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Optimal Power Flow Solution with Uncertain RES using Augmented Grey Wolf Optimzation

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***Abstract*—This work focuses on implementing the optimal power flow (OPF) problem, considering wind, solar and hydropower generation in the system. The stochastic nature of renewable energy sources (RES) is modelled using Weibull, Lognormal and Gumbel probability density functions. The system-wide economic aspect is examined with additional cost functions such as penalty and reserve costs for under and overestimating the imbalance of RES power outputs. Also, a carbon tax is imposed on carbon emissions as a separate objective function to enhance the contribution of green energy. For solving the optimization problem, a simple and efficient augmentation to the basic grey wolf optimization (GWO) algorithm is proposed, in order to enhance the algorithm's exploration capabilities. The performance of the new augmented GWO (AGWO) approach, in terms of robustness and scalability, is confirmed on IEEE-30, 57 and 118 bus systems. The obtained results of the AGWO algorithm are compared with modern heuristic techniques for a case of OPF incorporating RES. Numerical simulations indicate that the proposed method has better exploration and exploitation capabilities to reduce operational costs and carbon emissions.**

***Index Terms*—Optimal power flow, Renewable energy sources, Carbon emission, Meta-heuristic techniques**

I. Introduction

Optimal power flow (OPF) has proved to be an essential tool for the efficient and secure operation of power networks since its inception. The main objective of OPF is to find optimal settings of the control variables with certain objective functions while satisfying system equality and inequality constraints. The system control variables that need adjustment include generated active power, the voltage of all generation buses and tap settings of the transformer. During the optimization process, system constraints such as transmission line capacity, power flow balance, voltage profile of all buses and generator capability constraints need to be maintained.

OPF with only traditional thermal power generators (TPGs) is widely studied in the literature [1]. However, with increased penetration of RES, it is necessary to incorporate associated uncertainty into the power network. Under recent studies, systems that consider both TPGs and RES are in pursuit of similar objective functions studied in the past [2]–[6]. The work in [2] conducts an extensive study on the over/underestimation of wind power generation (WPG) in the classical economic dispatch model. In this study, the Weibull probability density function (PDF) is used to model the uncertainty of WPG output. For economic dispatch strategies, it provides valuable insight into the integrated wind system. However, the challenge of wind speed variation on the optimal dispatch schedule of power plants remains unaddressed. Also, the reactive power capability of WPGs, bus voltage constraints and loading effect of transmission line were not considered in [3].

Authors in [4] combined advanced variant of differential evolution with an effective constraint handling technique for a system that considers both solar and wind power generation in the OPF problem. The uncertain and intermittent nature of both RES were modelled with lognormal and Weibull PDFs. However, the resulting SHADE-SF algorithm sometimes attains premature convergence (i.e., becomes trapped in a local solution) and the convergence rate can be prolonged. The scalability and robustness of the proposed algorithm were not verified since the algorithm was only verified on the IEEE-30 bus system. This does not guarantee good performance over medium and higher bus systems (IEEE-57 and IEEE-118). In general, OPF with the incorporation of RES needs further attention.

II. Mathematical model

In this work, the IEEE-30, 57 and 118 bus systems are used to validate the performance of the proposed AGWO algorithm in the OPF problem. The essential characteristics of these bus systems are provided in Table I. Along with the TPGs, RES such as wind, solar and small hydro (WSH) generators are selected as power generation sources for the OPF framework. The power output from RES is variable in nature and power output instability needs to be minimized and balanced by the aggregation of the power outputs of all the generators and spinning reserve. Thus, total power generation cost is the combination of operating cost of all generators, reserve and penalty cost (due to the intermittent nature of power generation from RES). In subsequent subsections, cost models are discussed in detail.

