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An approach to solve OPF problems using a novel hybrid whale and sine cosine optimization algorithm

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Abstract: Nowadays, improvement in power system performance is essential to obtaine economic and technical benifits. To achieve this, optimize the large number of parameters in the system based on optimal power flow(OPF). For solving OPF problem efficiently, it needs robust and fast optimization techniques. This paper proposes the application of a newly developed hybrid Whale and Sine Cosine optimization algorithm to solve the OPF. It has been implemented for optimization of the control variables. The reduction of true power generation cost, emission, true power losses, and voltage deviation are considered as different objectives. The hybrid Whale and Sine Cosine optimization is validated by solving OPF problem with various intentions using IEEE30 bus system. To varidate the proposed technique, the results obtained from this are compared with other methods in the literature. The robustness achieved with the proposed algorithm has been analyzed for the considered OPF problem using statistical analysis and whisker plots.

Keywords: Active power loss; Optimal power flow; Sine Cosine optimization; Voltage deviation; Whale optimization.

1. **Introduction**

As the usage of power is increasing, i.e., the demand of the power increasing, it causes the voltage instability, line overloaded and power system blackouts. It can be avoided by building new transmission lines and increase power generation, but it creates environmental problems and consume more time and cost. Therefore, many authors have developed an alternative solution as better utilization of generators from numerous sources in an electrical system that need optimally organized for the economical and effective operation of the system [1]–[4]. This is called OPF, and this problem is expressed with generator outputs and explained successively to achieve the optimal settings.

Traditional Economic Dispatch (ED) has a significant role in the power system for optimal operation problem to design the load sharing of all generating units to reduce fuel cost with several physical and operational restrictions to satisfy. But with the increase of public awareness, generating plants may not be in a position to use the environmental pollution caused fossil fuel in future [5], [6]. Therefore the traditional ED does not meet the requirements of present trend. Because which may not optimize the generation values, therefore, they may produce an excessive amount of emission pollutions [7]–[10]. Taking low emission fuel may decrease emissions. This modification can be followed through the long term option, such as price and availability of low emission fuel.

To overcome this, an alternative solution is considered, i.e., OPF. It is more alluring for minimizing cost and emission concerns without fuel converting. But it is renowned as a difficult multi constrained problem. To solve the OPF problem, different methods have been used in literature. Warid [11] in 2020, proposes AMTPG-Jaya algorithm for solving mono objective OPF. The population is dived into a number of teams which are used to find the proper search direction, and the results reveal that the proposed method has fast convergence. Saberi Hossein. et al. [12] in 2020, use the decomposition algorithm for security-constrained OPF to handle the transient stability, where it is minimized the generation cost and applied to the IEEE39 bus system.

Recently Shuijia Li et al. [13] propose the adaptive differential evolutionary algorithm for solving OPF problem with constraint handling technique, and it is applied to IEEE30 bus system. Authors apply randomizing the parameters technique to improve the search efficiency. Chen Gonggui et al. [14] apply the pigeon based algorithm for Multi Objective OPF (MOOPF) problem. This MPIO solve the MOOPF problem effectively and provides better results compared to NSGA-II. Biswas Partha P et al.[15] propose the differential evolution with constraints to solve OPF. Authors use the superiority of feasibly and self-adaptive penalty techniques with DE to optimize the control variables and applied to IEEE30, IEEE57 and IEEE118 bus grids.

Attia Abdel Fattah et al. [16] use the modified sine cosine algorithm for OPF. In this levy flights are auxiliary to the actual SCA, which increase the computation speed. This Modified Sine-Cosine Algorithm (MSCA) applied to IEEE30 and IEEE118 bus grids to validate its effectiveness. Abdo Mostafa et al. [17] apply the developed GWO for reduction of fuel cost considering valve point effect, due to the incorporation of the adaptive operator in DGWO provides better search capabilities than GWO. Sakthivel S et al.[18] employ the bio-inspired fruit fly algorithm for SCOPF, due to less number of factors, it is easy to use and reduce the computation time. It is applied on IEEE30 bus grid. P Harish et al. [19] use the mixed cross over integrated enhanced self-adaptive DE for solving multi-objective OPF. Due to crossover incorporation, it provides the best solution compared to DE on IEEE57 and Algerian 59 bus grid. Mohamed Al Attar Ali et al.[20] present the moth swarmalgorithm for solving OPF on IEEE30, 57, 118 bus grids. The algorithm provides better results due to levy mutation.

