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WHALE OPTIMIZATION ALGORITHM FOR CONGESTION REMOVING IN TRANSMISSION NETWORK WITH GENERATORS REAL POWER RESCHEDULING

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ABSTRACT: Nowadays, energy management is one of the current research topics in power systems by means of controlling the system control variables to balance the abnormal load demand and fault conditions. In such cases, the optimal power flow was considered for determining the energy balancing in past research activities. In this research, the Whale Optimization Algorithm (WOA) is applied for providing the optimal power flow. It extends our previous research on rescheduling and congestion management of generators. Here, the performance WOA algorithm is checked with the IEEE test networks such as (a) IEEE 30-bus and (b) IEEE 50-bus test systems. The optimal power flow control by the change in real power of generators with minimization of total congestion cost. The overall process was carried out with MATLAB development tool to verify the power system outcome. The simulation results demonstrated that the WOA is effective in testing and it proves that it is one of the best congestion management (CM) scheme.

Keywords: Optimal power flow, Generator real power rescheduling, Optimization, Whale Optimization Algorithm.

1. INTRODUCTION

Recent years demand of electricity utilization continuously increasing due to the luxurious life style of humans beings. Similarly the generation capability increased with renewable energy sources due to lack of fossil fuels for balance the demand growth. The generation of output electricity is not-constant due to variable input energy sources. The power system control and co-ordination is crucial task for independent system operator (ISO) for maintaining the power system secure operation. The optimal power flow is one of the authoritative tool for maintaining the equality and inequality constraints. In recent years, the evolutionary optimization techniques in such as differential evolution algorithm combined with effective constraint handling techniques[1], artificial bee colony algorithm[2], moth swarm algorithm[3], improved strength Pareto evolutionary algorithm[4], Symbiotic organisms search algorithm[5], etc., have been applied for solving the OPF problem. Apart from single evolutionary algorithm, the hybrid algorithms, such as hybrid differential evolution and harmony search algorithm [6], modified bio-inspired optimisation algorithm with a centroid decision making approach [7], Hybrid genetic algorithm and particle swarm optimization [8] etc., have been applied for solving OPF problems. Duman (2017) utilized the Symbiotic Organisms Search (SOS) algorithm to solve the Optimal Power Flow (OPF) problems in recent modern power systems [10]. For verifying the functionary, it was tested with the modified IEEE 30-bus test system. The problem was separated into four different processes of with and without valve-point effect and with and without prohibited zones. Zamani et al., (2017) presented the Chaos embedded Symbiotic Organisms Search (CSOS) technique. It was tested with the IEEE 26-bus Reliability Test System for verifying the functionality of the CSOS. It summarizes that the CSOS is a good optimizer for FACTs devices when comparing it with the Particle Swarm Optimization and Evolutionary Programming. Some recent techniques to solve for optimal FACTS device allocation, are improved cuckoo search algorithm [12], Adaptive Hybrid Optimization Algorithm [13], Fuzzy unscented transform for uncertainty quantification of correlated wind/PV microgrids [14], etc. Other traditional algorithms have also been considered for processing the constraints based optimal power flow, but the limitations faced by them are increases in cost, losses and improper synchronizing of power iterations or fluctuation in power system module.

Zhang et al., (2017) proposed a population based parallel DE approach for solving the short-term optimal hydrothermal scheduling. The objective is to minimize the total fuel cost of the thermal unit generations with power balancing, water balance and other constraints in hydro or thermal units. It also considers the short-term hydrothermal scheduling (STHS) problem that arises due to the valve-point effect. The process is carried out based on the population size. It deploys the parallel DE approach to solve the low diversity in each process. It is implemented with a small population with communication among different running processes. To verify the standard of the model, transmission networks of standard IEEE 9-bus and IEEE 39-bus are considered [15]. Heidari et al., (2017) concentrated on optimal reactive power dispatch problem. It is effectively solved by the Gaussian bare-bones water cycle algorithm (NGBWCA) with IEEE 30, 57 and 118 bus streams [16].

In this research, the contribution of meta-heuristic optimisation is deployed in matching the objective of reducing the cost and energy. The major limitations of previous algorithms are sensitivity problems, converge to local optimum solutions, inefficient cost and transmission losses [9]. Apart from a fore-mentioned limitations, the iteration of each target is important in all swarm algorithms. Hence, the selection of algorithms is important to achieve the exact optimal result by encircling the objective. In the proposed modified WOA model, the impartial function is expressed as a constrained nonlinear optimization problem, to solve the identified issues with the generation rescheduling.

