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Weighted sum method based multi-objective optimal power flow considering various objectives: an application of whale optimization algorithm

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ABSTRACT

Nowadays, multi-objective optimization plays a vital role in solving optimal power flow problems. Multi-objective optimal power flow (MOOPF) is a nonlinear optimization problem aimed at optimizing control variables while balancing multiple objective functions and satisfying both equality and inequality constraints and addresses this by integrating two more objectives into a single objective using a weighting factor. In this paper this weighted sum type multi-objective technique has been used to formulate the objective function. The whale optimization algorithm (WOA) has been used to reduce the cost, emission, losses, and voltage stability by considering various multi objectives like fuel cost along with emission, fuel cost with losses, fuel cost with voltage stability, fuel cost with voltage deviation and finally fuel cost with emission, losses, voltage deviation. In this paper, the IEEE 30 bus structure has been used to analyze the effect of WOA on the improvement of system performance. Obtained results with WOA have been compared with other optimization techniques like ensemble constraint handling technique with differential evolution (ECHT-DE), the superiority of feasible differential evolution (SF-DE), moth swarm algorithm (MSA), and moth-flame optimization (MFO), available in the literature.

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1. INTRODUCTION

In the power system deregulation market, the optimal power flow (OPF) problem is very crucial. This issue is non-linear, static, controllable, large-scale and convex, non-convex type that optimizes based on objective function and its solving efficiency with limitations imposed on the power system model, lines, busses and all equipment's to satisfy all operating and physical constraints. There will be equality and inequality constraints to balance all the nodal power flow representations and limitations to control all the state variables involved. These variables are generator active and reactive powers, its bus voltages, transformer tap changing are considered as controllable parameters. The load reactive powers, load bus voltages, real and reactive power flow in the transmission lines are considered as load busses. The economic operation, optimal sharing of power between the sources and to the loads meeting all the constraints and also to meet the electric utilities and firms needs most optimally is referred to as OPF [1].

In the last few years, various bio-inspired optimization OPF algorithms are proposed by many authors to solve very effectively and easily large complex and multi-objective (MO), multi-constrained problems [2]. The trial and error methods are involved in solving these OPF to achieve the tolerance based optimal solution(s). The population or bio-inspired optimization problems developed and found to give most optimal desired solutions [3]. The bio-inspired algorithms are classified as four classes namely, evolution based, swarm intelligence [4], ecology and multi-objective based. The evolutionary OPF problems are artificial neural networks [5], genetic algorithms, evolution strategies [6], differential evolution and paddy-field algorithm [7]. The particle swarm, ant-colony [8], artificial bee, fish swarm, bacterial forging [9], fire-fly [10], group-search, artificial immune system [11], shuffled frog-leaping are famous methods in multi-objective OPF swarm optimization algorithms. In the ecology based OPF algorithms, invasive weed [12], bio-geography, multiple-species co-evolution [13] are few important types. The more advanced OPF methods are multi-objective bio-inspired algorithms such as nondominated sorting genetic algorithm (NSGA-II) method [14], population based ant-colony [15], strength-pareto, vector evaluated GA, pareto archived evolutionary strategy algorithms [16].

The differential evaluation, solved based on minimizing fuel-cost, increasing voltage stability and voltage profile. Modified differential evolution [17] algorithm is a non-smooth and non-convex technique for optimal fuel-cost constraints for a large power system network. An improved scatter search [18] technique is used to solve environmental and economic power dispatch problem to solve large network with multiple objectives and constraints. Pareto dominance and crowding distance based neo control method [19], enhanced genetic algorithm [20], decoupled quadratic load flow [21] for solving optimally fuel cost, line losses and voltage stability index. A distributed and parallel OPF algorithm for effective use of renewable energy sources (RES) in smart grid network with fuel cost minimization and carbon emission reduction as constraints to solve OPF problem. The biogeography-based optimization based on heuristic optimization algorithm to solve convex/non-convex fuel cost characteristics for OPF problem [22]. Modified shuffle frog leaping algorithm to solve emission & financial issues and fuzzy evolutionary and particle swarm optimization hybrid scheme for getting solution to OPF problem with fuel expenditure with various non-linear and linear constraints. Multi-objective harmony search technique, fast nondominated sorting GA (NSGA-II) technique [23], artificial bee colony algorithm [24] with multiple linear and non-linear, balanced and unbalanced constraints with multiple objectives to solve convex and non-convex fuel-price minimizing, environment-friendly with lowering carbon and other flue-gasses emission, voltage profile and stability enhancement, real power loss decreasing, and reactive power optimizing as major constraints. Firefly [25] is a hybrid new and effective algorithm, that improved particle swam optimization (PSO) for multi-objective OPF (MOOPF) issue considering the cost, voltage stability index, emission, and power loss [26].

