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Optimal power flow with distributed energy sources using whale optimization algorithm

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ABSTRACT

Renewable energy generation is increasingly attractive since it is non-polluting and viable. Recently, the technical and economic performance of power system networks has been enhanced by integrating renewable energy sources (RES). This work focuses on the size of solar and wind production by replacing the thermal generation to decrease cost and losses on a big electrical power system. The Weibull and Lognormal probability density functions are used to calculate the deliverable power of wind and solar energy, to be integrated into the power system. Due to the uncertain and intermittent conditions of these sources, their integration complicates the optimal power flow problem. This paper proposes an optimal power flow (OPF) using the whale optimization algorithm (WOA), to solve for the stochastic wind and solar power integrated power system. In this paper, the ideal capacity of RES along with thermal generators has been determined by considering total generation cost as an objective function. The proposed methodology is tested on the IEEE-30 system to ensure its usefulness. Obtained results show the effectiveness of WOA when compared with other algorithms like non-dominated sorting genetic algorithm (NSGA-II), grey wolf optimization (GWO) and particle swarm optimization-GWO (PSO-GWO).

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1. INTRODUCTION

Proper planning is necessary for improved usage of resources already existing in the power system. optimal power flow (OPF) has recently emerged as a popular issue for realizing the optimal planning of a real-timesystemfunction is very much necessary for achieving operation and control of modern power systems. Various objectives including power losses, emissions, and voltage stability are taken into account for optimizing the variable regulation using OPF. Different traditional optimization strategies for tackling OPF problems have been presented in the literature [1] and these procedures have occasionally failed to provide the desired effects. This can be overcome employing by a heuristic approach and metaheuristic methodology that take into account the randomization of controlled parameters. Various authors used a variety of strategies to address the OPF problem, some of which are described below. Particle swarm optimization (PSO) was used by [2] authors to solve the OPF. The PSO examined for IEEE thirty Bus test case for reduced goal operation like voltage stability improvement, power loss and total fuel cost. In [3] grey wolf optimizer (GWO) the differential evolution algorithms were proposed with voltage proficiency enhancement and actual power loss minimization as goals. The suggested algorithm's performance was evaluated for IEEE test cases of 57- buses and 118-buses. An improved genetic algorithm (GA) technique, [4] presents a linear adaptive genetic algorithm and It has tested for IEEE six and and 14-Bus systems. In [5], gravity search method was utilized to solve the OPF issue to address transmission losses. It has been examined on the Indiantwenty-four bus system. For tackling the OPF issue, the literature [6] suggested a multi-objective glow-worm swarm optimization method. The moth-flame optimizer (MFO) approach was utilized in this [7] to tackle the OPF problem. There are several objectives for improved management in power systems, including emissions, active power losses, running costs, the collision of voltage, and stability. This literature study presents several linear, nonlinear, and metaheuristic approaches available in literature for power system networks. While power systems have been extensively modified in recent years, classic optimization procedures have been reinstated. In this environment, optimum power flow is the most important technical, adaptive, and economic instrument OPF. We compare different OPF methods to considered objective function in this work. Finally, we will discuss some of the fundamental issues raised by the new OPF method for the contemporary grid. For the OPF issue, Bhowmik and Chakraborty [8] suggested a multi-objective non-dominated sorting GA II algorithm.

The objective function of increased voltage stability was this algorithm's key contribution. The salp swarm algorithm (SSA) was proposed in [9] for tackling the OPF issue. Jaya optimization method was employed by the authors [10] to solve the OPF issue. The goal functions are reduced using this algorithm. Samakpong *et al.* [11] used the random inertia weight particle swarm optimization (RANDIW-PSO) technique for the OPF issue which was investigated for the IEEE thirty-nine bus system. In [12] presented a cuckoo search strategy foraddressing the multi-objective OPF issue. In [13], [14], the whale optimization method, a novel metaheuristic algorithm was utilized for handling structural design for a single goal and restricted optimization problems. This approach emulates humpback whale social behavior.