T. Niknam et al.[21] presented a better particle swarm optimization (IPSO) method to OPF problem through computing instructed set points, which fulfill the security, environment and economic conditions at the same time. A fuzzy assessment recognized tool is used for selecting the finest solution of the Pareto set is achieved using the suggested algorithm. Many author solving OPF problem using different optimization algorithms, e.g. backtracking search optimization algorithm [22], Colliding Bodies Optimization [23], real coded biogeography[24], Wrapper Genetic Programming [25], Bat Optimization Algorithm [26], Teaching-Learning-Based Optimization [27], Boosting Algorithm [28], black-hole optimization[29], Differential Evolution [30], artificial bee colony [31], Improved Bagging Algorithm[32], Firefly Algorithm [33]. All said authors solve OPF with single optimization methods, where they can stuck at local optimal solution. It can be avoided by using a hybrid optimization method. In recent days, enhanced algorithms [34], [35], and hybridized algorithms [36], [37] are getting popular in solving numerous engineering problems. The graphical representation of the proposed hybrid optimization for OPF problem is shown in Fig.1.

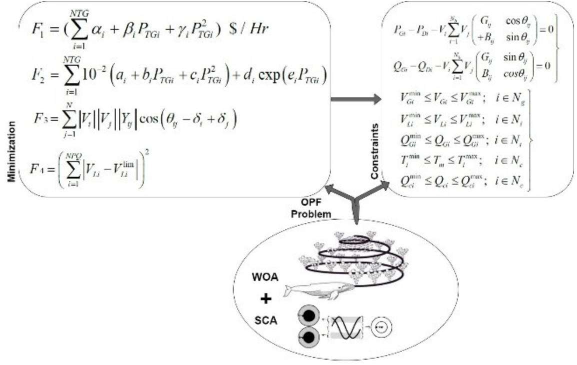


Fig 1. Graphical demonstration

The depth of the literature review demonstrates that there is a very less amount of hybrid metaheuristic optimization tools to solve OPF problems. This gap was attended with the below listed contributions in this paper:

a. An amalgamation of a recently developed population-based SCA with a swarm-intelligence based metaheuristic Whale Optimization Algorithm WOA to perform a strong and powerful Hybrid Whale and Sine Cosine Optimization Algorithm (HWSCOA)
b. Performing OPF on IEEE 30 bussystem using the suggested methodology to minimize:
    - Power generation cost
    - Emission of toxic gases
    - True power losses
    - Voltage Deviation

The paper is presented as follow: Section 2 presents the creation of OPF problem; Section 3 describes the considered optimization method; Results and discussion are showed in Section 4; Section 5 analyzed the robustness study of the proposed method Section 6, and; Finally, Section 6 shows the Conclusion.

2. Mathematical representation of OPF Problem

The significant objective of OPF problem is to minimize the objective function based on the optimized control variables without sacrificing the equality and inequality restrictions. This paper concerns in implementing a hybrid approach to perform OPF on IEEE test system to attain the following objectives:

- *Obj 1*: Minimization of cost
- *Obj 2*: Minimization of toxic gases in the atmosphere
- *Obj 3*: Minimization of true power losses
- *Obj 4*: Minimization of Voltage deviation.

These four objective functions are formulated in the succeeding section.

2.1 Objective function

a) Minimization of cost

Fuel cost function $\left(F_1\right)$ for thermal generating units is denoted by equation (1).

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

b) Minimization of emission

The thermal generator produces the emission of SO_x, NO_x with pollutes the environment, therefore, it is required to reduce the emission by taking this one as an objective. Emission of these gases is considered in ton/Hr using equation (2).

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

c) Minimization of true power Losses

Power loss calculated by using equation (3).

$$F_3 = \sum_{j=1}^{N} \left|V_i\right|\left|V_j\right|\left|Y_{ij}\right| \cos\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{3}$$

d) Minimization of Voltage Deviation

Enormous low voltages can lead to undesirable task of the system. Therefore, it is significant to control the voltage for the appropriate functioning of the equipment. The objective function for minimizing the voltage deviation is stated in equation (4).

$$F_4 = \left(\sum_{i=1}^{NPQ} \left|V_{Li} - V_{Li}^{\lim}\right|\right)^2 \tag{4}$$

2.2 Constraints

a) Equality constraints:

$$\left.\begin{aligned} P_{Gi} - P_{Di} - V_i \sum_{i=1}^{N_b} V_j \begin{pmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{pmatrix} = 0 \\ Q_{Gi} - Q_{Di} - V_i \sum_{i=1}^{N_b} V_j \begin{pmatrix} G_{ij} & \sin\theta_{ij} \\ B_{ij} & cos\theta_{ij} \end{pmatrix} = 0 \end{aligned}\right\} \tag{5}$$

b) Inequality constraints

$$\left.\begin{aligned} &V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}; \quad i \in N_g \\ &V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}; \quad i \in N_l \\ &Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}; \ i \in N_t \\ &T_i^{\min} \le T_m \le T_i^{\max}; \quad i \in N_c \\ &Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}; \ i \in N_c \end{aligned}\right\} \tag{6}$$

3. Proposed HWSCOA for OPF problem

With an aim to perform OPF on IEEE test system, the superior, well-organized and noval time-consuming optimization method was a matter of concern to deal with. Extensive literature survey clearly demonstrates that the usage of hybrid optimization methods are not that highly used for OPF on the test power systems. WOA is amalgamated with a recently developed and well-established algorithm SCA, which have previously showed their advantages and strength in handling engineering problems of larger dimension. Where WOA is recognized for a rough exploration capability within its multi-dimensional search space (water bodies) moving up, down and sideward, SCA is retain the balance between exploitation and investigation because it is proficient in switching between cosine and sine functions. HWSCOA exhibits both the properties of WOA and SCA in delivering a fast and superior quality optimized output.