The fuzzy adaptive chaotic ant swarm hybrid optimization with sequential quadratic programming technique employed for resolving economic load dispatch (ELD) issues. Gravitational search method with various objective functions for the minimization of fuel price, stability of the voltage and enhancement of profile [27]. The neo hybrid optimization technique employed for modified PSO and shuffled frog leaping algorithm (SFLA) called as MPSO-SFLA obtain OPF solution under the limitations like forbidden zones and valve point effect demonstrate their technique is effective in obtaining solution for OPF and ELD problem in the power systems. This method is found to be effective in improving the overall system profile meeting all the constraints compared to the earlier methods.

In this paper, five major objective functions like fuel cost, emission, true power losses and voltage stability and voltage deviation of the network are taken attention in planning of power system that is employed in whale optimization algorithm. This method is very strong, effective with superior speed to attain the outputs compared to earlier techniques. Also, with increase in the network size and constraints, its effectiveness also increases as compared with earlier methods. This is because, the method is a group algorithm and other reason is because of colonial groups competition based algorithm. The whale algorithm technique is estimated on the standard Institute of Electrical and Electronics Engineers thirty bus system. The work is studied under different combinations of five objectives and the best compromise solution is detailed here. The multi-objective OPF issues shows suggested whale technique is best while comparing to earlier techniques. This paper is categorized as five sections: section 2 involves in a multi-objective issues formulation section 3 demonstrates about architecture of whale optimization technique, section 4 is allocated for the results and performance analysis mentioned methods which are employed to encounter the literature studies of multi-objective OPF problem on IEEE thirty bus system and finally, in section 5, the conclusion of the implementation for the proposed technique is presented

2. MATHEMATICAL FORMULATION OF MULTI OBJECTIVE OPTIMAL POWER FLOW (MOOPF) PROBLEMS

Multi-objective optimal power flow (MOOPF) is nonlinear optimization issue . the primary focus is to optimize control variables while addressing two or more objective functions, while also satisfying both equality and inequality constraints. This paper accomplishes the integration of two objectives converts in one objective by introducing a weighting factor as crucial consideration.

2.1. Objective 1: cost minimization

The sum of cost function for fuel is set of generating units is represented in the following equation. The initial objective function aims to minimize the generation cost [28]. In (1), α, β, and γ are the cost coefficients of thermal power plants.

$$F_1 = (\sum_{i=1}^{NTG} \alpha_i + \beta_i P_{TGi} + \gamma_i P_{TGi}^2)\$/Hr \quad (1)$$

2.2. Objective 2: minimization of emission

The warm generator delivers the discharge of SOx, NOx with contaminates the environment. Thus, it is needed to decrease the emanation by accepting this one as an objective. In (2), a, b, c, d, and e are the emission coefficients of the thermal generation unit.

$$F_2 = \sum_{i=1}^{NTG} 10^{-2}\,(a_i + b_i P_{TGi} + c_i P_{TGi}^2) + d_i\, exp(e_i P_{TGi}) \quad (2)$$

2.3. Objective 3: minimization of actual power losses

These are calculated employing the (3) [29]. In (3), V_i is the voltage at ith bus, V_j is the voltage at jth bus. NT is the number of transmission lines.

$$F3 = \sum_{k=1}^{NT} G_{k(i,j)}[V_i^2 + V_j^2 - 2V_iV_j\, cos(\,\delta_{ij}) \quad (3)$$

2.4. Objective 4: voltage stability

To improve the voltage stability in the system, the L-index is calculated for all heap transports, with the highest value among them serving as the global indicator for system stability. In this manner, the main focus of system stability is defined as (4) [30].

$$F4 = \left|1 - \sum_{i=1}^{NG} F_{ji}\frac{V_i}{V_j}\right| \rightarrow where \rightarrow j = 1,2,\ldots.,NL\ and \rightarrow F_{ji} = -inv[Y_{LL}][Y_{LG}] \quad (4)$$

2.5. Objective 5: minimization of voltage deviation

Voltage deviation has been determined using (5), here V_n is the voltage at node n, and 1 is considered as reference voltage.

$$F_5 = VD = \sum_{n=1}^{Nb}|V_n - 1| \quad (5)$$

Considering the previously mentioned mono objectives, multiple objectives have been obtained in several technical studies [13].