Renewable energy sources (RES) such as solar and wind power with skill curves are used in large power transmission systems based on the maximum power extraction principle [15], [16]. The solar irradiance model [17], [18] and wind power model for the OPF [19], [20] are extensively discussed in this. The costs of solar photovoltaic (PV) and wind turbine generators for the OPF with constraints, goals, and fitness functions [21], [22]. Solar power's active power must be limited. Active and reactive power control objectives, as well as other objectives such as voltage stability, emission, costs, losses, and technical parameters, are controlled for large bus systems and efficiently used in the optimal power flow problem [23], [24]. Pandiarajan *et al.* discuss OPF problems in detail, with details on objectives, constraints, algorithms used, and their outcomes in [25], [26]. Recently, most of the works are built on RES, and such mixed integer linear programming and metaheuristic approaches are new with the goal of minimizing carbon emissions and acting as an eco-friendly system [27].

Linear programming's low suppleness and insufficient framework are primary limitations, therefore we need seek for non-linear programming, which has more flexibility and platform access, but still requires a specialized solution, thus metaheuristic optimization approaches are discovered to be more advantageous [28]. Among these ideal approaches, the genetic algorithm is the easiest to create, has the most flexibility, and is available on a variety of platforms, at the expense of a higher computational cost and comparably low performance [29]. To address this, PSO can give superior speed, flexibility, platform access, and ease of execution, but at a higher computational cost [30]. Mix-integer programming is a great deal method that has a solution to the above concerns and is more flexible and ideal for electric car charging control, but it still requires specific solvers and approaches and has a higher computational price for large scale dimensions problems [31]. Modern meta-heuristic approaches, such as whale optimization algorithm (WOA) developed by the previous authors, may overcome concerns such as computation cost and burden, as well as give more flexibility, diverse platform access, and better performance, but parameter setup remains complex [32], [33].

The contribution of the work is to create a one-of-a-kind WOA for the MOOPF-WS challenge, which incorporated solar PV, wind and thermal producers into the grid. Several probability density functions (PDFs) were utilised to represent uncertainty in RES and load demand. To determine the non-dominated ranks and densities of the solutions generated, WOA used rapid non-dominated sorting and crowding distance approaches. Furthermore, the Pareto archive selection approach was used for non-dominated solution distribution maintenance. For all discrete loading situations, the variable loading scenario has significantly worse predicted performance characteristics than the constant loading case. This shown that solving OPF under changing load conditions provides more flexible and effective generator scheduling than under steady load conditions, resulting in lower anticipated performance profiles. Furthermore, employing high voltage (HV) indicators, the multi-objective search group algorithms (MOSGA's) performance was compared to the non-dominated sorting genetic algorithm (NSGA-II), multi objective ant lion optimization (MOALO), and WOA. The WOA beat the other three techniques in terms of convergence and diversity of

Pareto optimum solutions in all cases. As a result, WOA could uncover the wider variety of non-dominated solutions for all objective functions. when compared to major studies in the literature, WOA obtained higher quality solutions in all similar circumstances. These demonstrated the WOA's capabilities and proved its capability in dealing with the MOOPF-WS challenge.

The WOA recently adopted to solve numerous power system challenges. It was driven to demonstrate the WOA's feasibility and efficacy in resolving the OPF problem. This work presents a WOA strategy to resolvethe OPF issue on IEEE 30 Bus system, with three distinct objectives to demonstrate the method's superiority over GWO and PSO-GWO. The manuscript is organized as: section 2 describes the determine optimal power flow and the modeling of RES units for optimal power flow is presented in section 3. Section 4 presents the WOA, section 5 presents the results and anlysis for numerous objective functions of the IEEE thirty bus system, followed by the 6 section conclusions.

2. DETERMINISTIC OPTIMAL POWER FLOW

2.1. Total generation cost minimization

Quadratic functions are utilized to represent the total generation cost function given in (1). The thermalgenerating unit's cost is determined by using (2). Wind generation cost is calculated with (3). The generation cost of the solar units is determined by using (4).

$$F = f_t(P_t) + f_{w,i}\left(P_{w,i}\right) + f_{so,j}\left(P_{so,j}\right) \tag{1}$$

$$f_t(P_t) = \left(\sum_{h=1}^{24}\sum_{i=1}^{N_g}\left(a_i P_{Gi,h}^2 + b_i P_{Gi,h} + c_i\right)\right) + \left| d_i \, sin\left(e_i (P_{Gi,h}^{min_{Gi,h}} ||\right.\right| \tag{2}$$