2. MATHEMATICAL CALCULATION

The main objective function of the proposed work has reduced the cost of congestion and at the same time satisfying the transmission network constraints without violation. The CM issue is solving by the method of generator real-power rescheduling. The cost associated with a change in real power output of the generator depends on the generating company's (Generating Companies.) price bids. Therefore, the objective of the problem may be stated as in Eq.(1) [6].

Minimize

$$F_c = \sum_{j \in N_g} \left(a_k \Delta P_{gj}^{+} + b_k \Delta P_{gj}^{-} \right) \$/h \tag{1}$$

The equality and inequality constraints have taken for the optimization problem as given below.

2.1. Equality constraints

The real and reactive power flow equations stated by Eq. (2)–(5) [7].

$$P_{gk} - P_{dk} = \sum_{j} |V_j||V_k||Y_{kj}| \cos(\delta_k - \delta_j - \theta_{kj});\ j = 1,2, \ldots, N_b \tag{2}$$

$$Q_{gk} - Q_{dk} = \sum_{j} |V_j||V_k||Y_{kj}| \sin(\delta_k - \delta_j - \theta_{kj});\ j = 1,2, \ldots, N_b \quad (3)$$

$$P_{gk} = P_{gk}^{c} + \Delta P_{gk}^{+} - \Delta P_{gk}^{-};\ k = 1,2, \ldots, N_g \quad (4)$$

$$P_{dj} = P_{dj}^{c};\ j = 1,2, \ldots, N_d \quad (5)$$

The Eq.(2) and Eq.(3) represent the active and reactive power balances at each node whereas Eq.(4) and Eq.(5) represent the final power as a function of market clearing price.

2.2. Inequality constraints

The details of the inequality constraints of operating and physical limits of all the generators, transmission lines, transformers are stated by Eq.(6) - (10) [7].

$$P_{gk}^{min} \leq P_{gk} \leq P_{gk}^{max},\ \forall k \in N_g \quad (6)$$

$$Q_{gk}^{min} \leq Q_{gk} \leq Q_{gk}^{max},\ \forall k \in N_g \quad (7)$$

$$(P_{gk} - P_{gk}^{min}) = \Delta P_{gk}^{min} \leq \Delta P_{gk} \leq \Delta P_{gk}^{max} = (P_{gk}^{max} - P_{gk}) \quad (8)$$

$$V_n^{min} \leq V_n \leq V_n^{max},\ \forall k \in N_l \quad (9)$$

$$P_{ij} \leq P_{ij}^{max} \quad (10)$$

Where the superscripts min and max represent the minimum and the maximum values of the respective variables and N_l represents the number of lines.

3. WHALE OPTIMIZATION ALGORITHM

The Whale optimization, work based on the principle of bubble-net attacking method for survival of life. It introduced by Mirjalili and Lewis in 2016[17]. The whales have spindle cells similar to the humans. It provides smart work and can able to think and learn to communicate over the life [18]. The levels of smartness of whales are high mostly for killer whales because they create their own language. A whale can live alone or in groups. Most of the time, they will be noticed in groups. It merits saying here that bubble-net feeding is an extraordinary conduct that can be seen in humpback whales. In this research the spiral bubble-net feeding manoeuvre is scientifically displayed with a specific end goal to perform improvement in solving OPF problems.

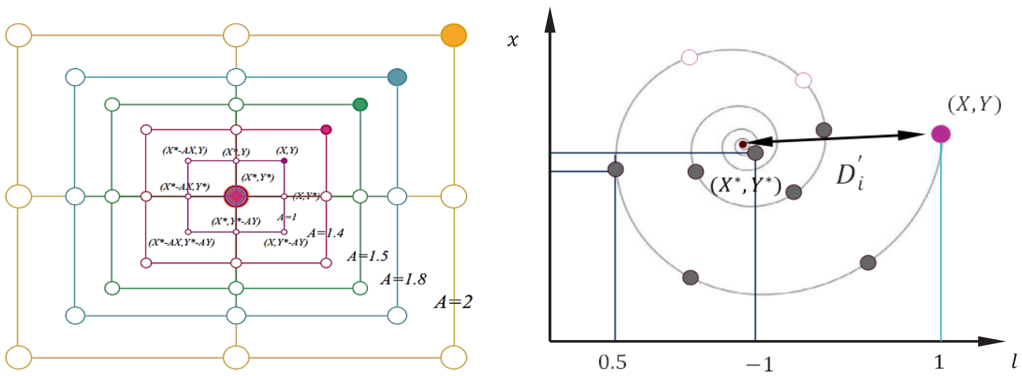


Figure 1: Exploration mechanism implemented in WOA (Mirjalili and Lewis, 2016) [16].