3.1. The Whale Optimization Algorithm

Different methods are applied to find the best values for the variable for a particular function under constraints to maximize or minimize it, where WOA is one of them. The involvement of fewer control parameters makes the evolution process faster. This technique was inspired by bubble-net feeding. This technique starts with attacking the prey, then encircle them by forming bubble-net around them in a spiral manner (exploitation phase) and then search for the prey (exploration phase) [38].

In the encircling mechanism, the humpback whales locate the position of prey and circularly enclose them. WOA assumes the best location is to target prey in search space, and other agents try to modify their location concerning the best search agent. This mechanism is mathematically formulated by equations (7,8).

$$\vec{G} = \left|\vec{C}.\vec{Y}_{rand} - \vec{Y}\right| \tag{7}$$

$$\vec{Y}(iter+1) = \vec{Y}^{*} - \vec{A}.\vec{G} \tag{8}$$

where, $iter$ is the existing iteration, $\vec{Y}$ is the location vector represents the current position, $\vec{Y}^{*}$ is the location vector of finest position, $\vec{G}$ is the difference vector, A and C are the coefficient vectors value of A is random value in [a, -a] and the value of 'a' decreases as iteration increases.

$$A = 2a.r_1 - a \tag{9}$$

$$C = 2.r_2 \tag{10}$$

where, r is a random vector in the interval [0,1] where a is linearly reduced from 2 to 0 given by (11).

$$a = 2 - \text{iter} * \left(\frac{2}{\text{Max\_iter}}\right) \tag{11}$$

The value of 'a' denotes the exploration and exploitation phase of the proposed algorithm with respect to the number of iterations.

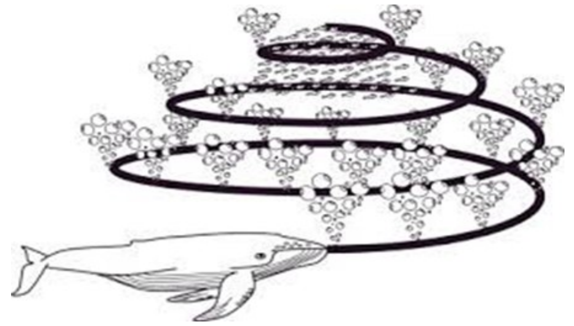


Fig. 2. Encircling mechanism of the whale [38].

In the bubble net attacking method, it is shown in Fig2 and two approaches are designed and described as,

a) Shrinking Mechanism:

The value of a is reduced from 2 to 0 above the progress of iteration that sets the random value of A in the interval [-1, 1], which gives a new position of whale anywhere between the original and current location of the agent.

b) Spiral Updating Mechanism:

The difference in whale and prey position is given by

$$\vec{G} = \left|\vec{C} * \vec{Y}_p(iter) - \vec{Y}(iter)\right| \tag{12}$$

where G' represents the best solution of the distance of ith whale and prey and then the spiral equation is created for helix-shaped movement

$$\vec{Y}(iter+1) = \vec{G}.e^{bl}.Cos(2\pi l) + \vec{Y}(iter) \tag{13}$$

There is 50% probability to choose between shrinking mechanism and spiral model, therefore, it is obtained equation (14),

$$\vec{Y}(iter+1) = \begin{cases} \vec{Y}_P(iter) - \vec{A}.\vec{G} & , p < 0.5 \\ \vec{G}.e^{bl}.Cos(2\pi l) + \vec{Y}_P(iter) & , p \geq 0.5 \end{cases} \tag{14}$$

where, p=Arbitrary number in [0,1].

The last step involves the hunt for prey in which Whales randomly explores the position of prey with positions relative to each another, therefore, the location of hunt agent is modified with the value of A >1 or<1.

$$\vec{G} = \left|\vec{Y}_p(iter) - \vec{Y}(iter)\right| \tag{15}$$

$$\vec{Y}(iter) = \vec{Y}_{rand} - \vec{A}.\vec{G} \tag{16}$$

3.2. Hybrid Whale and Sine Cosine Optimization Algorithm

This section amalgamates the above-mentioned WOA with a fast and powerful SCA to yield a superior hybrid WOASCA for optimization. The distance mapping parameter G from WOA is modified in hybrid WOASCA using probabilistic based sine-cosine functions. This modification increases the exploration capability within the search space in a rigorous manner and eliminates even the slightest chance of the solution getting stuck in local minima. Hybrid WOASCA is limited to the following modifications as mentioned below. Therefore, equation (7) of WOA is modified into equation (17):

$$\vec{G} = rand_1 * \sin(rand_2) * \left|\vec{C}.\vec{Y}_{rand} - \vec{Y}\right| \quad if\ rand < 0.5$$

$$\vec{G} = rand_1 * \cos(rand_2) * \left|\vec{C}.\vec{Y}_{rand} - \vec{Y}\right| \quad otherwise$$