$$\begin{aligned} f_{w,i}\left(P_{w,i}\right) &= \text{Direct cost of wind power+reserve cost+penalty cost+probabilistic density cost} \\ &= \sum_{i=1}^{RES}[g_{w,i}\left(P_{w,i}\right) + K_{Rw,i}\int_0^{P_{w,i}}(P_{w,i} - P_{wr,i})f_{wr}(P_{wr,i})dP(wr,i) + \\ &K_{Pw,i}\int_{P_{w,i}}^{P_{wr,i}} (P_{wr,i} - P_{w,i})f_{wr}(P_{wr,i})dP(wr,i)] + \left(\frac{K}{c}\right)\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \\ &(for 0 \le v \le \infty) \end{aligned} \tag{3}$$

$$\begin{aligned} f_{so,i}\left(P_{so,i}\right) &= \text{Direct cost of solar power+reserve cost+penalty cost} \\ &= \sum_{j=1}^{RES}[f_{so,j}\left(P_{so,j}\right) + K_{Rs,j}f_s(P_{s,j} < P_{sr,j})(P_{sr,j} - E(P_{s,j} > P_{sr,j})) + \\ &K_{Ps,j}f_s(P_{s,j} > P_{sr,j})(E(P_{s,j} > P_{sr,j}) - P_{sr,j})] \end{aligned} \tag{4}$$

$f_t(P_t)$ is the sum of electrical thermal generator sources cost and valve point effect cost. $f_{w,i}\left(P_{w,i}\right)$ and $f_{so,j}\left(P_{so,j}\right)$ is wind (w) and solar (so) based renewable energy i^{th} and j^{th}units cost characteristics, respectively.

2.2. Constraints

Power balance and power flow equations are represented by equality constraints. The power balance equations of renewable and non-renewable energy sources with RES units are expressed as (5), (6):

$$P_{injk,h} - \sum_{i=1}^{N} V_{k,h} V_{L,h}[\left(G_{ks}\,cos(\delta_{l,h} - \delta_{k,h})\right) + \left(B_{kl}\,sin(\delta_{l,h} - \delta_{k,h})\right)] = 0 \tag{5}$$

$$Q_{injk,h} - \sum_{i=1}^{N} V_{k,h} V_{L,h}[\left(G_{ks}\,sin(\delta_{l,h} - \delta_{k,h})\right) + \left(B_{kl}\,cos(\delta_{l,h} - \delta_{k,h})\right)] = 0 \tag{6}$$

N_R represents No. of RES units with renewable energy sources. The load bus is restricted by functional operational limitations incorporating voltage magnitude and the information regarding the reactive power capabilities and limits the branch flow of the DG units are the inequality constraints and expressed as (7)-(9):

$$V_i^{min} \le V_i \le V_i^{max} i = 1, \dots, NL \tag{7}$$

$$Q_i^{min} \le Q_i \le Q_i^{max} i = 1, \dots, NPV \tag{8}$$

$$S_i \le S_i^{max} i = 1, \dots, N \tag{9}$$

Below constraints define the feasibility region problem of control variables. The variables may be active power output limits of RES unit, root node voltage magnitude limits and such.

$$P_i^{min} \leq P_i \leq P_i^{max} i = 1, \dots, NNR \tag{10}$$

$$V_0^{min} \leq V_0 \leq V_0^{max} i \tag{11}$$

$$V_i^{min} \leq V_i \leq V_i^{max} i = 1, \dots, NPV \tag{12}$$

$$t_i^{min} \leq t_i \leq t_i^{max} i = 1, \dots, NT \tag{13}$$

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} i = 1, \dots, NC \tag{14}$$

The magnitude of Load bus voltage along with the reactive power output of the RES unit and its branch loading are included concerning theobjective function in the form of a quadratic penalty term [18]. These constitute the Inequality constraints of the dependent variables.

3. MODELING OF RES UNITS FOR OPTIMAL POWER FLOW

3.1. Wind turbine

Wind turbine power output mainly dependent on wind turbine power curve and wind speed at a certain locality. The output is at zero for wind speeds lying between the cut-off speed and the cut-in speed, and equal to the rated power for speeds between the rated speed and the cut-off speed. The wind turbine power curve can be mathematically designed by splitting the function into four different parts [19]–[22]:

$$P_{out} = \begin{cases} 0, & v \leq v_{in} \\ \frac{v^2 - v_{in}^2}{v_r^2 - v_{in}^2} \cdot P_{wr}, & v_{in} < v \leq v_r \\ P_{wr}, & v_r < v \leq v_{out} \\ 0, & v > v_{out} \end{cases} \tag{15}$$