A. *Stochastic Wind Power*

The behaviour of the wind speed $v(m/s)$ distribution can be modelled with the help of Weibull PDF $f_v(v)$ by adjusting scale parameter c and shape parameter k as established by [3] and [4]. The probability of wind speed during any time interval is expressed as follows:

$$f_v(v) = \frac{k}{c}(\frac{v}{c})^{k-1} \exp\left[-(\frac{v}{c})^k\right], \quad 0 < v < \infty \tag{1}$$

In the modified IEEE-30 bus system, TPGs at bus 5 and bus 11 are replaced with the WPGs. The values for scale c and shape k parameters are given in Table II. The wind speed behavior for WPG 1 and WPG 2 at buses 5 and 11 follow the Weibull PDF. For each WPG, the relationship between wind speed and output power is expressed in Eq. 2 [3]:

$$P_W = \begin{cases} 0, & v < v_{ci} \ or \ v > v_{co} \\ P_{Wr}, & v_r < v \leq v_{co} \\ P_{Wr}(\frac{v-v_{ci}}{v_r-v_{ci}}), & v_{ci} \leq v \leq v_r, \end{cases} \tag{2}$$

where v is forecasted wind speed in m/s, v_{ci}, v_{co} and v_r are cut-in, cut-out and rated wind speeds, P_{Wr} is rated output power for the WPG.

B. *Stochastic Solar Power*

Similarly, the TPG at bus 13 of the modified IEEE-30 bus system is replaced with the solar power generator (SPG). The output power from SPG depends upon the solar irradiance which follows lognormal PDF. The probability with standard deviation λ and mean σ can be calculated as follows [4]:

$$f_X(X) = \frac{1}{X\sigma\sqrt{2\pi}} \exp\left\{\frac{-[\ln X - \lambda]^2}{2\sigma^2}\right\}, \quad X > 0 \tag{3}$$

The values for λ and σ are given in Table II. The relationship between the solar irradiance X (W/m^2) and output power of SPG is expressed as follows:

$$P_S(X) = \begin{cases} P_{Sr}(\frac{X^2}{X_{std}C_I}), & 0 < X < C_I \\ \\ P_{Sr}(\frac{X}{X_{std}}), & X > C_I, \end{cases} \tag{4}$$

where X is forecasted solar irradiance, X_{std} is standard solar irradiance value set as 800 W/m^2, C_I is certain irradiance point ($120W/m^2$) and P_{SR} is rated SPG power output.

C. *Stochastic Hydropower*

It is well known that the Gumbel distribution is followed for river flow rate calculations. The probability calculation of Gumbel distribution for river flow rate with scale parameter ω and location parameter γ is formulated in Eq. 5 [5]:

$$f_H(G_h) = \frac{1}{\omega} \exp\left[-\frac{(G_h-\gamma)}{\omega}) \exp\left[-\exp\frac{(G_h-\gamma)}{\omega}\right]\right] \tag{5}$$

In the modified IEEE 30-bus system, the conventional TPG at bus 13 is replaced together with 45 MW SPG and 5 MW small HPG. Table II provides PDF values for these fittings and many of these values are realistically chosen in a study given by Ref. [5]. The output of HPG as a function of pressure head and water flow rate is calculated as follows:

$$P_h(G_h) = \alpha\beta g G_h P_h \tag{6}$$

where α and β represent efficiency of the generating unit and density of water volume, respectively. The numerical values for calculation of HPG output are assumed: α = 0.85, β 1000 kg/m^3, P_h = 25m and g = 9.81m/s^2.

D. *Cost Model for Thermal Power Generators*

TPGs require fossil fuel for their operation. The relationship between generated power (MW) and fuel cost ($/h) can be calculated with the help of following quadratic equation:

$$C_T = \sum_{i=1}^{N_T} a_i + b_i P_{Tg,i} + c_i P_{Tg,i}^2 \tag{7}$$

Practically, the valve point loading effect needs to be considered to model accurate cost function. Hence, the overall thermal power generation cost ($/h) becomes:

$$C_T = \sum_{i=1}^{N_T} a_i + b_i P_{Tg,i} + c_i P_{Tg,i}^2 + \left| d_i \times sin\Big(e_i \times (P_{Tg,i}^m - P_{Tg,i})\Big)\right| \tag{8}$$

where a_i, b_i, c_i are the cost coefficients and d_i, e_i are fuel cost coefficients for the i-th TPG. $P_{Tg,i}$ is the output power, N_T is total number of the TPGs in the system and $P_{Tg,i}^m$ the minimum power when i-th TPG is in operation. All emission and cost coefficients pertaining to TPGs are given in Table III.

