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An Optimal Power Flow Solution of a System Integrated with Renewable Sources Using a Hybrid Optimizer

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Abstract: A solution to reduce the emission and generation cost of conventional fossil-fuel-based power generators is to integrate renewable energy sources into the electrical power system. This paper outlines an efficient hybrid particle swarm gray wolf optimizer (HPS-GWO)-based optimal power flow solution for a system combining solar photovoltaic (SPV) and wind energy (WE) sources with conventional fuel-based thermal generators (TGs). The output power of SPV and WE sources was forecasted using lognormal and Weibull probability density functions (PDFs), respectively. The two conventional fossil-fuel-based TGs are replaced with WE and SPV sources in the existing IEEE-30 bus system, and total generation cost, emission and power losses are considered the three main objective functions for optimization of the optimal power flow problem in each scenario. A carbon tax is imposed on the emission from fossil-fuel-based TGs, which results in a reduction in the emission from TGs. The results were verified on the modified test system that consists of SPV and WE sources. The simulation results confirm the validity and effectiveness of the suggested model and proposed hybrid optimizer. The results confirm the exploitation and exploration capability of the HPS-GWO algorithm. The results achieved from the modified system demonstrate that the use of SPV and WE sources in combination with fossil-fuel-based TGs reduces the total system generation cost and greenhouse emissions of the entire power system.

Keywords: renewable energy sources; emission; wind turbine; solar photovoltaic; hybrid particle swarm gray wolf optimizer

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1. Introduction

Due to the rapid increase in energy demand, the impact of optimization in power flow is significant. Optimization enables effective and inexpensive power flow operation in the electrical system. It is helpful to keep in mind that most of the power system problems regularly need to optimize two or more different objectives due to their nonlinear nature. The fundamental OPF problem is the optimal allocation of real power and voltages of generators by changing the control parameters, so as to ensure the optimization of a particular objective during the operation of electric power flow in the system [1]. In the optimization process, system equality and inequality constraints such as power flow equilibrium, generator capacity, line capacity, generation and load bus voltages must be fulfilled [2].

Various OPF formulation techniques have been developed and used over the past two decades to optimize the operation of power flow in electrical power systems, and each

technique is equipped with a distinct mathematical feature and has different computational requirements [3,4]. To optimally manage the energy resources of customers and their energy demand profiles, an effective technique called demand side management (DSM) can be used [5]. Due to the intermittent nature of renewable energy sources (RES) such as wind energy (WE) and solar photovoltaic (SPV) sources, the complexity of OPF has increased and become a challenging problem for researchers after the incorporation of RES into the system [6]. The probabilistic nature of SPV and WE sources needs to be taken into account to ensure a reliable and effective integration of these RES into the electrical power system [7].

Various conventional methods have been used for optimization of power flow in electrical power systems such as Newton's method, the interior point method (IP) [8], linear programming (LP) [9], quadratic programming (QP) [10] and nonlinear programming (NLP) [11]. To minimize cost with nonlinear pricing, a mixed integer quadratic programming energy scheduling algorithm has been used by researchers in [12] for the scheduling of energy activities in smart homes with controllable loads, renewable energy sources and energy storage systems. All these conventional methods have shown excellent results to solve OPF problems, though these methods are insufficient for large systems with non-differentiable and non-convex objective functions due to their extensive calculation and high reliance on the early assumption values.

To cope with the weaknesses of conventional techniques, the domain of numerical optimization has suffered a surge over the past few years with the emergence and development of various evolutionary algorithms [13]. Over the last few years, various evolutionary algorithms such as differential evolution (DE) [14], moth flame optimization (MFO) [15], the genetic algorithm (GA) [16], the barnacle mating optimizer (BMO) [17], particle swarm optimization (PSO) [18], the moth swarm algorithm (MSA) [19], glowworm swarm optimization (GSO) [20] and the gravitational search algorithm (GSA) [21] have been applied to solve different optimization problems in power systems. An efficient Harris hawk optimization (HHO) has been applied for the optimization of modern distribution framework reconfiguration where the effectiveness of the algorithm has been validated on the IEEE 33 and 85 bus systems [22]. A water cycle algorithm (WCA) has been used for the optimization, sizing and setting of distributed generations. The results have been tested on IEEE 33 and 69 bus systems [23].