Humpback whales know the areas of prey and encompass them. They consider the present best hopeful arrangement as the best gotten arrangement and close to the ideal arrangement. Subsequent to allocating the best hopeful arrangement, alternate specialists attempt to refresh their positions towards the best hunt operation as in the following condition.

$$D = |C.X^{*}(t) - X(t)|$$

$$X(t+1) = X^{*}(t) - A.D$$

where is the current instant, A and C are coefficient vectors, X* is the position vector of the best solution, and X indicates the position vector of a solution, | x | means absolute value of x. Figure 1 displays that the X∗ as a randomly chosen search agent. For encircling prey, the vectors A and C are calculated as follows:

$$A = 2a.r.a$$

$$C = 2.r$$

where components of ‘a’ are linearly decreased from 2 to 0 over the course of iterations and r is a random vector in [0; 1]

3.1.Pseudo code for WOA algorithm

To Define the initial population size (n).

Initialize the parameters and coefficients (α,A,C, Maxiter).

Initialize the counter (t=0)

While (t<Max iteration)

for (i=1;i≤n)

% Selection Phase

Random allocation of population

% assigning the best search agent

Proceed with the steps by incrementing the step size (t)

% updating phase

Update the parameters with the respective search agents

Find the random position of current agent

% fitness evaluation

Update the exact search agent represented as X* and find the terminating condition

Find the fitness evaluation based on the search agent

Achieve the best result

Terminate

From the pseudo code, it is demonstrated that the standard WOA is initiated by setting the initial values of the population size (n), parameter (a), coefficients (A & C) and the maximum number of iterations (Maxiter). Based on the respective functions, the iteration counter is calculated and updated with the new position. Then update the iteration count (t). Generate the initial population (n) randomly with the search agent Xi in the population and by compute its fitness function f (Xi). Mention the best search agent by repeating the task until its termination criterion is satisfied.