E. *Cost Model for Renewable Energy Sources*

The total cost of the RES consists of the direct cost associated with scheduled power, reserve cost for overestimation and penalty cost for underestimation. These models are developed in line with the concept presented in Refs. [3]–[6].

The direct, reserve and penalty costs of WPG as a function of scheduled power are represented in Eqs. 9–11 as follows:

$$C_{DW,j} = d_{w,j} P_{WS,j} \tag{9}$$

$$C_{RW,j} = r_{w,j} \int_0^{P_{WS,j}} (P_{WS,j} - W) f_w(W) dW \tag{10}$$

$$C_{PW,j} = p_{w,j} \int_{P_{WS,j}}^{P_{WR,j}} (W - P_{WS,j}) f_w(W) dW \tag{11}$$

where $d_{w,j}$, $r_{w,j}$ and $p_{w,j}$ are direct, reserve and penalty cost coefficients pertaining to j-th WPG. $P_{WS,j}$ is the scheduled power and $f_w(W)$ is PDF of same WPG.

The total cost of WPG can be calculates as:

$$C_{TW,j} = C_{DW,j} + C_{RW,j} + C_{PW,j} \tag{12}$$

Likewise, the SPG also has uncertain power output. The direct, reserve and penalty costs pertaining to the k-th SPG are represented as:

$$C_{DS,k} = d_{s,k} P_{SS,k} \tag{13}$$

$$C_{RS,k} = r_{s,k} \cdot Pr(P_{AS,k} < P_{SS,k}) \cdot [(P_{SS,k} - E(P_{AS,k} < P_{SS,k})] \tag{14}$$

$$C_{PS,k} = p_{s,k} \cdot Pr(P_{AS,k} > P_{SS,k}) \cdot [(E(P_{AS,k} > P_{SS,k}) - P_{SS,k}] \tag{15}$$

In Eqs. 13–15, $d_{s,k}$, $r_{s,k}$ and $p_{s,k}$ are direct, reserve and penalty cost coefficients pertaining to k-th SPG. $P_{AS,k}$ and

TABLE I: **Characteristics of Bus Systems under Consideration**

Items	IEEE-30 Bus System		IEEE-57 Bus System		IEEE-118 Bus System	
	Quantity	Details	Quantity	Details	Quantity	Details
Number of buses	30	[4]	57	[5]	118	[1]
Number of branches	41	[4]	80	[5]	186	[1]
Number of TPGs	3	Connect at bus 1 (Swing), 2 and 8	5	Connect at bus 1 (slack), 3, 8 and 12	54	[1]
Number of WPGs	2	Connect at bus 5 and 11	2	Connect at bus 2 and 6	2	Connect at bus 5 and 11
Number of SPGs	1	Connect at bus 13	1	Connect at bus 9	1	Connect at bus 9
Number of HPG	1	Connect at bus 11	1	Connect at bus 11	1	Connect at bus 11
Connected load	—	283.4 MW, 126.2 MVAr	—	1250.8 MW, 336.4.2 MVAr	—	4242 MW, 1439 MVAr
Control variables	24	—–	33	—–	120	—–
Load bus voltage range	24	[0.95-1.06] p.u.	50	[0.94-1.06] p.u.	64	[0.94-1.06] p.u.

TABLE II: **PDF Parameters for Wind, Solar and Hydropower Generation [5], [7].**

Wind power generation plants				Solar + Hydropower generation plant (bus 13)			
Windfarm #	No. of wind turbines	Total rated power	Weibull PDF parameters	Rated power of SPG	Lognormal PDF parameters	Rated power of HPG	Gumbel PDF parameters
1 at bus 5	25	75 MW	c = 9, k = 2	45 MW	$\lambda = 6$, $\sigma = 0.6$	5 MW	ω = 15, γ = 1.2
2 at bus 11	20	60 MW	c = 10, k = 2				

TABLE III: **Thermal Power Generators Cost and Emission Coefficients for the System [4], [7].**