(17)

In hybrid WOASCA, equation (12) of WOA is modified into equation (18).

$$\vec{G} = rand_3 * \sin(rand_4) * \left|\vec{C} \times \vec{Y}_P(iter) - \vec{Y}(iter)\right| \quad if\ rand < 0.5$$
$$\vec{G} = rand_3 * \cos(rand_4) * \left|\vec{C} \times \vec{Y}_P(iter) - \vec{Y}(iter)\right| \quad otherwise \tag{18}$$

Equation (15) of WOA is expressed as equation (19) in hybrid WOASCA:

$$\vec{G} = rand_5 * \sin(rand_6) * \left|\vec{Y}_p(iter) - \vec{Y}(iter)\right| \quad if\ rand < 0.5$$
$$\vec{G} = rand_5 * \sin(rand_6) * \left|\vec{Y}_p(iter) - \vec{Y}(iter)\right| \quad otherwise \tag{19}$$

Rest of the equations remain unchanged and the algorithm follows as in WOA.

3.3. Implementation of OPF using HWSCOA

The steps for the implementation of OPF using HWSCOA are as follows:

Step 1. Initialize the parameters.

Step 2. Random control variables are generated in between the given limits.

Step 3. Fitness function is calculated, and the present the distance mapping parameter G

Step 4. G is modified using probabilistic based sine cosine functions.

Step 5. By using equations (17)-(19), G values are calculated, and the corresponding position of the particle gets updated.

Step 6. Update the G value and repeat the steps 3 and 5 till the iterations are satisfied.

4. Results and Discussion:

The projected algorithm trains all constraints of voltages at buses, transmission line flows, and restrictions on the active and reactive power output of generators. It has been well-designed to the IEEE30 bus system. These systems have six generators individually. The total controllable variables are 24. Table 1 indicates the parameters of the algorithms.

Table 1. Algorithm parameters

	WOA	HWSCOA
Search Agents	20	20
Max No. of Iterations	500	500
No. of Evaluations	30	30

Table 2 indicates the limits of power generating stations and their cost coefficients. Table 3 represents the emission coefficients of the generating stations.

Table 2. Limits of Power plants and their Cost Coefficients

Generating Unit No	Limits of Real Power in MW		Cost Coefficients		
	Low	High	*α*	*β*	*γ*
1	50	200	0	2	0.00375
2	20	80	0	1.75	0.0175
5	15	50	0	1	0.0625
8	10	35	0	3.25	0.00834
11	10	30	0	3	0.025
13	12	40	0	3	0.025