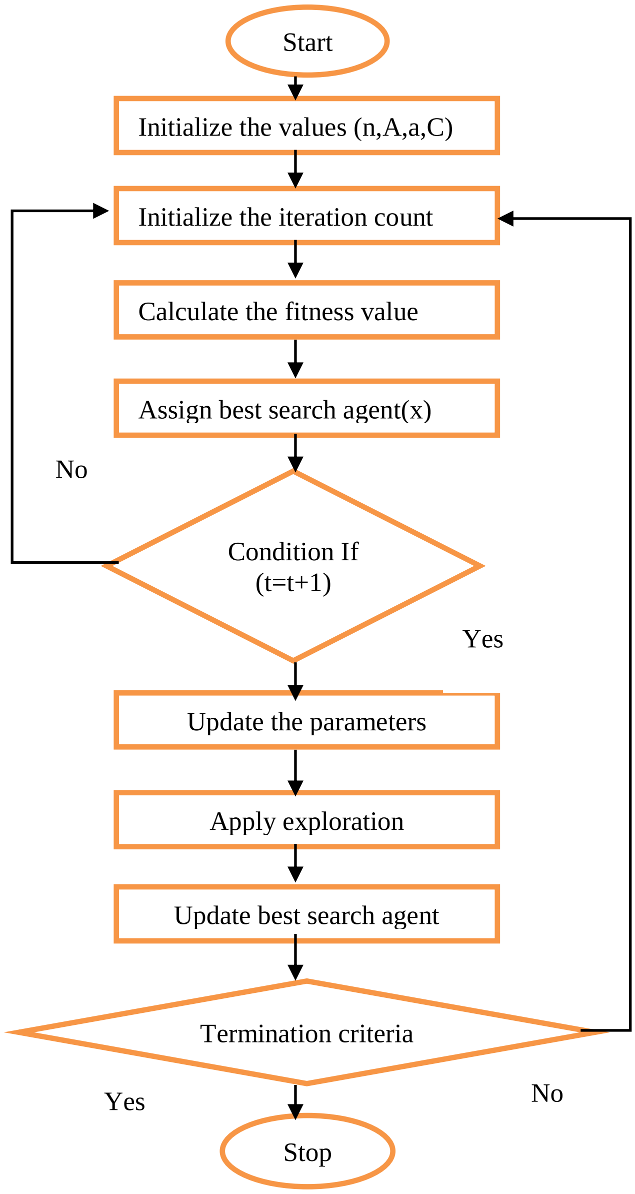


Figure 2: Flow chart for WOA

3.2. PROPOSED MBMMOA ALGORITHM FOR CM

In this work, the dimension is the number of generators participating in the CM problem. The penalty functions added to the objective function to construct the fitness function from transferred inequality constraints. The equality constraints and the reactive-power inequality constraints efficiently managed by Newton–Raphson power flow while the real-power inequality constraints are dealing with during the iteration process. Other inequality constraints of line power flow and load bus voltage considered as quadratic penalty functions. The fitness function of CM problem analyzed by the following:

$$\text{Minimize } F=F_c + PF_1 \times \sum_{i=1}^{vol} \left(P_{ij} - P_{ij}^{max}\right) + PF_2 \times \sum_{j=1}^{VBL} \left((\Delta V_j)^2{}_j + P_{ij}^{max}\right) + PF_3 \times (\Delta P_g)^2 \tag{19}$$

Where

$$\Delta V_j = \begin{cases} \left(V_j^{min} - V_j\right); \text{if } V_j \leq V_j^{min} \\ \left(V_j - V_j^{max}\right); \text{if } V_j \leq V_j^{max} \end{cases} \tag{20}$$

$$\Delta Pg = \begin{cases} \left(P_g^{min} - P_g\right); \text{if } P_g \leq P_g^{min} \\ \left(P_g - P_g^{max}\right); \text{if } P_g \leq P_g^{max} \end{cases} \tag{21}$$

Here, F is the fitness function, vol represent the line overloading, VBL represents the line limit and PF_i(i = 1, 2, 3) represents the penalty factor taken as 10, 000 throughout the simulation process [10].

4. RESULTS AND DISCUSSION

Based on the above procedure, the fitness value of each element is calculated through the given objective function. The real-value position of a whale consists of active and reactive power generation, generator /load bus voltages, transformer taps and shunt capacitors/inductors. The normal position is improved with the help of mixed-variable vector that is used to calculate the objective function based on Newton–Raphson power flow analysis.

The proposed WOA is tested for CM to verify the effectiveness of the different test cases mentioned in the Table 6.

Table 1. Details of creating contingency on IEEE bus systems with the various test cases

Bus system	**Test case**	**Contingency considered**
Modified IEEE 30-bus	1A 1B	Line terminate in-between 1–2 Line terminate in-between 1-7 at same time increase the load 50% at all buses
Modified IEEE 57-bus	2A 2B	Reduced the power carrying capacity of the lines from 200 MW to 175 MW and 50 MW to 35 MW in-between 5-6 and 6-12 Power carrying capacity reduced from 85 MW to 20 MW in-between line 2–3
IEEE 118-bus	3	Line terminate in-between 8-5 at the same time load increased 57% at buses 11-20

Table 2. Details of the line flow of the IEEE-bus system with different Cases

Test Classes	**Line in-between buses**	**Line flow(MW)**		**Particular of the line limit, (MW)**
		Before CM	After CM	
1A	1–7	147.57	**129.5**	130
	7–8	140.23	**125.04**	130
1B	1–2	314.01	**130**	130
	2–8	97.86	**63.35**	65
	2–9	103.66	**64.81**	65
2A	5–6	188.69	**172.74**	175
	6–12	49.53	**18.16**	35
2B	2–3	36.60	**17.22**	20
3	16–17	209.24	**98.91**	175
	30–17	580.29	**498.62**	500
	8–30	363.52	**141.92**	175

The modified IEEE 30-bus test system contains 41 transmission lines, 6 generator buses and 24 load buses. The total testing network real-power is 283.4 MW and reactive-power is 126.2 MVAR. In this test system, two different cases are taken as shown in table.1 for evaluating the performance of the proposed algorithm, viz. Case 1A and 1B.