Thermal generator	Bus number	a	b	c	d	e	f	g	h	k	l
TPG1	1	0	2	0.00375	18	0.037	4.091	-5.554	6.49	0.0002	6.667
TPG2	2	0	1.75	0.0175	16	0.038	2.543	-6.047	5.638	0.0005	3.333
TPG3	8	0	3.25	0.00834	12	0.045	5.326	-3.55	3.38	0.002	2

$P_{SS,k}$ represent available and scheduled power from SPG. Finally, the total cost of SPG can be calculated as:

$$C_{TS,k} = C_{DS,k} + C_{RS,k} + C_{PS,k} \tag{16}$$

As a third RES, we consider a small hydropower generator (HPG) in this study. The output of HPG is very less (10–20 % of total install capacity) [5]. It is therefore combined with SPG and assumed to be owned by a single private operator. Following Eqs 13–15, the direct, reserve cost for overestimation and penalty cost for underestimation of combined solar hydropower generation system is:

$$C_{SH} = d_s P_{SSH,s} + d_h P_{SSH,h} \tag{17}$$

$$C_{RSH} = r_{sh,m} \cdot Pr(P_{ASH} < P_{SSH}) \cdot [(P_{SSH} - E(P_{ASH} < P_{SSH})] \tag{18}$$

$$C_{PSH} = p_{sh,m} \cdot Pr(P_{ASH} > P_{SSH}) \cdot [(E(P_{ASH} > P_{SSH}) - P_{SSH}] \tag{19}$$

where $P_{SSH,s}$ and $P_{SSH,h}$ represent scheduled power from SPG and HPG, respectively. $d_{h,m}$, $r_{sh,m}$ and $p_{sh,m}$ are direct, reserve and penalty cost coefficients pertaining to m-th HPG. P_{ASH} and P_{SSH} represent available and scheduled output power from combined solar hydropower generator. Finally, the total cost of HPG is calculated as follows:

$$C_{TSH} = C_{DSH} + C_{RSH} + C_{PSH} \tag{20}$$

F. *Carbon Tax based Emission Model*

Unlike RES, producing power from TPGs emits the harmful gases into the environment. The emission E (ton/h) is calculated as follows:

$$F_C = \sum_{i=1}^{N_T} [(a_i + b_i P_{Ti} + c_i P_{Ti}^2) \times 0.01 + d_i e^{l_i P_{Ti}}] \tag{21}$$

The combustion fossil fuels on which TPGs run is the main source of greenhouse gases (GHGs) emission. To control GHGs and make clean energy economy, the carbon emission tax (emission cost) is modelled as follows:

$$C_E = E \cdot C_{tax} \tag{22}$$

where C_E is the emission cost and C_{tax} represents the carbon tax per unit of carbon emission.

III. Problem Formulation

The main objective of the OPF problem is formulated by incorporating all the cost functions described in the above sections. The first objective F_1 of the optimization problem is to achieve a minimum total generation cost. However, emission cost is not included in its formulation. To analyze the impact of the carbon tax on generation scheduling, the second objective F_2 is modelled by adding the carbon emission cost within the first objective function.

The objective is as follows: Minimize

$$F_1 = \sum_{i=1}^{N_T} C_{TG} + \sum_{j=1}^{N_W} C_{TW} + \sum_{k=1}^{N_S} C_{TS} + \sum_{m=1}^{N_{SH}} C_{TSH} \tag{23}$$

where N_{Wg}, N_{Sg} and N_{SHg} are the numbers of WSH generators in the system. The second objective F_2 of the optimization is: Minimize

$$F_2 = F_1 + C_E \tag{24}$$

where C_E is the emission cost, calculated in Eq. 22. Both OPF objective functions in Eqs. 23 and 24 are based on system equality and inequality constraints.

