Kumar, "Multiobjective Economic Load Dispatch Problem Solved by New PSO", *Advances in Electrical Engineering*, Vol. 2015, ID. 536040, pp. 1-6, 2015.

[23] N. Singh, T. Chakrabarti, P. Chakrabarti, M. Margala, A. Gupta, S. P. Praveen, S. B. Krishnan, and B. Unhelkar, "Novel heuristic optimization technique to solve economic load dispatch and economic emission load dispatch problems", *Electronics*, Vol. 12, No. 13, pp. 1-16, 2023.

[24] A. Kumar, M. Thakur, and Mittal, "Planning optimal power dispatch schedule using constrain ed ant colony optimization", *Applied Soft Computing*, Vol. 115, 2022.

[25] B. Hadgii, B. Mahdad, K. Srairi, and N. Mancer, "Multi - objective Economic Emission Dispatch Solution using Dance Bee Colony with Dynamic Step Size", *Energy Procedia*, Vol.74, pp. 65-76, 2015.

[26] F. Waiel, A. A. Mousa, and M. A. Elsisy, "Solving Economic Emissions Load Dispatch problem by using Hybrid ACO-MSM approach", *The Online Journal on Power and Energy Engineering (OJPEE)*, Vol. 1, No. 1, 2008.

[27] S. S. RAO, *Engineering optimization Theory and Practice*, Fourth edition, John Wiley & Sons, Inc., Wiley Eastern Limited, Publishers, and New Age International Publishers, Ltd, 1996.

[28] Y. Sonmez, "Multi-objective environmental/economic dispatch solution with penalty factor using artificial bee colony algorithm", *Scientific Research and Essays*, Vol. 6, No. 13, pp. 2824-2831, 2011.

[29] A. F. Shafeeq, and I. I. Ali, "Simple Strategy for Finding Optimal Location and Size of Distributed Generators and SVC Devices in Radial Distribution Systems", *International*

Journal of Intelligent Engineering and Systems, Vol. 15, No. 5, pp. 261-272, 2022, doi: 10.22266/ijies2022.1031.24.

[30] E. Sathyanarayana, Ph. Krishna1, and Th. Arunkumar "Hybrid Particle Swarm and Gray Wolf Optimization Algorithm for IoT Intrusion Detection System", *International Journal of Intelligent Engineering and Systems*, Vol. 14, No. 4, pp. 66-75, 2021, doi: 10.22266/ijies2021.0831.07.

[31] P. D. Kusuma, and A. Dinimaharawati, "Swarm Bipolar Algorithm: A Metaheuristic Based on Polarization of Two Equal Size Sub Swarms", *International Journal of Intelligent Engineering and Systems*, Vol. 17, No. 2, pp. 377-389, 2024, doi: 10.22266/ijies2024.0430.31.

[32] P. D. Kusuma, and M. Kallista, "Migration-Crossover Algorithm: A Swarm-based Metaheuristic Enriched with Crossover Technique and Unbalanced Neighbourhood Search", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.1, pp. 698-710, 2024, doi: 10.22266/ijies2024.0229.59.

[33] S. Mirjalili, S. M Mirjalili, and A. Lewis, "Grey wolf optimizer", *Advances in EngineeringSoftware*,Vol. 69, pp. 46-61,2014.

[34] L. H Abood, and R. Haitham, "Design an optimal fractional order PI controller for congestion avoidance in internet routers", *Mathematical Modelling of Engineering Problems*, Vol. 9, No. 5, pp.1321-1326, 2022.

[35] A. Alyu, A. Salau, B. Khan, and J. Eneh, "Hybrid GWO-PSO based optimal placement and sizing of multiple PV-DG units for power loss reduction and voltage profile improvement", *Scientific Reports*, Vol. 13, 2023.

[36] S. S. A. Al-Kubragyi, "STATCOM Application in 400kv Iraqi Super Grid for Voltage Magnitude Improvement", *Al-Qadisiya Journal for Engineering Sciences*, Vol. 7, No. 3, pp. 290-305, 2014.