2.6. Case 1: reduction of fuel cost and emission

The formulation of the objective function, containing of fuel cost and emission, and the selected weight factor is 100. In (6), F1 is the objective1 which is reduction cost and F2 is the objective2 which is emission reduction. These are combined with weighting factor W1.

$$FF1(X,U) = F1 + W1 * F2 \quad (6)$$

2.7. Case 2: curtailment of fuel cost and losses

In the power systems operation transmission loss is the most important element to determine effectiveness. To minimize the transmission loss in the network together with minimization of cost generation. The formulation of the objective function, which consists of fuel costs and losses with a chosen weight factor, is 40.

$$FF2(X,U) = F1 + W2 * F3 \quad (7)$$

2.8. Case 3: reduction of fuel cost and improvement of voltage stability

This objective function is focused to reduce cost of fuel while improving system voltage stability. The multiple objectives are consolidated into one objectively as (8).

$$FF3(X,U) = F1 + W3 * F4 \tag{8}$$

Taken the weight factor is hundred from [9].

2.9. Case 4: reduction of cost of fuel and voltage deviation

The main focus of the objective function is to reduce system's voltage variation and fuel expense. Multiple objective functions are reduced to a single goal as (9).

$$FF4(X,U) = F1 + W4 * F5 \tag{9}$$

The weight factor 100 is taken [10].

2.10. Case 5: minimization of fuel cost, emission, voltage deviation and losses

This case study combines four objective functions. The simultaneous minimization of fuel cost, emissions, voltage variation, and real power loss in the network. The objective function is given by (10).

$$FF5(X,U) = F1 + W5 * F2 + W6 * F3 + W7 * F5 \tag{10}$$

W5=19, W6=21, and W7=22 are taken to balance between the objectives.

2.11. Equality constraints

Basic load flow equations like these require that the power produced match the power demand and losses [28]. In below equations P_{Gi} is the true power generation and P_{Di} is the true power demand. Q_{Gi} is the imaginary power generation and Q_{Di} is the imaginary power demand.

$$P_{Gi} - P_{Di} - V_i \sum_{i=1}^{N_b} V_j \begin{pmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{pmatrix} = 0 \tag{11}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{i=1}^{N_b} V_j \begin{pmatrix} G_{ij} & \sin\theta_{ij} \\ B_{ij} & \cos\theta_{ij} \end{pmatrix} = 0 \tag{12}$$

2.12. Inequality constraints

Maximum and minimum values of generator bus voltages and load bus voltages considered as inequality restrictions. They get along with imaginary power generation limits, limits of the transformer tap settings and capacitor banks minimum and maximum values [30].

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max},\ i \in N_g \tag{13}$$

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max},\ i \in N_l \tag{14}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max},\ i \in N_t \tag{15}$$

$$T_i^{min} \leq T_m \leq T_i^{max},\ i \in N_c \tag{16}$$

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max},\ i \in N_c \tag{17}$$

3. WHALE OPTIMIZATION ALGORITHM (WOA)

Whales are magnificent creatures, with humpback whales standing out due to their remarkable hunting strategy known as the bubble-net feeding technique. This foraging behavior involves two distinct maneuvers known as 'upwinding' and 'double loops.' During the former, humpback whales dive approximately 12 meters deep and then create a twisting pattern of bubbles around their prey as they ascend toward the surface. The latter maneuver consists of 3 distinct phases: coral circle, lob tail, and capture circle. You can find more detailed information about this behavior elsewhere. It's important to emphasize that bubble-net feeding is a unique behavior exclusive to humpback whales. The bubble net method of the whale is shown in Figure 1 [2].

$$\vec{D} = |\vec{C}.\vec{X}*(t) - \vec{X}(t)| \tag{18}$$

$$\vec{X}(t) = \vec{X}*(t) - \vec{A}.\vec{D}| \tag{19}$$

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a}. \tag{20}$$

$$\vec{c} = 2.\vec{r}. \tag{21}$$

Whale, denoted as 'r' is expressed as vector comprising of actual values are written as (22) [27].