As a result, the Weibull PDF was utilized for wind speed estimation, and the international global factor (IGF) for defining wind speed. As a result, (16) and (17) gives the Weibull PDF:

$$f_w(P_w)|_{P_w=0} = C_{df}(v_{in}) + (1 - C_{df}(v_{out}) = 1 - exp(-\frac{v_{in}}{C})^k + exp(-\frac{v_{out}}{C})^k \tag{16}$$

$$f_w(P_w)|_{P_w=P_r} = C_{df}(v_{out}) + (1 - C_{df}(v_r) = exp(-\frac{v_r}{C})^k - exp(-\frac{v_{out}}{C})^k \tag{17}$$

Overall generator cost.

$$C_{WG} = \sum_{j=1}^{Nwh} \left[C_{w,j}(P_{ws,j}) + C_{Rw,j}(P_{ws,j} - P_{wav,j}) + C_{Pw,j}(P_{wav,j} - P_{ws,j}) \right] \tag{18}$$

3.2. Photovoltaic cost

Solar irradiance and ambient temperature are detrimental factors to output power of PV module along with the characteristics of the module itself [25]–[27]. The output power of the PV module P_{pv} (19) is given by (19)-(22):

$$P_{pv} = P_{STC} \frac{Is}{1000} [1 + \gamma(T_c - 25)] \tag{19}$$

$$C_{s,k}(P_{ss,k}) = G_k P_{ss,k} \tag{20}$$

$$\begin{aligned} C_{Rs,k}(P_{ss,k} - P_{sav,k}) = K_{Rs,k}(P_{ss,k} - P_{sav,k}) = K_{Rs,k} f_s(P_{sav,k} < P_{ss,k}) \\ (P_{ss,k} - E(P_{sav,k} < P_{ss,k})) \end{aligned} \tag{21}$$

$$\begin{aligned} C_{Ps,k}(P_{sav,k} - P_{ss,k}) = K_{Ps,k}(P_{sav,k} - P_{ss,k}) = K_{Ps,k} f_s(P_{sav,k} > P_{ss,k}) \\ (E(P_{sav,k} > P_{ss,k}) - P_{ss,k}) \end{aligned} \tag{22}$$

Log normal PDF at irradiance (G_s): at any one time, the future system load requirement is unknown. Normal and uniform PDFs are the two most often utilized PDFs for predicting load demand uncertainty. Normal PDF is utilized to represent the load distribution in this work. The normal distribution's PDF for an undetermined load 'l' is given by (23),

$$f_G(G_s) = \frac{1}{G_s\sigma\sqrt{2\pi}} exp\left(\frac{-(l_a x-\mu)^2}{2\sigma^2}\right) \text{ for } G_s>0 \tag{23}$$

here μL and σL are the mean and standard deviation of the uncertain load.

$$C_{SG} = \sum_{k=1}^{N_{SG}}\left(C_{s,k}(P_{ss,k}) + C_{Rs,k}(P_{ss,k} - P_{sav,k}) + C_{Ps,k}(P_{sav,k} - P_{ss,k})\right) \tag{24}$$

4. WHALE OPTIMIZATION ALGORITHM

The methodology proposed in this paper for identifying the optimum size for OPF solution is obtained by using WOA. It is a meta-heuristic algorithm first introduced by Seyedali Mirjalili and Andrew Lewis in 2016. This algorithm emulates the communal hunting behavior of Humpback whales. The special hunting method of humpback whales called the bubble-net attacking method which includes encircling the prey, spiraling update position, and searching for the prey is utilized. The algorithm performs the exploitation phase based on the first two approaches and the exploration phase based on the last approach.

– Searching the prey
  Position of whale is modified by employing,

$$\vec{H} = \left|\vec{D}.\vec{Z}_{rand} - \vec{Z}\right| \tag{25}$$

$$\vec{Z}(iter + 1) = \vec{Z}_{rand} - \vec{B}.\vec{H} \tag{26}$$

$$\vec{B} = 2.\vec{a}.\vec{r_1} - \vec{a} \tag{27}$$

$$\overrightarrow{D =} 2.\vec{r}_2 \tag{28}$$

  a ε [2, 0], r_1 and r_2 ε [0, 1]