IV. The Grey Wolf Optimization Algorithm

In GWO algorithm [7], there are four different categories of wolves namely alpha (α), beta (β), delta (δ) and omega (ω) wolves. The optimization problem (fittest solution) is accessed with the accurate determination of prey location in search space while the wolves' position relative to the prey determines the best solution. The alpha wolves' position is considered to be the best solution found so far in the search space because they are expected to be closer to the prey than the other three wolves in the pack. To allocate their position in the search space, these wolves are represented as X_α, X_β and X_δ. Fourth level ω wolves update their position X_ω following the relative position of the alpha, beta and delta wolves. Finally, three main steps are adopted to achieve hunting, namely searching, encircling and attacking the prey. The prey encircling behaviour of the grey wolves is:

$$\overrightarrow{X}(t+1) = \overrightarrow{X}_p(t) - \overrightarrow{A} \times \overrightarrow{D} \quad \text{where,} \quad \overrightarrow{D} = \mid \overrightarrow{C} \times \overrightarrow{X}_p(t) - \overrightarrow{X}(t) \mid \tag{25}$$

where t is current iteration, $\overrightarrow{X}_p(t)$ is position vector for prey location and $\overrightarrow{X}(t)$ is position vectors for grey wolf in search space. The coefficient vectors $\overrightarrow{A}$ and $\overrightarrow{C}$ are calculated below:

$$\overrightarrow{A} = 2\overrightarrow{a} \times \overrightarrow{r}_1 - \overrightarrow{a} \quad \text{and} \quad \overrightarrow{C} = 2 \times \overrightarrow{r}_2 \tag{26}$$

Over the course of an iteration, exploration and exploitation processes are controlled by $\overrightarrow{A}$ which further depends on $\overrightarrow{a}$, $\overrightarrow{r}_1$, $\overrightarrow{r}_2$ are randomly generated vectors lies in the range of [0, 1]. The current position of a grey wolf (X, Y) is updated with Eqs. 25–26 to reach prey position (X_p, Y_p). Note that for a population of grey wolves, the value of $\overrightarrow{a}$ is assumed same. A wolf can update its position randomly in different places nearer to the best agent by setting the values of $\overrightarrow{A}$ and $\overrightarrow{C}$.

After approaching the prey, the grey wolves pursue and encircle it. The alpha wolves make the decision and dictate the pack for prey hunting (optimization). The beta and delta wolves acknowledge and reinforce the pack activity towards prey hunting. Initially, the top three level wolves (alpha, beta and delta) position are saved as the 'locations, indicating their improved information to identify prey location. The remaining fourth level search agents (omega wolves) obey these three wolves. For alpha, beta and delta wolves, position location is calculated as follows:

$$\overrightarrow{D}_\alpha = \mid \overrightarrow{C}_1 \times \overrightarrow{X}_\alpha(t) - \overrightarrow{X}(t) \mid, \overrightarrow{D}_\beta = \mid \overrightarrow{C}_2 \times \overrightarrow{X}_\beta(t) - \overrightarrow{X}(t) \mid \tag{27}$$

$$\overrightarrow{D}_\delta = \mid \overrightarrow{C}_3 \times \overrightarrow{X}_\delta(t) - \overrightarrow{X}(t) \mid, \overrightarrow{X}_1 = \mid \overrightarrow{X}_\alpha - A_1 \times \overrightarrow{D}_\alpha \mid \tag{28}$$

$$\overrightarrow{X}_2 = \mid \overrightarrow{X}_\beta - A_2 \times \overrightarrow{D}_\beta \mid, \overrightarrow{X}_3 = \mid \overrightarrow{X}_\delta - A_3 \times \overrightarrow{D}_\delta \mid \tag{29}$$

$$\overrightarrow{X}(t+1) = \frac{\overrightarrow{X}_1 + \overrightarrow{X}_2 + \overrightarrow{X}_3}{3} \tag{30}$$

At iteration t, the distance between $\overrightarrow{X}(t)$ and the three best hunt agents $(\overrightarrow{X}_\alpha)$, $(\overrightarrow{X}_\beta)$ are $(\overrightarrow{X}_\delta)$ are determined using Eqs. 27–29, in which A_1, A_2 and A_3 are random vectors as defined in Eq. 26. Finally, wolves movement towards prey is updated by Eq. 30.