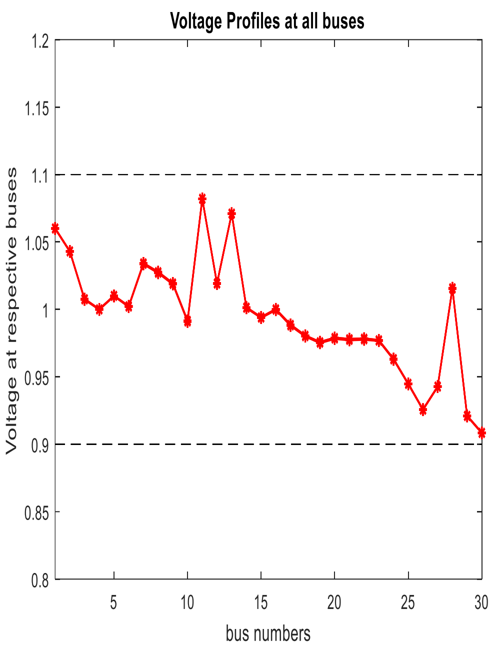
Table 3: Comparative results of cost with changed in real-power for the case 1A and Case 1B with different algorithms

CASE 1A					
Parameters	SA	RSM	PSO	FA	WOA [Proposed]
TCC, \$/h	719.86	716.25	538.95	511.8737	**509.642**
ΔPG1, MW	−9.076	−8.808	−8.61	−8.7783	-8.75734
ΔPG2, MW	3.133	2.647	10.4	15.0008	14.12063
ΔPG3, MW	3.234	2.953	3.03	0.1068	0.10019
ΔPG4, MW	2.968	3.063	0.02	0.0653	0.25014

ΔPG5, MW	2.954	2.913	0.85	0.1734	0.01485
ΔPG6, MW	2.443	2.952	−0.01	-0.618	0.36393
TGR, MW	23.809	23.33	22.93	24.7425	23.60708

CASE 1B					
TCC, $/h	6068.7	5988	5335.5	5304.4	5296.53
ΔPG1, MW	NR	NR	NR	−8.5798	-9.00530
ΔPG2, MW	NR	NR	NR	75.9954	74.66020
ΔPG3, MW	NR	NR	NR	0.0575	41.05022
ΔPG4, MW	NR	NR	NR	42.9944	2.08224
ΔPG5, MW	NR	NR	NR	23.8325	25.96590
ΔPG6, MW	NR	NR	NR	16.5144	13.50039
TGR, MW	164.53	164.5	168	167.974	166.264

In Case 1A, congestion is created in the test system by considering an terminating of line between the buses 1-2. Due to the termination of line, congestion occurs in the lines between 1–7 and 7-8. For secured operation, corrective actions are taken to alleviate these over loading lines. The proposed modified WOA algorithm is applied for the minimization of congestion cost. The proposed WOA is compared with those reported in the literature like SA, RSM, PSO and FA in Table 3. The proposed WOA obtained best optimal value of total congestion cost is found to be 509.642 $/h as shown in Table 3. In Case 1A, after congestion management losses reduced from 16.13 MW to 13.29 MW.



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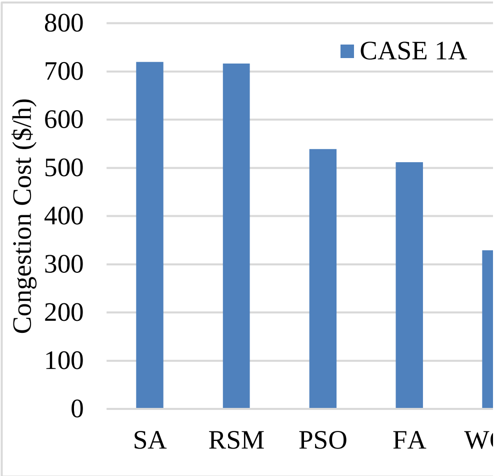

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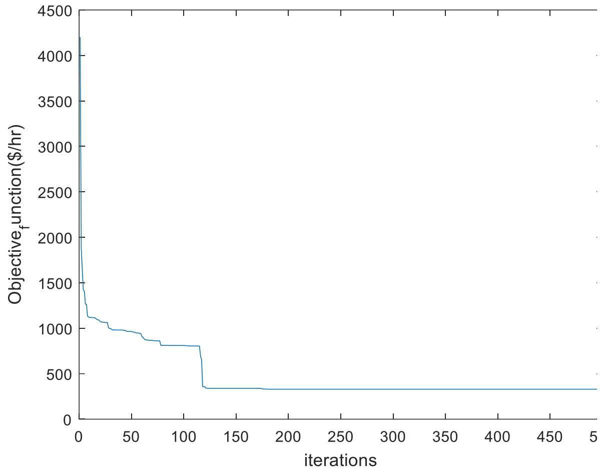