$$Y_i = \left(Y_{i,1}, Y_{i,2}, \ldots . x_{i,k}\right)^T subjected\ to\ 0 < x_{i.1} \ldots \ldots < x_{i,k} < L \tag{22}$$

The positions of the whales are determined arbitrarily using (23).

$$Y_{i,j} = g_{min} + rand(0,1) * (g_{max} - g_{min}) \tag{23}$$

Control parameter limits are provided in Table 1 and values of WOA are given in Table 2. Steps to Implementing the WOA to solve the MOOPF:

- Randomly generate initial positions of whales and set algorithm parameters such as population size, maximum iterations, and convergence criteria.
- Calculate the fitness function value of each whale based on the MOOPF objective function
- Update the positions of the whales using the encircling prey, bubble-net attacking, and search for prey mechanisms of WOA.
- Repeat the evaluation and update steps for a set number of iterations.
- After convergence, take the values of optimal generator settings, power losses, fuel cost, and fitness function value.

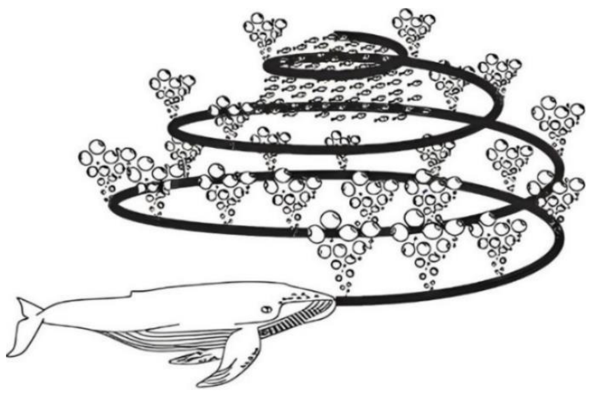

Figure 1. Bubble net method of whale

Table 1. Control parameters limits

Control parameters	Min – Max (p.u)
Generator voltages	0.95 – 1.10
Transformers tap settings	0.90 – 1.10
Shunt capacitors	0.00– 0.20

Table 2. Control - parameters values for WOA

S.No	Parameter
Search Agents_no	30
Max_iteration	500
a	Linearly is reduced from 02 to 00
r1 and r2	Random numbers in [0,1]

4. RESULTS AND DISCUSSION

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [14], [15]. The discussion can be made in several sub-sections.

This paper introduces an optimization approach aimed at minimizing the total cost of real power generation while considering factors such as losses, emissions, and voltage stability. The proposed method involves the control of generator bus voltages, the adjustment of reactive power compensation device ratings, and the optimization of transformer tap settings. Table 3 gives information about IEEE 30 bus system. The cost coefficient values of generators, bus data, load data, and line data are taken from [27].

From Table 4 it is observed that by optimizing only fuel cost, cost has been reduced to 800.3196 \$/hr but emission is 0.5437 p.u, with emission optimization fuel cost is 944.921 \$/hr but emission getting reduced to 0.2048. By applying single objective optimization that particular objective value became lower but other objectives have high values, therefore to avoid this multi-objective optimization has been used. From this table it is also observed that by combining fuel cost and emission provides the moderate values. Here cost is 802.172 \$/hr and emission is 0.3293 p.u. From the Table 4 it has been also observed that by combining fuel cost and losses provides the moderate values. Here cost is 857.81 \$/hr and losses are 4.4755 MW. From Table 5 obtained multi objective values, cost is 800.36 \$/hr and voltage stability is 0.1266 p.u. Table 5 also obtained multi objective values, cost is 800.36 \$/hr and deviation of voltage is 0.2011 p.u.

Table 3. The main characteristics of the studied system

Characteristics	IEEE 30 Value	Details
Buses	30	--
Branches	41	--
Generators	06	Buses: 1, 2, 5, 8, 11, and 13
Load voltage limits	24	[0.94 p.u - 1.06 p.u]
Shunt VAR compensation	09	Buses:10, 12, 15, 17, 20, 21, 23, 24, and 29
Transformers with off-nominal tap ratio	04	Branches: 11, 12, 15, and 36
Control variable	24	--

Table 4. Optimal solutions obtained for combined fuel cost and emission and combined fuel cost and power losses by WOA for IEEE 30 bus system