Recently, several metaheuristic algorithms have been hybridized to enhance the global search capability and to eliminate the chance of trapping the solution at the local optimal point in various metaheuristic algorithms. In Reference [20] the author used a hybrid PSO and GSA algorithm for an OPF solution considering different objectives such as the minimization of cost, power losses and voltage stability improvement in the network. Other hybrid algorithms that have been used for OPF solutions are the hybrid DE and harmony-search algorithm (DE-HSA) [21], the hybrid artificial bee colony and DE algorithm [22] and the hybrid Harris hawk and DE (HH-DE) algorithm [23].

This paper proposes the utilization of a newly developed hybrid optimizer named particle swarm gray wolf optimizer (HPS-GWO) to solve OPF problems. This optimizer is integrated with a WE and SPV source taking into consideration the balance and imbalance constraints. Minimization of total generation cost with valve point effect, emission and system power losses are the three objective functions to be optimized in each optimization case. The execution of the suggested technique is carried and examined on the modified IEEE 30 bus test case. The rest of this paper has the following structure: Section 2 explains the mathematical formulation of the OPF problem, and Section 3 provides details of the proposed HPS-GWO. Section 4 provides a description of the simulation results obtained through the proposed method, while the conclusions of the study are offered in Section 5.

2. Mathematical Formulation of OPF Problem

Mathematically, the problem OPF can be formulated as a nonlinear optimization problem. The key purpose of the OPF is to reduce the total generation cost of the system

by choosing suitable values of the control variables subjected to various system constraints. Mathematically, the OPF problem is expressed in the form:

$$\text{Minimize } F(x, y) \quad (1)$$

Subject to equality and inequality constraints:

$$\begin{aligned} h(x, y) &= 0 \\ g(x, y) &\leq 0 \end{aligned} \quad (2)$$

where x represents the control variables while y represents the state variables. Consideration of the state variable is also important for the security of the electrical system. The adopted system consists of thermal generators and WT and SPV sources; therefore, the total generation cost is the sum of the cost of all these sources, which are described in the subsequent subsections. Moreover, replacing thermal generators with RES, the generation at a bus should not breach line capacity constraints; in this research, the same approach of replacing thermal generators with RES was adopted as in References [24,25]. The online diagram of the modified IEEE 30-bus test case under consideration is provided in Figure 1.

Figure 1. Adopted IEEE 30-bus test case with modification.

2.1. Cost Model of TGs

The cost function of TGs with valve point effect is expressed as:

$$C_{TG} = \sum_{i=1}^{nT} a_i + b_i + c_i P_{TGi}^2 + \left| d_i \times \sin \left\{ e_i \times \left(P_{TGi}^{\min} - P_{TGi} \right) \right\} \right| \quad (3)$$

where the values of coefficients a , b , c , d and e are given in Table 1.

Table 1. Cost and emission coefficients of thermal generators.

Bus#	$P_G^{\min}(\text{MW})$	$P_G^{\max}(\text{MW})$	a	b	c	d	μ	Ω	e	α	β	γ
1	50	200	0	2.00	0.00375	18	0.0002	2.857	0.037	4.091	−5.554	6.490
2	20	80	0	1.75	0.0175	16	0.0005	3.333	0.038	2.543	−6.047	5.638
8	10	35	0	3.25	0.00834	12	0.002	2.00	0.045	5.326	−3.550	3.380
11	10	30	0	3.00	0.025	13	0.00001	8.00	0.042	4.258	−5.094	4.586

The emission from TGs can be calculated by the following expression.

$$E_{emi} = \left[\sum_{i=1}^{nT} \left(\alpha_i + \beta_i P_{TGi} + \gamma_i P_{TGi}^2 \right) \times 0.01 + \omega_i e^{(\mu^T P_{TGi})} \right] \quad (4)$$

where values of the emission coefficients are mentioned in Table 2.

Table 2. Weibull parameters and cost coefficients for WT.

Bus #	$P_{wr}(\text{MW})$	Scale Factor (c)	Shape Factor (k)	Weibull Mean	Direct Cost Coeff.	Reserve Cost Coeff.	Penalty Cost Coeff.
5	75	9	2	$V = 7.976 \text{ m/s}$	$K_{Gw,5} = 1.6$	$K_{Rw,5} = 3$	$K_{Pw,5} = 1.5$

The emission cost in \$/h can be calculated as below:

$$C_{emi} = C_t \times E_{emi} \quad (5)$$

where C_t is the carbon tax applied on a per unit ton of emission from TGs.