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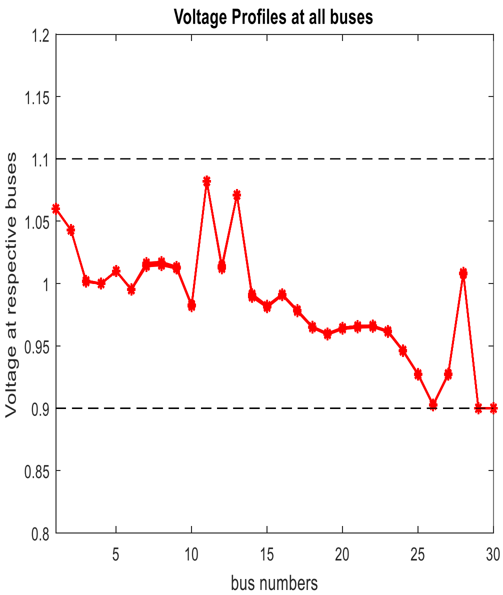
Figure 3: Simulation results for Case 1A. (a) Voltage magnitude in p.u.; (b) change in generator real-power in MW (c) congestion cost $/hr (d) convergence profile

The voltage magnitude, obtained after CM while using modified WOA is shown in Fig. 3 (a). It is observed that, after CM, the voltage magnitude is within limits between 0.9 and 1.1. A comparative graphical representation of the real power rescheduling and congestion cost with different algorithms is shown in Fig. 3(b) and 3(c). Similarly the case 1B details are shown in table 3 and Fig.4. In the case of IB losses reduced to 15.83 MW after congestion management instead of 37.24 MW before the congestion management.



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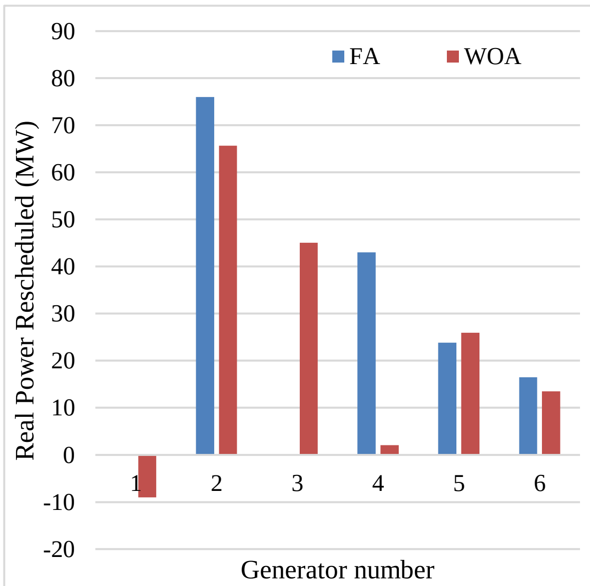

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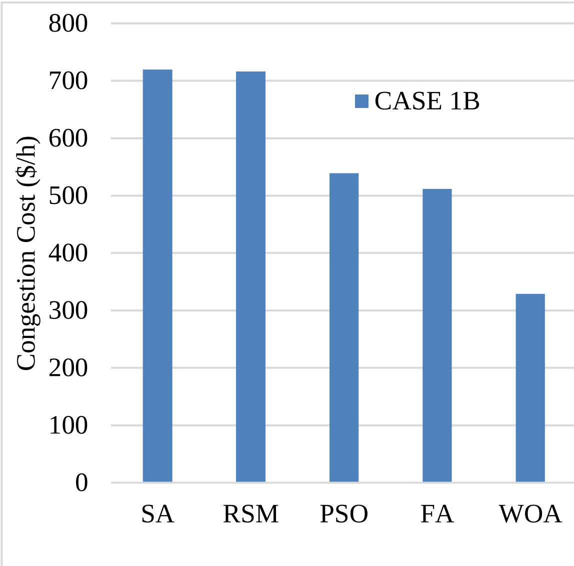
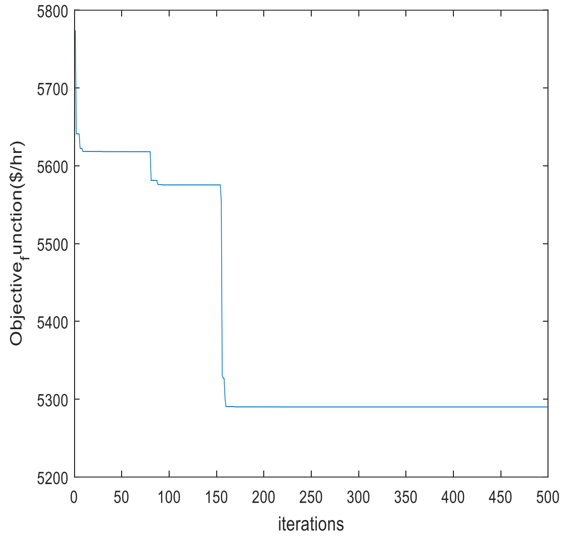