– Encircling prey
  In this stage whale identifies its prey with the below:

$$\vec{H} = \left|\vec{D} \times \vec{Z}_p(iter) - Z(\vec{iter})\right| \tag{29}$$

$$\vec{Z}(iter + 1) = \vec{Z}_p(iter) - \vec{B} \times \vec{H} \tag{30}$$

– Bubble-net aggressive method:

$$\vec{Z}(iter + 1) = \vec{H}e^{bl}.cos(2\pi l) + \vec{Z}(iter) \tag{31}$$

$$\vec{H} = \left|\vec{Z}_p(iter) - \vec{Z}(iter)\right| \tag{32}$$

  The measured model for this is given as (33):

$$\vec{Z}(iter+1) = \begin{cases} \vec{Z}(iter) - \vec{B}.Hifp\langle 0.5 \\ H.e^{bl}\cos(2\pi l) + \vec{Z}_p(iter) ifp \geq 0.5 \end{cases} \tag{33}$$

5. RESULT AND ANALYSIS

In this result analysis, the proposed WOA results are distinguished from other promising methods to show the effectiveness of the work. In this section, results are compared with NSGA-II, GWO, and hybrid

PSO-GWO and the proposed WOA shows the effectiveness of the work. Optimization of total generation cost for an IEEE thirty bus system considered as a case study. The total generation cost optimization is for both conventional power sources and renewable energy resources like wind and solar considered. The maximum operating point of RES makes the operating and maintenance cost lower it causing to reduction in total generation cost.

5.1. Total generation cost optimization for an IEEE 30 bus system

The total generation cost is considered as an objective in this case. The NSGA-II, GWO, hybrid PSO-GWO and the proposed WOA are compared to show the effectiveness of the work as in Table 1. For total generation cost, the final results after 100 iterations with the generator buses (1, 2, 5, 8, 11 and 13) for real and reactive power, their voltage at these nodes and the objective results. It can be observed that thermal power generation decreased and RES increased considerably with WOA than other methods.

From Figures 1 to 5, shows the performance of different algorithms when fitness function/objective function is set as cost reduction. In this, with WOA, the voltage profile is maintained consistently at all nodes compared to the other two algorithms as in Figure 1. The real and reactive power generations are almost the same for all the metaheuristic methods as in Figures 2 and 3, but a small difference is observed with hybrid PSO-GWO and WOA having better real power generation with RES and reactive power with thermal power plants, hence leading to optimal generation to meet the cost optimization objective. It can be observed from Figure 4, with an increase in the iteration run count, the fitness value is set up early with WOA and finally having lower value than the other three methods. In this, it is observed that the NSGA-II and GWO are varying much before reaching their final steady objective value.

Table 1. Output results of IEEE thirty Bus system at generator nodes for Fuel cost optimization

	Parameters	Minimum. Value	Maximum. Value	NSGA-II	GWO	PSO-GWO	WOA
Real power generation	PTG1 (MW)	50	140	114.1256	110.057	103.0652	79.0096
	PTG2 (MW)	20	80	57.812	59.312	62.1012	43.406
	PwTG5 (MW)	0	75	39.642	39.337	39.344	69.256
	PTG8 (MW)	10	35	10	10.128	12.578	11.3337
	PwTG11 (MW)	0	60	33.696	33.277	33.257	50.574
	PsTG13 (MW)	0	50	31.037	33.768	35.174	31.5514
Reactive power generation	QTG1	-20	150	-11.682	-18.768	-6.721	-2.494
	QTG2	-20	60	18.863	27.808	4.773	12.444
	QTG5	-30	35	25.51	23.526	35	22.954
	QTG8	-15	40	40	40	40	40
	QTG11	-25	30	19.147	19.221	17.862	30
	QTG13	-20	25	21.706	21.759	22.235	14.879
Generator bus voltages	V_1	.95	01.1	01.014	01.049	01.0504	01.0381
	V_2	.95	01.1	0.989	01.0189	01.0288	01.0365
	V_5	.95	01.1	01.047	01.0071	01.0179	01.0458
	V_8	.95	01.1	01.0286	0.9982	01.0299	01.0345
	V_{11}	.95	01.1	01.01	01.0297	01.0199	01.0296
	V_{13}	.95	01.1	01.0099	01.0129	0.9905	01.0331
Gen	Thermal (MW)			181.9376	179.497	177.7444	133.7493
	Wind (MW)			73.338	72.614	72.601	119.83
	Solar (MW)			31.037	33.768	35.174	31.5514
Loss	Ploss (MW)			2.9126	2.479	2.1194	1.7307
Fitness function	Total Gen Cost ($/h)			800.213	803.046	802.545	799.979