V. Augmented Grey Wolf Optimization

In this work, we propose a new modification to augment the exploration capabilities of the GWO algorithm without affecting its flexibility, simplicity and global optimization characteristics. In the GWO algorithm, parameter A is the most important parameter responsible for controlling the exploration and exploitation abilities in the search space stated in Eq. 26. The value of A depends on a, which changes linearly from 2 to 0 in the GWO algorithm. In the proposed augmentation (AGWO) algorithm, the value of parameter a changes randomly and non-linearly from 2 to 1 to avoid stagnation given in Eq. 31. Due to this modification, chances of exploration gets higher than exploitation [8].

$$\overrightarrow{a} = 2 - cos(rand) \times t/Max\_iter \tag{31}$$

In the original GWO algorithm, α, β and δ wolves are involved in the hunting and decision-making process of the algorithm as in Eqs. 27 and 28. However, in the proposed AGWO algorithm, these processes are controlled only by α and β wolves expressed as:

$$\overrightarrow{D}_\alpha = \mid \overrightarrow{C}_1 \times \overrightarrow{X}_\alpha(t) - \overrightarrow{X}(t) \mid, \ \overrightarrow{D}_\beta = \mid \overrightarrow{C}_2 \times \overrightarrow{X}_\beta(t) - \overrightarrow{X}(t) \mid \tag{32}$$

$$\overrightarrow{X}_1 = \mid \overrightarrow{X}_\alpha - A_1 \times \overrightarrow{D}_\alpha \mid, \ \overrightarrow{X}_2 = \mid \overrightarrow{X}_\beta - A_2 \times \overrightarrow{D}_\beta \mid \tag{33}$$

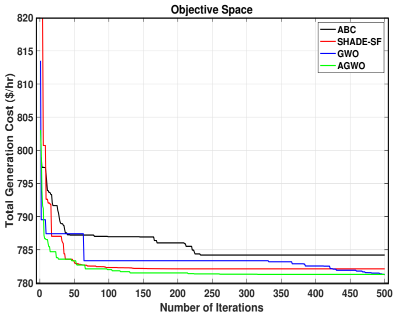
$$\overrightarrow{X}(t+1) = \frac{\overrightarrow{X}_1 + \overrightarrow{X}_2}{2} \tag{34}$$

Due to the proposed augmentation, the AGWO gains many advantages over the basic GWO algorithm. Some of these are better convergence to find global optima, computational efficiency and better exploration and exploitation capabilities.

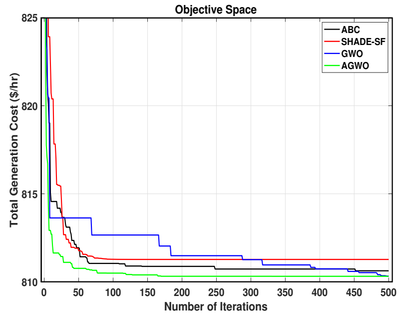
VI. Case Studies for IEEE-30 Bus System

A. *Case 1: Optimization of Total Generation Cost*

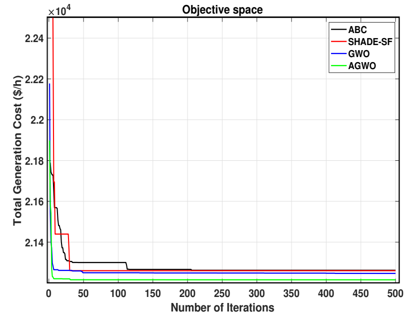
The objective of Case-1 is to optimize the power generation schedule of all RES and TPGs to reduce total power generation cost using Eq. 23. For illustrative purposes, the values of direct, reserve and penalty cost coefficients for WSH generation system are d = 1.6, r = 3 and p = 1.5, respectively. The total generation cost achieved by AGWO is 781.13 \$/h and that of GWO is 781.77 \$/h shown in Table IV. These results are compared with the results obtained from ABC and SHADE-SF algorithms, i.e., 784.24 \$/h and 782.82 \$/h. More details about these algorithms can be found in Refs. [2] and [4]. Fig. 1a shows that AGWO has faster convergence and less computational time than the other three algorithms.