2.2. Cost Model of SPV Source

The cost function of the SPV source can be expressed as:

$$C_{s,k} = h_k \times P_{s-sch,k} \quad (6)$$

In this equation the direct cost coefficient of the SPV source is represented by h_k . Other details related to the cost function of the SPV source are provided in [24].

2.3. Cost Model of WE Source

The cost function formulation of the WE source is expressed in the form:

$$C_{w,j} = g_{w,j} \times P_{w-sch,j} \quad (7)$$

where the direct cost coefficient of the WE source is represented by g_w . Detailed discussion on the cost function formulation can be found in [24].

2.4. Uncertainty Model of SPV and WE Sources

The output power of SPV and WE sources relies on solar irradiance and wind speed, respectively. There may be a state in which the schedule power is less than the actual power or a state in which the output power of these sources is greater than scheduled power, which is termed as overestimation and underestimation, respectively. Reserve and penalty cost function for SPV and WE sources can be expressed as:

$$C_{Rs,k} = K_{Rs,k}(P_{ssch,k} - P_{sac,k}) \\ = K_{Rs,k} * f_s(P_{sac,k} < P_{ssch,k}) * [P_{ssch,k} - E(P_{sac,k} < P_{ssch,k})] \quad (8)$$

$$C_{Ps,k} = K_{Ps,k}(P_{sac,k} - P_{ssch,k}) \\ = K_{Ps,k} * f_s(P_{sac,k} > P_{ssch,k}) * [E(P_{sac,k} > P_{ssch,k}) - P_{ssch,k}] \quad (9)$$

where K_{Rs} is the reserve cost coefficient of the SPV source.

$$C_{Rw,j} = K_{Rw,j}(P_{wsch,j} - P_{wac,j}) \\ = K_{Rw,j} \int_0^{P_{wsch,j}} (P_{wsch,j} - P_{wac,j}) f(p_{w,j}) dp_{w,j} \quad (10)$$

$$C_{Pw,j} = K_{Pw,j}(P_{wac,j} - P_{wsch,j}) \\ = K_{Pw,j} \int_{P_{wsch,j}}^{P_{wr,j}} (P_{w,j} - P_{wsch,j}) f_w(p_{w,j}) dp_{w,j} \quad (11)$$

where K_{Rw} is the reserve cost coefficient of the WE source. The values of reserve cost coefficients for SPV and WE sources are provided in Tables 2 and 3. A detailed discussion on SPV and WE sources, reserve and penalty cost can be found in [24]. After running 8000 Monte Carlo scenarios, the lognormal and Weibull PDF frequency distribution were plotted as shown in Figures 2 and 3, respectively.

The output power of WT as a function of wind speed can be modeled as shown in Equation (12).

$$P_w(v) = \begin{cases} 0, & \text{for } v < v_{in} \text{ and } v < v_{out} \\ P_{wr}, & \text{for } v_{in} \leq v \leq v_r \\ P_{wr}, & \text{for } v_r \leq v \leq v_{out} \end{cases} \quad (12)$$

where v_r , v_{in} and v_{out} represent the rated, cut in and cut out wind speeds of WT, respectively.

Table 3. Lognormal parameters and cost coefficients for SPV source.

Bus #	P_{sr} (MW)	Mean (μ)	Standard Deviation (σ)	Lognormal Mean	Coefficient for Direct Cost	Coefficient for Reserve Cost	Coefficient for Penalty Cost
13	50	5.8	0.6	$G = 483 \text{ W/m}^2$	$K_{hs,13} = 1.6$	$K_{Rs,13} = 3$	$K_{Psw,13} = 1.5$

Figure 2. Lognormal frequency distribution of SPV source.

Figure 3. Weibull frequency distribution of WT source.

The output power of the SPV source which is a function of solar irradiance (G) can be mathematically modeled as shown in Equation (13).

$$P_{SPV}(G) = \begin{cases} P_{sr} \left(\frac{G^2}{G_{std} R_c} \right) & \text{for } 0 < G < R_c \\ P_{sr} \left(\frac{G^2}{G_{std} R_c} \right) & \text{for } G \geq R_c \end{cases} \quad (13)$$

R_c represents an irradiance point, the value of which was set to 120 W/m^2 in this study.

2.5. Objective Functions for Optimization

Two objective functions for optimization were considered in this study: total generation cost with the valve point effect and power losses in the system.