C

d

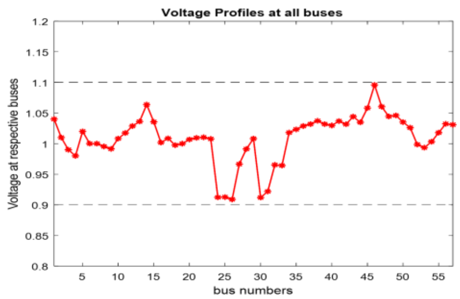
Figure 4: IEEE 57: Simulation results with comparison of different algorithms for Class-2A

. (a) Voltage magnitude in p.u.; (b) change in generator real-power in MW (c) congestion cost in $/hr (d) convergence profile

Table 4: Comparative results of cost with changed in generator real-power for the case 2A and Case 2B with different algorithms

Parameters	SA	RSM	PSO	FA	WOA[Proposed]
CASE 2A					
TCC, $/h	7114.3	7967.1	6951.9	6150.1	**6031.4**
ΔPG1, MW	74.499	59.268	23.13	5.6351	5.07306
ΔPG2, MW	0	0	12.44	2.523	2.60977
ΔPG3, MW	−1.515	37.452	7.49	0.5098	0.40739
ΔPG4, MW	9.952	−47.39	−5.38	0.107	0.44053
ΔPG5, MW	−85.92	−52.12	−81.21	−39.1514	-39.15113
ΔPG6, MW	0	0	0	−35.1122	-34.74636
ΔPG7, MW	0	0	39.03	63.1938	62.1982

TGR, MW	168.78	196.23	171.87	146.227	144.6264
CASE 2B					
TCC, $/h	4072.9	3717.9	3117.6	2618.1	**2103.34**
ΔPG1, MW	NR	NR	N	0.3704	-0.22150
ΔPG2, MW	NR	NR	NR	−27.5084	1.08662
ΔPG3, MW	NR	NR	NR	31.6294	22.04924
ΔPG4, MW	NR	NR	NR	0.3308	0.17019
ΔPG5, MW	NR	NR	NR	−2.2549	-10.50832
ΔPG6, MW	NR	NR	NR	−1.9354	-0.00000
ΔPG7, MW	NR	NR	NR	−0.5101	16.00743
TGR, MW	97.88	89.32	76.314	64.5393	50.04330



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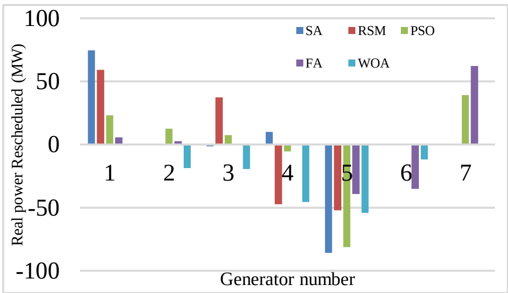

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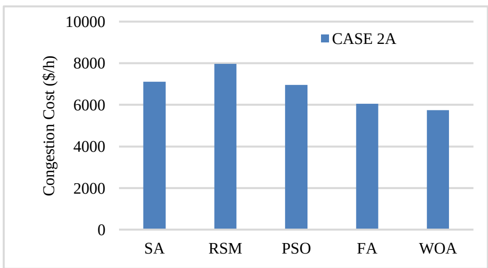

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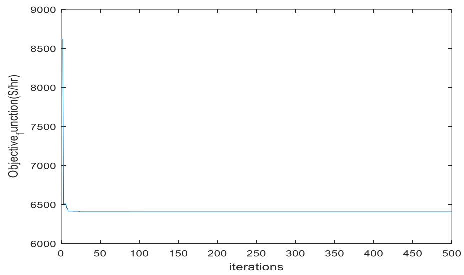

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Figure 5: IEEE 57: Simulation results with comparison of different algorithms for Class-2A. (a) Voltage magnitude in p.u.; (b) change in generator real-power in MW (c) congestion cost in $/hr (d) convergence profile

In Case 2A, the details of the congested line flow is given in the Table 2. The optimum value of the generator real power rescheduling performed by using a proposed WOA algorithm completely alleviates the violation of the overloading lines. The WOA based bus voltages, as obtained after the application of CM are displayed in Fig. 5(a) which is an acceptable one. The generator real-power rescheduling and congestion cost of the proposed WOA method compared with other algorithms is shown in Fig. 5(b) and Fig.5(c). Fig.5(d) shows the convergence profile. The total system loss before CM was 69.64 MW and it decreased to 27.71 MW after the CM.