	Combined fuel cost and emission			Combined fuel cost and power losses		
Control variables and parameters	In fuel cost minimization scheduling of generator units and other parameters	In emission minimization scheduling of generator units and other parameters	In combined (Case 1) scheduling of generator units and other parameters	In fuel cost minimization scheduling of generator units and other parameters	In power loss minimization scheduling of generator units and other parameters	In combined (Case 2) scheduling of generator units and other parameters
PTG1	176.0386	64.1557	162.75	176.0386	51.299	102.64
PTG2	48.5459	67.6433	51.7207	48.5459	80.0000	54.4114
PTG5	21.2817	50.0000	21.8936	21.2817	50.0000	36.7556
PTG8	21.6116	35.0000	27.1089	21.6116	035	035
PTG11	12.5939	30.0000	13.6142	12.5939	030	29.6401
PTG13	12.1423	40.0000	14.8104	012.1423	040	29.5766
VTG1	01.1	01.10	1.1000	01.1	01.1	0 1.10
VTG2	01.1	01.10	01.10	01.1	01.1	01.10
VTG5	01.1	01.10	01.10	01.1	01.08	01.0838
VTG8	01.08869	01.10	01.0903	01.08869	01.1	01.10
VTG11	01.1	01.10	01.10	01.1	01.1	01.0432
VTG13	01.1	01.10	01.10	01.1	01.1	01.1000
QC10	4.32262	0.4593	0	4.32262	05	3.2100
QC12	0	1.8154	4.6101	0	05	05.0
QC15	0	4.1381	0	0	05	05.0
QC17	2.57489	5.0000	0	2.57489	05	05.0000
QC20	4.11584	5.0000	4.6122	4.11584	05	5.0000
QC21	2.5457	5.0000	1.9727	2.5457	05	5.0000
QC23	1.75619	5.0000	4.6147	1.75619	05	5.0000
QC24	3.97527	5.0000	4.6099	3.97527	05	5.0000
QC29	1.86436	5.0000	4.6108	1.86436	02.5237	5.0000
T11	0.983227	1.1000	1.0022	0.983227	00.9458	0.9740
T12	1.00358	1.1000	1.0022	1.00358	01.10	1.1000
T15	0.992703	1.1000	0.9983	0.992703	00.9960	1.1000
T36	1.00521	1.1000	1.0021	1.00521	00.9849	1.0356
Fuel cost (\$/hr)	800.3196	944.921	802.172	800.3196	966.69	857.81
Total power loss (MW)	8.8140	3.399	8.1001	8.8140	2.899	4.4755
Voltage stability p.u	0.1542	0.1455	0.1299	0.1542	0.1260	0.1355
Voltage deviation p.u	1.7624	1.0149	1.6701	1.7624	2.0857	1.3687
Emission p.u	0.5437	0.2048	0.3293	0.5437	0.20724	0.2283
Fitness function value	800.3196	0.2048	834.91	800.3196	2.899	1036.53

Table 5. Optimal solutions obtained for combined fuel cost and voltage stability and combined fuel cost and voltage deviation by WOA for IEEE 30 bus system