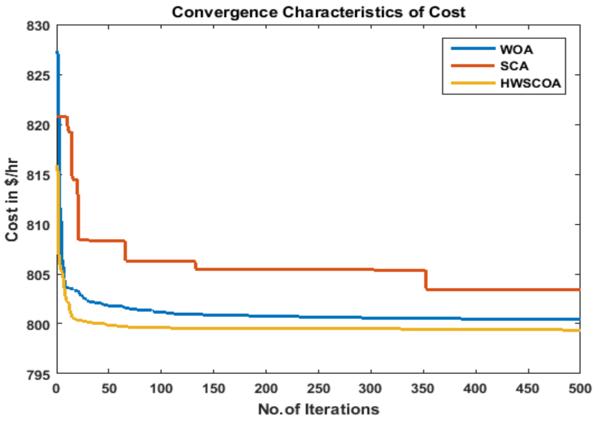


Fig. 3. Convergence characteristics of cost

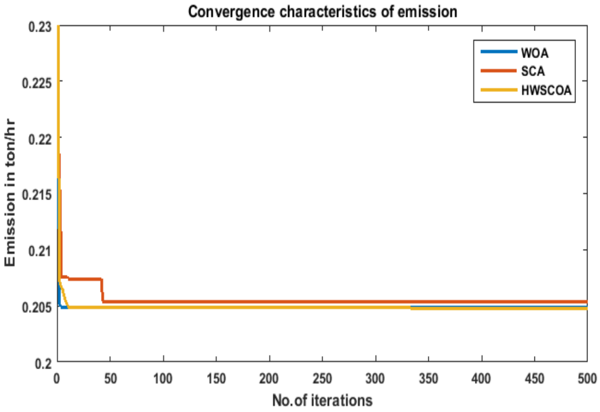


Fig. 4. Convergence characteristics of emission

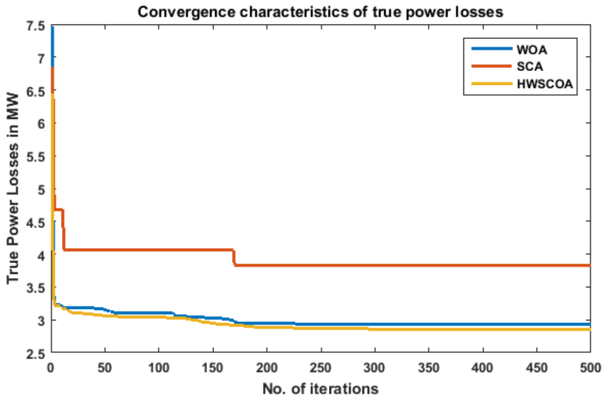


Fig. 5. Convergence characteristics of losses

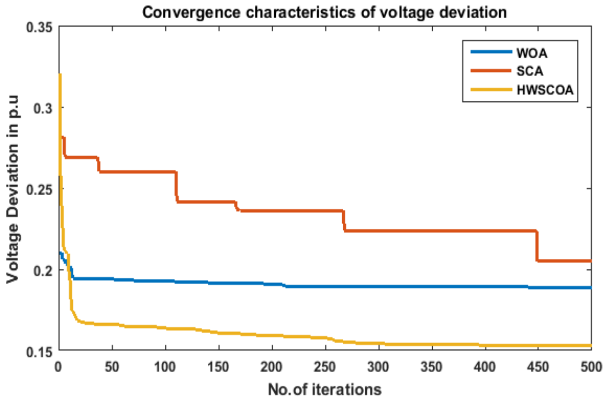


Fig. 6. Convergence characteristics of voltage deviation

The analysis of the test system with the suggested algorithm has been presented with diverse objectives as presented in Section 2.1. Hence, the reduction of generation cost, emission, true power losses and voltage deviation are considered as case 1, 2, 3 and 4, correspondingly.

Table 3. Generator Emission Coefficients

Gen No	Emission Coefficients				
	a	b	c	d	e
1	0.4091e	-0.555e	0.649e	0.2e-3	0.2857e
2	0.2543e	-0.604e	0.5638e	0.5e-3	0.3333e
5	0.4258e	-0.509e	0.4586e	0.1e-5	0.8e
8	0.5326e	-0.355e	0.3380e	0.2e-2	0.2e
11	0.4258e	-0.509e	0.4586e	0.1e-5	0.8e
13	0.6131e	-0.555e	0.5151e	0.1e-4	0.6667e

Fig 3 shows the convergence characteristics of a cost function using three different algorithms called SCA, WOA and proposed HWSCOA. From this, it is observed that cost is less in HWSCOA compared to other algorithms and converges quickly. It is also seen in Fig 4.

Table 4 presents the total 24 control variables values and other power system parameters of case1 study with three different algorithms. In this case, optimization of the cost is the objective, therefore, it optimizes effectively, and the proposed hybrid method gives better results compared to the individual algorithms. The optimized generation cost with HWSCOA is 799.3822 $/hr.

Table 4: Simulation results for optimal WOA, SCA and HWSCOA for *Obj 1* of IEEE 30-bus system.

Regulated Variables and parameters	WOA	SCA	HWSCOA
P_{TG1}(MW)	175.4249	174.549	177.1746
P_{TG2}(MW)	47.4128	44.3807	48.8628
P_{TG5}(MW)	20.5296	23.2409	21.3055
P_{TG8}(MW)	23.8495	19.7169	20.7778
P_{TG11}(MW)	12.8645	15.5039	12.0058
P_{TG13}(MW)	12.1139	15.1141	12.00
V_{TG1}(pu)	1.1	1.10	1.10
V_{TG2}(pu)	1.0888	1.1000	1.0876
V_{TG5}(pu)	1.0658	1.1000	1.0614
V_{TG8}(pu)	1.0696	1.1000	1.0695
V_{TG11}(pu)	1.0269	1.0706	1.1000
V_{TG13}(pu)	1.1000	1.1000	1.1000
Q_{C10} (MVAR)	0.6817	0.38	0.1607
Q_{C12} (MVAR)	1.0859	1.03	4.6520
Q_{C15} (MVAR)	2.9190	2.05	3.5355
Q_{C17} (MVAR)	3.0013	4.67	2.3463
Q_{C20} (MVAR)	0.0206	0.23	1.7419
$Q_{C2}1$ (MVAR)	2.0222	2.3936	0.4167
Q_{C23} (MVAR)	2.7348	2.8	0.6750
Q_{C24} (MVAR)	1.4716	2.56	3.6975
Q_{C29} (MVAR)	0.6274	0.6909	0.0084
T_{11}	1.1000	0.9285	0.9651
T_{12}	0.9573	1.0869	1.0274
T_{15}	1.1000	1.1000	1.0509
T_{36}	1.0665	1.1000	0.9780
Total Power Gen. PG(MW)	292.1952	292.506	292.1265
Total cost ($/h)	800.4309	803.384	799.3822
Emission (t/h)	0.362	0.358	0.367
Ploss (MW)	8.7952	9.1064	8.7265
VD (pu)	0.904	0.9354	0.9012

Table 5: Simulation results for optimal WOA, SCA and HWSCOA for *Obj 2* of IEEE 30-bussystem.