*Generator bus voltage in per unit, *reactive power flow is in MVAR

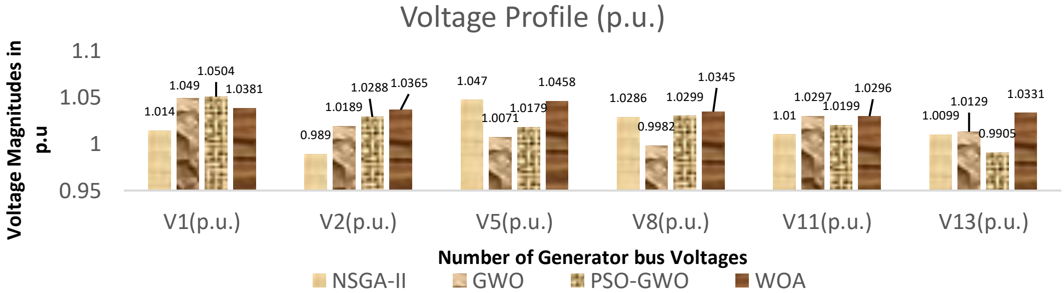

Figure 1. Voltage of the generator node buses with the considered optimization algorithms with fuel cost optimization

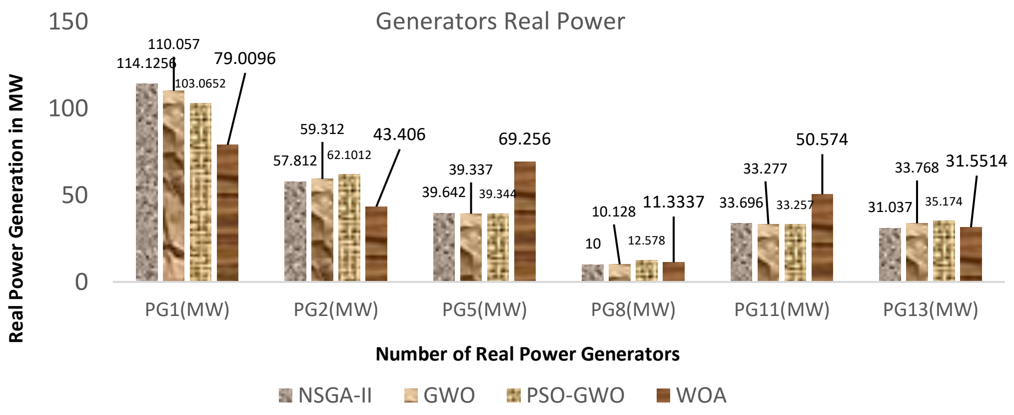

Figure 2. Real power generation at node buses for fuel cost optimization

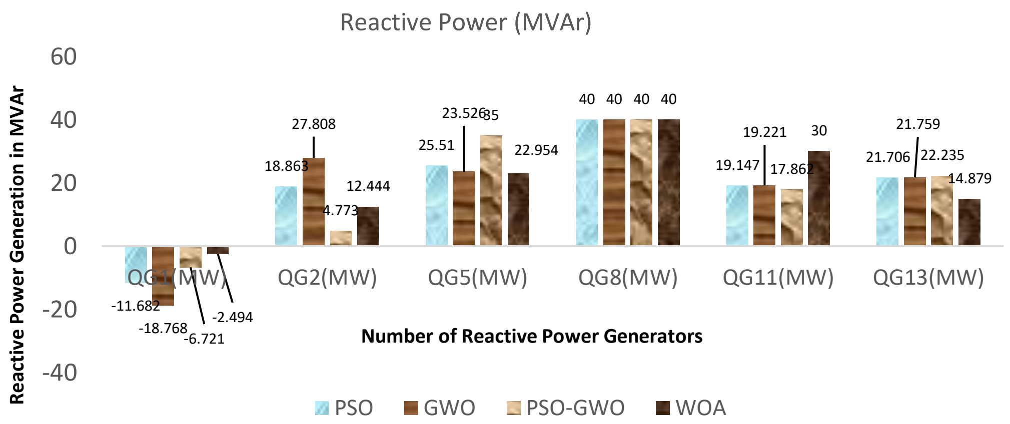

Figure 3. Reactive power generation at node buses for fuel cost optimization

The fitness curve of total generation cost optimization as objective using WOA algorithm is shown in Figure 5 for 100 iterations. The objective function with WOA started at 819 $/hr in the1st iteration, reached 804, 802, and almost 800 in the next 10, 20 and 30 iterations. The value at 100 iteration is almost equal to the value at 50 iterations as the system is running towards convergence.