Total generation cost without levying carbon tax can be expressed as:

$$F_1 = C_{TG} + \sum_{j=1}^{N_w} [C_{w,j} + C_{Rw,j} + C_{Pw,j}] + \sum_{k=1}^{N_s} [C_{s,k} + C_{Rs,k} + C_{Ps,k}] \quad (14)$$

Total generation cost after levying carbon tax can be expressed as:

$$F_2 = C_{TG} + \sum_{j=1}^{N_w} [C_{w,j} + C_{Rw,j} + C_{Pw,j}] + \sum_{k=1}^{N_s} [C_{s,k} + C_{Rs,k} + C_{Ps,k}] + C_{emi} \quad (15)$$

Power losses in the network can be calculated through the following expression:

$$P_{loss} = \sum_{i=1}^{nl} \sum_{j \neq i}^{nl} G_{ij} V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_{ij}) \quad (16)$$

Voltage deviation (p.u.) can be calculated through the following expression.

$$VD = \sum_{p=1}^{nl} |1 - V_{lp}| \quad (17)$$

where V_{lp} represents load bus voltage in per unit.

3. HPS-GWO for OPF Solution

In this study the HPS-GWO algorithm was utilized for the optimization of the two objective functions stated in the previous section. The PSO draws inspiration from the social behavior of gathering birds, while the GWO simulates the hunting and governance chain

of command of gray wolves. Hybridization of PSO with GWO enhances the exploitation capability in PSO with the exploration capability of GWO.

4. Results and Discussion

Two objective functions for optimization were considered in this study: total generation cost with valve point effect and power losses in the system. The simulation results were obtained while ensuring a number of equality, inequality and security constraints, details of which can be found in [15]. Three metaheuristic algorithms, namely PSO, GWO and HPS-GWO, were utilized for the optimization of both objectives.

4.1. Case 1: SPV and WE Source Cost vs. PDF Parameters

In this case SPV and WE source total cost, that is the sum of penalty cost, reserve cost and direct cost, are plotted against a PDF parameter. In the case of the SPV source, the PDF parameter mean (μ) varies from 1 to 7 at a fixed value of standard deviation $\delta = 0.6$, whereas in the case of the WE source the PDF scale parameter (c) varies from 2 to 18 at a fixed value of shape parameter $k = 2$. The results show that a minimum total cost of the SPV source is observed at $\mu = 5.8$, while the minimum total cost of the WE source is observed at $c = 9$, as illustrated in Figures 4 and 5, respectively.

4.2. Case 2: Minimization of Total Generation Cost

In this case total generation cost of the system with the valve point effect was optimized. Each algorithm was run 5 times for 300 iterations, and the best values of the control variables and other constraints variables achieved are shown in Table 4. The minimum cost was achieved by HPS-GWO followed by GWO, PSO and SHADE-SF, as indicated by bold in Table 4. The minimum power losses in the network were achieved by SHADE-SF followed by HPS-GWO, GWO and PSO, while minimum emission was achieved by PSO followed by HPS-GWO, GWO and SHADE-SF. The convergence curve for the mentioned algorithms is shown in Figure 6, indicating that the suggested HPS-GWO has a better and steady convergence curve as compared to PSO, GWO and SHADE-SF.

Figure 4. SPV total cost vs. lognormal mean (μ).

Figure 5. WT total cost vs. Weibull scale parameter (c).

Table 4. Case 2 simulation results.

	Parameters	Lower Limit	Upper Limit	PSO	GWO	HPS-GWO	SHADE-SF
Swing Generator	P _{TG1} (MW)	50	140	134.908	135.661	135.112	124.156
	P _{TG2} (MW)	20	80	43.546	41.029	42.645	34.883
Control Variables	P _{WT5} (MW)	0	75	50.845	51.001	49.779	46.985
	P _{TG8} (MW)	10	35	10.000	10.610	10.000	10.000
	P _{TG11} (MW)	10	30	10.000	10.094	10.025	30.000
	P _{SPV13} (MW)	0	50	40.085	41.361	42.018	42.830
	V ₁ (p.u.)	0.95	1.10	1.100	1.100	1.100	1.070
	V ₂ (p.u.)	0.95	1.10	1.901	1.089	1.091	1.056
	V ₅ (p.u.)	0.95	1.10	1.071	1.074	1.071	1.035
	V ₈ (p.u.)	0.95	1.10	1.096	1.100	1.097	1.097
	V ₁₁ (p.u.)	0.95	1.10	1.100	1.094	1.100	1.100
	V ₁₃ (p.u.)	0.95	1.10	1.100	1.095	1.092	1.053
Generator Reactive Power	Q _{TG1} (MVar)	−20	150	−12.332	−13.435	−6.721	−3.397
	Q _{TG2} (MVar)	−20	60	18.230	27.184	4.773	10.439
	Q _{WT5} (MVar)	−30	35	24.611	18.841	35.000	21.969
	Q _{TG8} (MVar)	−15	40	40.000	40.000	40.000	40.000
	Q _{TG11} (MVar)	−10	50	18.464	17.998	17.862	30.000
	Q _{SPV13} (MVar)	−20	25	23.689	22.144	22.235	16.357
Objective Functions	Gen. cost (\$/h)	-	-	796.556	796.254	796.164	797.324
	Emission (ton/h)	-	-	0.19592	0.19703	0.19628	0.924
	P _{loss} (MW)	-	-	5.9845	5.9841	5.9832	5.453