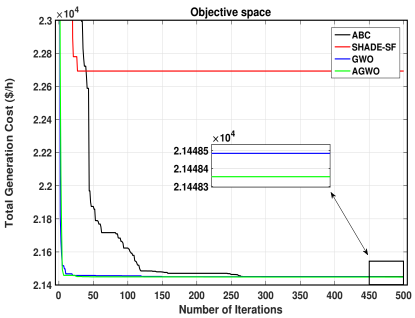
(a) IEEE-30 Bus System Convergence Characteristics for Case-1



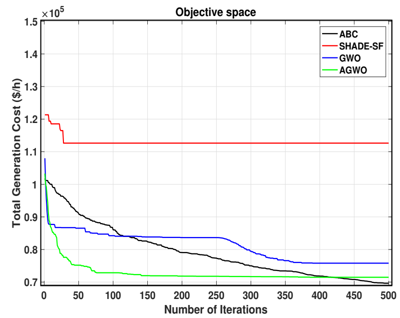
(b) IEEE-30 Bus System Convergence Characteristics for Case-2



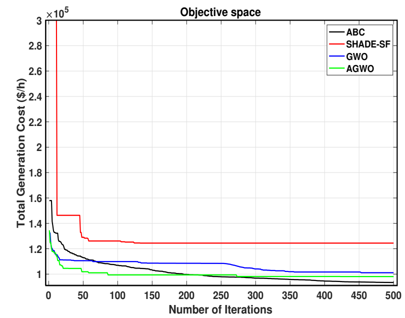
(c) IEEE-57 Bus System Convergence Characteristics for Case-3



(d) IEEE-57 Bus System Convergence Characteristics for Case-4



(e) IEEE-118 Bus System Convergence Characteristics for Case-5



(f) IEEE-118 Bus System Convergence Characteristics for Case-6

Fig. 1: **Convergence Characteristics of AGWO and Recent Techniques for Case-1–Case-6.**

TABLE IV: **Comparison Between AGWO and other Algorithms for IEEE-30 bus System using Case-1 and Case-2.**

			Case-I				**Case-II**			
	Min	Max	**(ABC)**	**(SHADE-SF)** [4]	**(GWO)** [7]	**(AGWO)**	**(ABC)**	**(SHADE-SF)** [4]	**(GWO)** [7]	**(AGWO)**
$P_{Tg,1}$ (MW)	50	140	131.4	130.6	129.6	130.1	108.4	109.6	109.8	108.1
$P_{Tg,2}$ (MW)	20	80	38.5	37.6	38.1	36.2	43.7	44.7	44.7	41.3
$P_{Wg,1}$ (MW)	0	75	37.5	43.8	48.9	39.5	42.8	43.5	42.4	41.7
$P_{Tg,3}$ (MW)	10	35	10.4	10	10	10	12.1	10.5	11.05	16.3
$P_{Wg,2}$ (MW)	0	60	39.8	40.0	37.8	40.1	44.0	43.9	43.9	43.7
P_{Sg} (MW)	0	50	31.2	31.9	31.9	32.8	36.9	35.7	36	36.3
Total cost ($/hr)			784.24	782.82	781.77	**781.13**	813.81	811.43	810.17	**810.15**
Elapsed time (Seconds)			367	272	279	**230**	395	272	286	**246**
Carbon emission (ton/h)			1.42	1.35	1.28	1.48	0.7	0.58	0.42	0.39

B. *Case 2: Optimizing Fuel Cost and Carbon Emission*

The main objective of Cas-2 is to minimize total generation costs while imposing a carbon tax on the amount of carbon emission from TPGs. Total generation cost, including the carbon tax, is calculated with the help of Eq. 24. Carbon tax (Ctax) is considered at the rate of $20/ton [4]. The optimized generation schedule of all generators, total power generation cost, values of carbon emissions and other parameters for all algorithms are provided in Table IV. It is clearly depicted that RES contribution gets higher when the carbon tax is imposed in Case-2, compared to Case-1 (when there is no tax on carbon emission). The obtained result of emission gases by AGWO is 0.39259 ton/h, which is the lowest value compared with 0.42503 ton/h, 0.58487 ton/h and 0.7049 ton/h achieved by GWO, ABC and SHADE-SF, as given in Table IV. The convergence properties of AGWO, basic GWO and other approaches are shown in Fig. 1b.