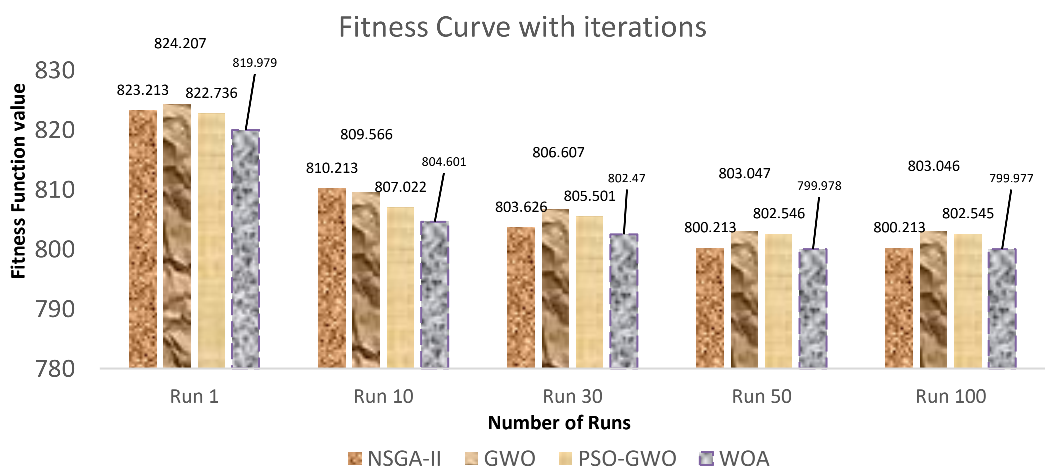

Figure 4. Objective functions during the iterations run under fuel cost optimization

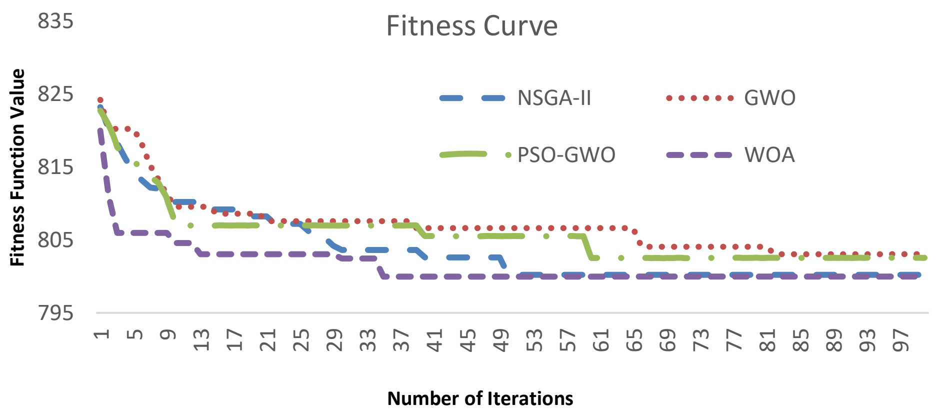

Figure 5. Optimal cost fitness curve for Fuel cost optimization with a different algorithm for an IEEE thirty bus system

6. CONCLUSION

This paper proposed a novel WOA incorporating issue of MOOPF-WS. It has taken into account several energy sources including distributed energy resources into the grid. Also, various PDFs were utilized for representing uncertainty in RES and load demand. In order to define non-dominated ranks and also the solutions' densities, the WOA used rapid non-dominated sorting approach methodology and the crowding distance methodology. WOA was successfully deployed on the modified 30-bus system with RES. Furthermore, the WOA performance was compared to that of the NSGA-II, GWO and PSO-GWO. In all situations, the WOA outperformed the other three approaches in terms of convergence. Furthermore, when compared to major studies in the literature, WOA obtained higher-quality solutions in all similar circumstances. These demonstrated the WOA's capabilities and proved its capability in dealing with the MOOPF-WS challenge.WOA can also help in maintaining a better voltage profile, reduce real and reactive power flow losses, and minimize generation costs by optimally using RES as compared to other algorithms.

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