Regulated Variables and parameters	WOA	SCA	HWSCOA
P_{TG1}(MW)	63.9	71.9	63.8
P_{TG2}(MW)	67.6300	60.0786	67.5601
P_{TG5}(MW)	50	50	50
P_{TG8}(MW)	35	35	35
P_{TG11}(MW)	30	30	30
P_{TG13}(MW)	40	40	40
V_{TG1}(pu)	1.10	1.10	1.10
V_{TG2}(pu)	1.10	1.10	1.10
V_{TG5}(pu)	1.10	1.0519	1.0875
V_{TG8}(pu)	1.10	1.10	1.10
V_{TG11}(pu)	1.10	0.95	1.10
V_{TG13}(pu)	1.0769	0.9500	1.0562
Q_{C10} (MVAR)	3.2573	4.64	5.00
Q_{C12} (MVAR)	5.0000	5.000	5.00
Q_{C15} (MVAR)	5.0000	1.7431	4.8686
Q_{C17} (MVAR)	4.8738	0.5853	5.00
Q_{C20} (MVAR)	5.0000	5.00	5.00
Q_{C2}1 (MVAR)	4.8736	5.00	5.00
Q_{C23} (MVAR)	5.00	0.1446	5.00
Q_{C24} (MVAR)	5.00	5.0	5.00
Q_{C29} (MVAR)	5.00	5.0	5.00
T_{11}	1.0156	1.1000	1.10
T_{12}	1.10	1.0864	1.0853
T_{15}	1.10	1.10	1.10
T_{36}	1.10	0.90	1.0526
Total Power Generation P_G(MW)	286.53	286.978	286.36
Total cost (\$/h)	944.2228	934.205	943.6872
Emission (t/h)	0.2049	0.2066	0.2048
Ploss (MW)	3.13	3.5786	2.96
VD (p.u.)	0.8668	0.8721	0.8549

Table 6: Simulation results for optimal WOA, SCA and HWSCOA for *Obj 3* of IEEE 30-bus system.

Regulated Variables and parameters	WOA	SCA	HWSCOA
P_{TG1}(MW)	51.33	52.23	51.248
P_{TG2}(MW)	80.00	80.00	80.00
P_{TG5}(MW)	50.00	50.00	50.00
P_{TG8}(MW)	35.00	28.0927	35.00
P_{TG11}(MW)	30.00	27.7663	30.00
P_{TG13}(MW)	40.00	40.00	40.00
V_{TG1}(pu)	1.10	1.10	1.10
V_{TG2}(pu)	1.10	1.10	1.0976
V_{TG5}(pu)	1.10	1.0690	1.0799
V_{TG8}(pu)	1.0959	1.10	1.0871
V_{TG11}(pu)	1.0959	1.10	1.10
V_{TG13}(p.u)	1.1000	1.10	1.10
Q_{C10} (MVAR)	3.9265	4.4204	5.0000
Q_{C12} (MVAR)	5.0000	5.0	3.2781
Q_{C15} (MVAR)	5.0000	5.0	3.0878
Q_{C17} (MVAR)	5.0000	5.0	2.3394
Q_{C20} (MVAR)	2.6672	2.5255	5.0000
Q_{C2}1 (MVAR)	5.0000	4.5	4.1059
Q_{C23} (MVAR)	5.0000	5.0	3.2614
Q_{C24} (MVAR)	5.0000	4.8	4.8073
Q_{C29} (MVAR)	2.0302	0.0070	2.8772
T_{11}	1.1000	1.1000	1.0030
T_{12}	0.9000	0.9000	0.9551
T_{15}	0.9959	1.1000	0.9793
T_{36}	0.9835	1.1000	0.9753
Total Power Generation P_G(MW)	286.33	287.23	286.248
Total cost (\$/h)	967.2568	969.406	967.0613
Emission (t/h)	0.2083	0.2086	0.2082
Ploss (MW)	2.9331	3.835	2.8488
VD (p.u.)	0.8904	0.8967	0.8812

Table7: Simulation results for optimal WOA, SCA and HWSCOA for *Obj 4* of IEEE 30-bus system.