VII. Case studies for IEEE-57 bus system

A. *Case 3: Optimization of Total Generation Cost*

The Case-3 objective is to minimize the power generation schedule of three RES and TPGs to reduce total power generation costs in the IEEE-57 bus system. It is identical to Case-1 in the IEEE-30 bus system and the objective function of the quadratic fuel cost is given in Eq. 23. The total cost achieved by the AGWO algorithm is 21215 $/h, which hits the best minima in search space compared to the ABC, SHADE-SF and GWO. The fuel cost value by ABC is 21262 $/h, by SHADE-SF is 21260 $/h and by the GWO is 21247 $/h, as given in Table V. The convergence properties of AGWO and recent optimization methods are presented in Fig. 1c.

TABLE V: **Simulation Results for IEEE-57 Bus system using Case-3 and Case-4.**

Bus System	**IEEE-57**							
Objective function	ABC		SHADE-SF [4]		GWO [7]		**AGWO**	
	Case-3	Case-4	Case-3	Case-4	Case-3	Case-4	Case-3	Case-4
Cost (MW/h)	21262	21450	21260	22693	21247	21448	21215	21448
Carbon emission (ton/h)	33	16	39	23	36	10	31	9.42
Computational time (Sec)	870	448	330	298	247	255	220	243

TABLE VI: **Simulation results for IEEE-118 Bus System using Case-5 and Case-6.**

Bus System	**IEEE-118**							
Objective function	ABC		SHADE-SF [4]		GWO [7]		**AGWO**	
	Case-5	Case-6	Case-5	Case-6	Case-5	Case-6	Case-5	Case-6
Cost (MW/h)	69934	93416	113523	124438	77606	101114	70014	980851
Carbon emission (ton/h)	128	119	133	99	144	97	113	95
Computational time (Sec)	6319	7700	1223	1772	2200	3679	2377	3517

B. Case 4: Optimizing Fuel Cost and Carbon Emission

This Case study is conducted to optimize the OPF solution for quadratic fuel cost and carbon emission control for the objective function given in Eq. 24. It is evident from Table V that AGWO obtains the lowest values for this Case study with fuel cost and carbon emission values of 21448 \$/h and 9.42 ton/h, respectively. The variation of total fuel cost between AGWO and other algorithms are shown in Fig. 1d.

VIII. CASE STUDIES FOR IEEE-118 BUS SYSTEM

A. Case 5: Optimization of Total Generation Cost

In this Case study, the generation system total fuel cost minimization is taken as an objective function given by Eq. 23. The cost computed by AGWO for this Case is 70014 \$/h, which is better than SHADE-SF and the original GWO [7], which are respectively 77606 \$/h and 129509 \$/h. The ABC algorithm achieves the minimum cost for this case study with an obtained value of 69934 \$/h. Table VI provides obtained values comparison for generation costs, carbon emissions and computational time for all algorithms. The convergence graph in Fig. 1e reveals that AGWO has better convergence properties than GWO and other recent approaches reported in the literature.

B. Case 6: Optimizing Fuel Cost and Carbon Emission

Both quadratic fuel cost and emission gases minimization is the aim of this Case study. The objective function calculation is based on Eq. 24. With carbon tax imposition, the value of emission is significantly reduced from 113 ton/h in Case 5 to 95 ton/h. The ABC algorithm obtained lower costs for Case-5 and Case-6 but the computational cost has been increased. The AGWO algorithm needs the least computation time, recommending that it is a highly capable algorithm for industrial applications. Fig. 1f compares the convergence characteristics of all algorithms for 500 trial runs.

IX. CONCLUSION

In this paper, a solution strategy for OPF study is proposed that considers traditional TPGs and the stochastic nature of renewable energy sources (RES) in the system. Different PDFs were used to realistically model wind, solar and hydropower generation uncertainty, and their integration procedures were discussed. To prove the effectiveness of proposed algorithm, several case studies were investigated, and detailed results were numerically precisely given. Thus, novel contributions comprise the proposed objective functions that consider RES; the use of an AGWO method to tackle the non-convex OPF problem, and its application in small, medium and higher bus systems with assessment via simulation for six case studies.

From the article's findings, it was evident that AGWO is very useful and reliable with a remarkable fast convergence rate to search a global solution for considered objective functions. It beats other approaches in terms of convergence time and generation cost and minimization, whilst simultaneously addressing the essential system constraints.

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