Control variables and parameters	Combined fuel cost and voltage stability			Combined fuel cost and voltage deviation		
	In fuel cost minimization scheduling of generator units and other parameters	In voltage stability minimization scheduling of generator units and other parameters	In combined (Case 3) scheduling of generator units and other parameters	In fuel cost minimization scheduling of generator units and other parameters	In voltage deviation minimization scheduling of generator units and other parameters	In combined (Case 4) scheduling of generator units and other parameters
PTG1	176.0386	80.528	175.67	176.0386	127.8870	180.5493
PTG2	48.5459	80.0000	48.0976	48.5459	73.2439	49.0249
PTG5	21.2817	50.0000	20.7299	21.2817	30.8068	23.3954
PTG8	21.6116	35.0000	23.2889	21.6116	15.2479	14.9210
PTG11	12.5939	30.0000	12.2847	12.5939	18.6419	11.8863
PTG13	12.1423	12.0000	12.1561	12.1423	29.5643	14.2723
VTG1	01.1	01.1000	01.1000	1.1	0.9661	1.0298
VTG2	01.1	01.1000	01.0891	01.01	1.0306	1.0106
VTG5	01.1	01.1000	01.0616	01.01	1.0025	1.0019
VTG8	01.08869	01.1000	01.0795	01.08869	1.0288	1.0162
VTG11	01.1	01.1000	01.1000	1.1	1.0596	1.0330
VTG13	01.1	01.1000	01.1000	1.1	1.0098	1.0399
QC10	4.32262	5.0000	0.3549	4.32262	0.2454	0
QC12	0	5.0000	0	0	2.5816	2.0817
QC15	0	5.0000	3.0558	0	1.6725	3.9460
QC17	2.57489	5.0000	0.8241	2.57489	2.2052	1.1293
QC20	4.11584	5.0000	0	4.11584	0	1.9271
QC21	2.5457	5.0000	2.2320	2.5457	4.2276	4.2315
QC23	1.75619	5.0000	2.1422	1.75619	2.7822	0.6253
QC24	3.97527	5.0000	1.7377	3.97527	4.0040	1.1877
QC29	1.86436	5.0000	1.8542	1.86436	4.5123	1.7332
T11	0.983227	0.9000	0.9183	0.983227	0.9560	0.9462
T12	1.00358	0.9000	1.1000	1.00358	1.0546	1.0074
T15	0.992703	0.9000	0.9321	0.992703	0.9474	0.9432
T36	1.00521	0.9000	0.9504	1.00521	0.9713	0.9660
Fuel cost ($/hr)	800.3196	919.692	800.36	800.3196	855.5189	806.105
Total power loss (MW)	8.8140	4.128	8.8442	0.5437	0.2676	0.3751
Voltage stability p.u	0.1542	0.1088	0.1266	8.8140	11.89	10.609
Voltage deviation p.u	1.7624	3.4375	1.7154	1.7624	0.2011	0.2022
Emission p.u	0.5437	0.2250	0.3621	0.1542	0.1463	0.1482
Fitness function value	800.3196	0.1088	813.03	800.3196	0.2011	826.1644

Figure 2 shows the convergence curves for case 1 to case 5. From the Figure 2 it has been observed that case 5 consisting of multiple objectives produce the compromising solution. Table 6 presents the control variables of all single objectives and multi objective consisting of all the objectives. From this it is observed that by combining all the objectives best optimal values have been achieved. Table 7 presents the comparison of case 2, case 3, and case5 of WOA with other algorithm available in literature. From this table it is observed that fitness function value with WOA is best compared to ensemble constraint handling technique with differential evolution (ECHT-DE), superiority of feasible differential evolution (SF-DE), moth swarm algorithm (MSA), and moth-flame optimization (MFO).

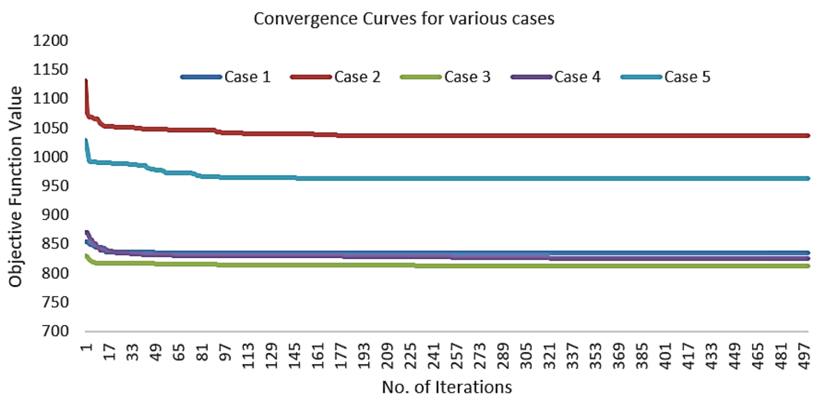

Figure 2. Convergence curves for various cases

Table 6. Optimal solutions obtained for combined fuel cost, voltage deviation, power losses and emission by WOA for IEEE 30 bus system