Regulated Variables and parameters	WOA	SCA	HWSCOA
P_{TG1}(MW)	128.248	145.248	158.448
P_{TG2}(MW)	41.3496	33.3052	31.8096
P_{TG5}(MW)	45.9007	36.1493	23.2271
P_{TG8}(MW)	20.1692	32.3087	32.0049
P_{TG11}(MW)	29.3868	11.4050	21.9145
P_{TG13}(MW)	25.4334	32.1647	22.6768
V_{TG1}(pu)	0.9773	1.0409	0.9977
V_{TG2}(pu)	0.9905	0.9500	1.0684
V_{TG5}(pu)	0.9739	1.0253	1.0245
V_{TG8}(pu)	1.0502	1.0238	0.9816
V_{TG11}(pu)	1.0528	0.9500	1.0728
V_{TG13}(pu)	1.0144	1.1000	0.9971
Q_{C10} (MVAR)	2.5615	4.7243	4.8977
Q_{C12} (MVAR)	3.8432	0.0000	1.8259
Q_{C15} (MVAR)	1.9596	2.9	4.0556
Q_{C17} (MVAR)	1.6486	2.8	1.0917
Q_{C20} (MVAR)	4.4622	4.3029	4.5925
Q_{C2}1 (MVAR)	3.2020	3.3	0.7914
Q_{C23} (MVAR)	2.8857	1.89	3.2279
Q_{C24} (MVAR)	0.6783	2.5	2.6185
Q_{C29} (MVAR)	0.0178	0.892	1.7676
T_{11}	0.9924	0.9609	0.9415
T_{12}	1.0087	0.9000	1.0324
T_{15}	0.9659	1.1000	0.9512
T_{36}	0.9590	0.9145	0.9486
Total Power Generation P_G(MW)	290.4877	290.580	290.0809

Total cost ($/h)	869.201	838.662	812.5572
Emission (t/h)	0.259	0.2893	0.316
Ploss (MW)	7.087	7.1809	6.6809
VD (p.u.)	0.1888	0.2048	0.1534

Table 5 presents the values with emission minimization. So, in this case, emission values less compared to other cases. It is observed that emission value reduces to 0.2048 ton/hr in HWSCOA compared to 0.2049 ton/hr in WOA. This reduction is obtained because of the hybridization. Table 6 and Table 7 indicate the control variables of other objectives losses and voltage deviation, respectively. Table 6 shows losses, being 2.8488 MW using HWSCOA. Table 7 shows the voltage deviation is 0.1534 p.u. using the proposed method, being low values compared to individual algorithms. From all the tables, it is also observed that the optimized parameter value is less compared to other parameters in each case. The convergence characteristics of losses and voltage deviation are shown in Fig.5 and Fig.6. Fig7 shows the real power generation for various case studies. It is observed that in cases 1 and 4 the slack bus generation is more compared to other cases because of this in these two cases, generation cost is less compared to other cases. Table 8 presents the comparison of various case studies with different algorithm results available in literature. This table illustrates that in all the cases proposed HWSCOA algorithm gives better results. It indicates the usefulness of the suggested technique matched to other approaches.

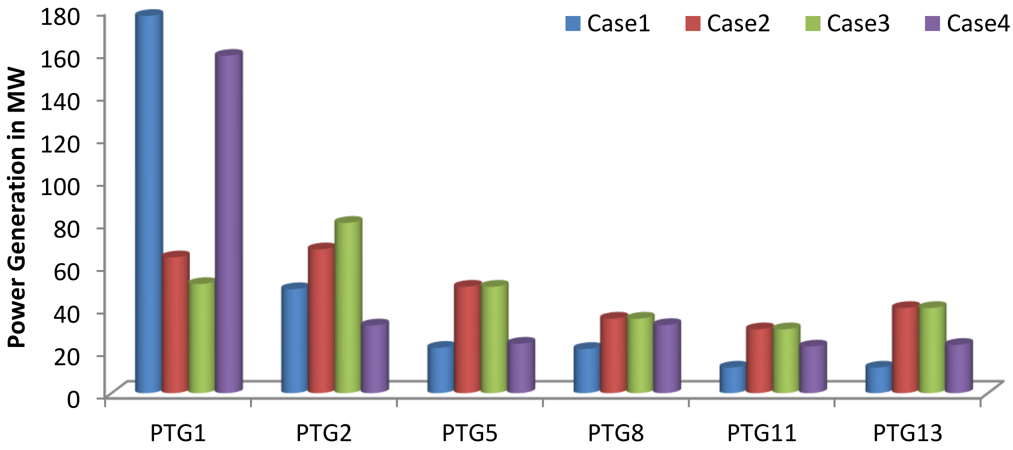


Fig. 7. Real Power Generation for Various case studies

Table 8: Evaluation of solutions realized for different cases (IEEE 30-bus system).

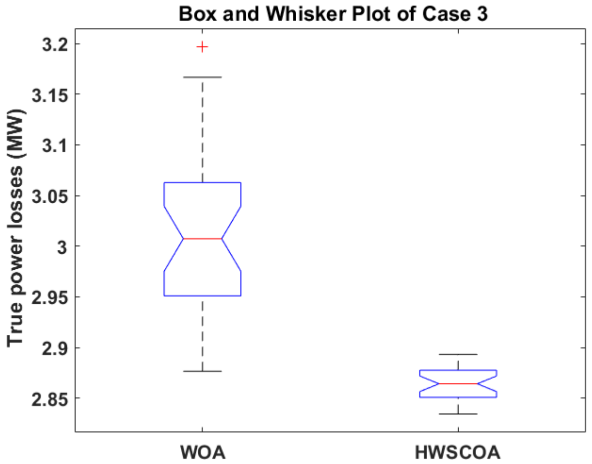
Method	Case1 ($/h)	Case2 (t/h)	Case3 (MW)	Case4 (p.u)
MSA [20]	800.5099	0.20482	3.1005	-
GWO [39]	801.41	-	3.41	-
DE [40]	801.23	-	3.38	
GBICA [40]	801.1513	0.2049		-
ABC [41]	800.66	0.20483	3.1078	-
ARCBBO [24]	800.5159	0.2048	3.1009	-
ECHT-DE [15]	800.4148	0.20482	3.085	-
SF-DE [15]	800.4131	0.20482	3.0845	-
SP-DE [15]	800.4293	0.20482	3.0844	-
PSO [10]	800.45	-	3.12	-
AMTPG-Jaya [11]	800.1946	-	3.0802	-
TLBO [11]	800.1946	-	3.1138	-