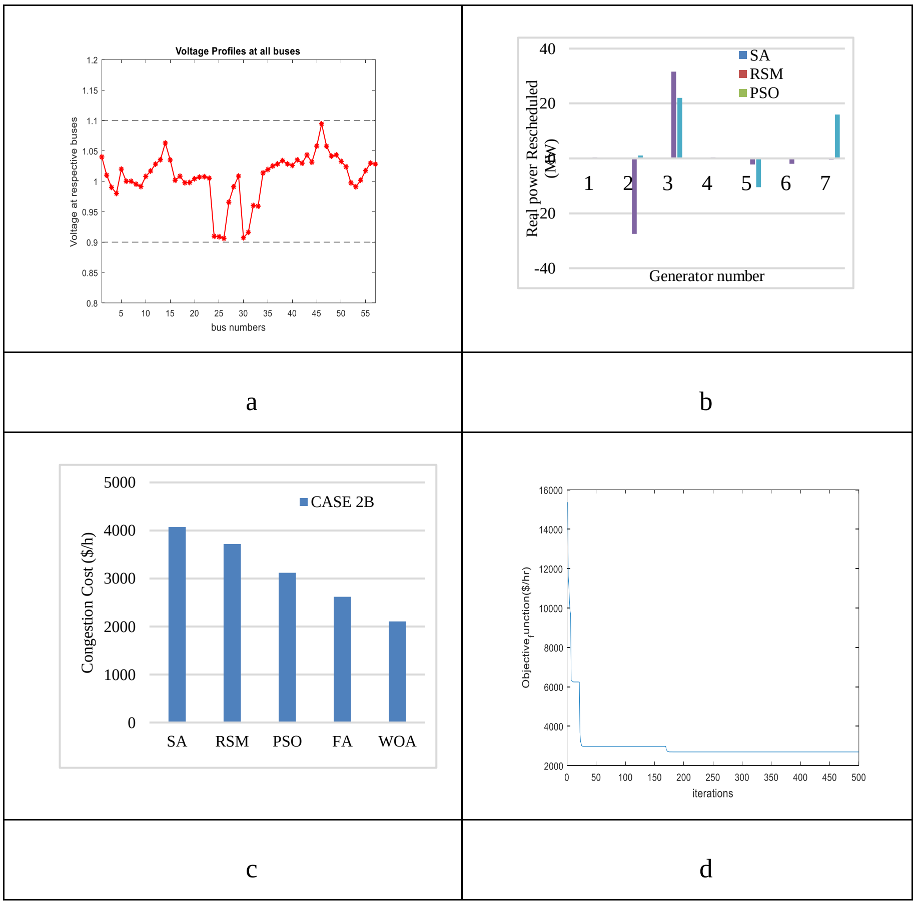

Figure 6: IEEE 57: Simulation results with comparison of different algorithms for Class-2B. (a) Voltage magnitude in p.u.; (b) change in real power rescheduling concept (c) congestion cost (d) convergence profile

Case 2B shows in Table 4, the results obtained after applying the proposed modified WOA. It clearly shows the cost incurred for CM is only 2103.34 $/h for the proposed modified WOA method and it is the lowest among all the costs obtained so far. The comparative congestion costs, offered by different algorithms and the proposed WOA method are displayed in Fig. 6(c). In this case, after CM losses reduced to 29.32 MW instead of 78.23 MW before CM.

5. CONCLUSION

The major objectives of congestion cost, power loss minimization are achieved by Whale Optimization Algorithm (WOA). From the investigation, it is noticed that the proposed algorithm is capable of providing the best optimal power flow in power system. The proposed approach of utilizing WOA is compared with existing algorithms in literature such as SA, RSM, PSO, FA, EP, RCGA and DE. The results depict the superiority of WOA over these algorithms. The process of balancing the objective function is estimated with IEEE 30-bus and 57-bus systems. The evaluation proves that the proposed algorithm is best, when compared with other optimizations.

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