Control variables and parameters	In fuel cost minimization scheduling of generator units and other parameters	In voltage deviation minimization scheduling of generator units and other parameters	In power loss minimization scheduling of generator units and other parameters	In emission minimization scheduling of generator units and other parameters	In combined (Case 5) scheduling of generator units and other parameters
PTG1	176.0386	127.887	51.299	64.1557	125.49
PTG2	48.5459	73.2439	80.000	67.6433	53.9522
PTG5	21.2817	30.8068	50.000	50.0000	31.0859
PTG8	21.6116	15.2479	35.000	35.0000	35.0000
PTG11	12.5939	18.6419	30.000	30.0000	21.5385
PTG13	12.1423	29.5643	40.000	40.0000	21.7013
VTG1	1.1	0.9661	1.1000	1.1000	1.1000
VTG2	1.1	1.0306	1.1000	1.1000	1.0864
VTG5	1.1	1.0025	1.0862	1.1000	1.0599
VTG8	1.08869	1.0288	1.1000	1.1000	1.0690
VTG11	1.1	1.0596	1.1000	1.1000	1.0832
VTG13	1.1	1.0098	1.1000	1.1000	1.0173
QC10	4.32262	0.2454	5.0000	0.4593	1.6604
QC12	00	2.5816	5.0000	1.8154	4.0284
QC15	00	1.6725	5.0000	4.1381	3.8585
QC17	2.57489	2.2052	5.0000	5.0000	0.1981
QC20	4.11584	00	5.0000	5.0000	4.0745
QC21	2.5457	4.2276	5.0000	5.0000	4.1727
QC23	1.75619	2.7822	5.0000	5.0000	4.2522
QC24	3.97527	4.0040	5.0000	5.0000	4.8502
QC29	1.86436	4.5123	2.5237	5.0000	4.3251
T11	0.983227	0.9560	0.9458	1.1000	1.1000
T12	1.00358	1.0546	1.1000	1.1000	1.0052
T15	0.992703	0.9474	0.9960	1.1000	1.0635
T36	1.00521	0.9713	0.9849	1.1000	1.0478
Fuel cost ($/hr)	800.3196	855.518	966.69	944.921	824.82
Emission p.u	0.5437	0.2676	0.20724	0.2048	0.2584
Total power loss (MW)	8.8140	11.89	2.899	3.399	5.5871
Voltage deviation p.u	1.7624	0.2011	2.0857	1.0149	0.4943
Voltage stability p.u	0.1542	0.1463	0.1260	0.1455	0.1468
Fitness function value	800.3196	0.2011	2.899	0.2048	962.96

Table 7. Comparison of the WOA with ECHT-DE, SF-DE, MSA, and MFO for IEEE 30 bus system considering various cases

Objective function	Objective	WOA	ECHT-DE	SF-DE	MSA	MFO
Case 5	Fuel cost ($/h)	824.82	830.1156	830.1366	830.639	830.9135
	Emission (ton/h)	0.2584	0.25293	0.25313	0.25258	0.25231
	PLoss (MW)	5.5871	5.5894	5.5887	5.6219	5.5971
	L-index	0.1468	0.14748	0.14756	0.14802	0.14556
	Fitness function	962.96	964.1331	964.1254	965.2905	965.8077
Case 3	Fuel cost ($/h)	800.36	800.4321	800.4203	801.2248	801.668
	Emission (ton/h)	0.3621	0.36585	0.36592	0.36106	0.34299
	PLoss (MW)	8.8442	9.0043	8.9985	8.9761	8.5578
	L-index	0.1266	0.13739	0.13745	0.13713	0.13759
	Fitness function	813.03	814.1708	814.1649	814.9378	815.4270
Case 2	Fuel cost ($/h)	857.81	858.867	859.1458	859.1915	858.5812
	Emission (ton/h)	0.2283	0.22902	0.2289	0.22899	0.22947
	PLoss (MW)	4.4755	4.5321	4.5245	4.5404	4.5772
	L-index	0.1355	0.13796	0.13785	0.13814	0.13806
	Fitness function	1036.53	1040.151	1040.125	1040.808	1041.671

5. CONCLUSION

The whale optimization algorithm (WOA) combined with optimal power flow (OPF) demonstrates superior performance across multiple objectives, including fuel cost, emissions, losses, voltage stability, and voltage deviation. From the results, it has been observed that by using weighted sum type multi-objective all the objectives optimized simultaneously and provided the compromising solution. In case 2, minimizing the fuel cost along with emission the objective function value is 1036.53 p.u. In the case 3, minimizing the fuel cost along with losses the objective function value in 813.03 p.u, to get the compromising solution by combining all the cases the objective function value became 962.96 p.u. it indicated that all the objectives were optimized simultaneously. The results indicate that, when compared to ECHT-DE, SF-DE, MSA, and MFO, the WOA-based approach with regulated variables consistently delivers superior outcomes. These findings have been validated using the IEEE 30 bus system. Additionally, future research could explore the integration of flexible AC transmission system (FACTS) devices to further optimize system performance.

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