WOA	800.4309	0.2049	2.9331	0.1888
SCA	803.3845	0.2066	3.835	0.2048
HWSCOA	**799.3822**	**0.2048**	**2.8488**	**0.1534**

Table 9: Numerical values achieved as thirty runs of HWSCOA and WOA for IEEE30-bus system

Case 1	Case 2
	

Algorithm	Best value attained	Worst value attained	Mean value	SD	Algorithm	Best value attained	Worst value attained	Mean value	SD
	($/h)	($/h)	($/h)			(t/h)	(t/h)	(t/h)	
WOA	799.4907	801.5813	800.4153	0.4869	**WOA**	0.2048	0.2049	0.2049	3.5994e-05
HWSCOA	799.0310	799.5786	799.2727	0.1333	**HWSCOA**	0.2048	0.2049	0.2048	3.3474e-05

Case 3	Case 4
	

Algorithm	Best value attained	Worst value attained	Mean value	SD	Algorithm	Best value attained	Worst value attained	Mean value	SD
	(MW)	(MW)	(MW)			(p.u.)	(p.u.)	(p.u.)	
WOA	2.8765	3.1969	3.0122	0.0865	**WOA**	0.1478	0.2172	0.1807	0.0168
HWSCOA	2.8343	2.8932	2.8647	0.0148	**HWSCOA**	0.1199	0.2028	0.1461	0.0175

5. Robustness analysis on the proposed HWSCOA for the OPF problem:

To calculate the robustness of the hybrid WOA and SCOA solver, a numerical study has been executed. The hybrid WOA and SCOA solver has been implemented with 30 times for random initial populations to all measured cases. Table 1 displays the parameters of the projected technique. In this paper, 4 numerical pointers are used to shows the effectiveness of the HWSCOA. The attained optimum, poorest, mean & standard deviation values for the HWSCOA and WOA algorithms are disclosed in Table 9. These values are close after 30 runs in proposed HWSCOA compared to WOA, demonstrating the less value of standard deviation in HWSCOA. The results of the numerical test declare the toughness of HWSCOA method compared to WOA in terms of discovering the best value in each test. Box plots for various case studies shown in Table9.

6. Conclusions

In this paper, a newly suggested hybrid Whale and Sine Cosine optimization algorithm was stated and functional to resolve OPF problem. The hybrid Whale and Sine Cosine optimization algorithm approach was worthy and yield improved results related to other techniques on IEEE30 bus system. This approach was successfully executed to discover the optimal sites of the regulated variables of the assessment system.

Finally, the advantages of bubble-net hunting strategy in this optimization algorithm are used to stretch the penetrating process to determine a new area, but sometimes there is a possibility to stuck at local optima. Therefore, the distance mapping parameter G from WOA is modified in hybrid WOASCA using probabilistic based sine-cosine functions. This modification increases the exploration capability within the search space in a rigorous manner and eliminates even the slightest chance of the solution getting stuck in local minima. The results display the robustness of the suggested HWSCOA method for answering the OPF problem.

As future work, the novel proposed HWSCA can be used to perform OPF in larger systems like IEEE 57 and 118 bussystems. It can be further extended to applications like the placement of FACTS devices and sizing and placing of shunt capacitor in distribution system.

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Nomenclature:

OPF	-OptimalPowerFlow
FACTS	-FlexibleAlternatingCurrent Transmission System
HWSCOA	-Hybrid Whale & Sine Cosine Optimization Algorithm
WOA	-WhaleOptimizationAlgorithm
SCA	-SineCosine algorithm
ED	-Economic Dispatch
MOOPF	-Multi-Objective OPF
AMTPG-Jaya	-Adaptive Multiple teams perturbation guiding Jaya
MPIO	-Modified pigeon inspired optimization algorithm
MSCA	-Modified SineCosine algorithm
MSA	-Moth Swarm Algorithm
DGWO	-Developed Grey Wolf Optimizer
GWO	-GreyWolfOptimization
DE	-DifferentialEvolution
SCOPF	-Security-constrained optimal power flow
ABC	-Artificial Bee Colony
ARCBBO	-Adaptive real coded biogeography-based optimization
PSO	-ParticleSwarmOptimization
TLBO	-Teaching Learning Based Optimization

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