Figure 6. Convergence curve of HPS-GWO for OPF problem.

4.3. Case 3: Minimization of Total Generation Cost with Carbon Tax on Emission

In this case total generation cost was optimized, while a carbon tax of 20 \$/ton was imposed on emission from TGs [26–29]. The statistical data obtained after simulation of 300 iterations for every optimization algorithm are shown in Table 5. The results presented in Table 5 clearly indicate that the proposed HPS-GWO offers effective and steady solutions in comparison to PSO, SHADE-SF and GWO algorithms. The convergence curves obtained for every optimization algorithm are presented in Figure 7. It has been noted that the emissions were reduced and power penetration from RES was increased after imposing a carbon tax on emission from TGs.

Figure 7. Case 3: Convergence curve of for OPF problem.

Table 5. Case 3 simulation results.

	Parameters	Lower Limit	Upper Limit	PSO	GWO	HPS-GWO	SHADE-SF
Swing Generator	P _{TG1} (MW)	50	140	134.908	135.119	134.400	125.123
	P _{TG2} (MW)	20	80	42.564	40.830	42.205	38.093
Control Variables	P _{WE5} (MW)	0	75	50.566	51.442	51.211	48.562
	P _{TG8} (MW)	10	35	10.000	10.166	10.294	10.000
	P _{TG11} (MW)	10	30	10.000	10.000	10.020	30.000
	P _{SPV13} (MW)	0	50	41.341	41.969	40.525	37.094
	V ₁ (p.u.)	0.95	1.10	1.100	1.100	1.100	1.071
	V ₂ (p.u.)	0.95	1.10	1.090	1.089	1.091	1.057
	V ₅ (p.u.)	0.95	1.10	1.071	1.071	1.074	1.036
	V ₈ (p.u.)	0.95	1.10	1.099	1.092	1.089	1.085
	V ₁₁ (p.u.)	0.95	1.10	1.100	1.098	1.100	1.100
	V ₁₃ (p.u.)	0.95	1.10	1.100	1.100	1.100	1.051
Generator Reactive Power	Q _{TG1} (MVar)	−20	150	−12.297	−13.141	−17.772	−3.151
	Q _{TG2} (MVar)	−20	60	18.114	14.729	37.803	10.776
	Q _{WE5} (MVar)	−30	35	24.626	27.588	9.715	21.943
	Q _{TG8} (MVar)	−15	40	40.000	40.000	40.000	40.000
	Q _{TG11} (MVar)	−10	50	18.443	18.902	18.835	30.000
	Q _{SPV13} (MVar)	−20	25	23.761	25.000	24.052	15.664
Objective functions	Gen. cost (\$/h)	-	-	800.6517	800.8232	800.5614	801.320
	Emission (ton/h)	-	-	0.19597	0.19634	0.19524	0.997
	P _{loss} (MW)	-	-	5.9787	6.0013	5.9436	5.471

5. Conclusions

In this paper, a solution towards OPF integrated with RES such as SPV and WE sources is proposed. The HPS-GWO was applied to solve the OPF problem considering various system constraints. The stochastic nature of SPV and WE sources was modeled using lognormal and Weibull PDFs, respectively. A modified IEEE 30-bus test system was considered to verify the efficiency of the suggested HPS-GWO. The simulation results show that the proposed HPS-GWO achieved a minimum total generation cost as compared to PSO, GWO and SHADE-SF, and the HPS-GWO has a steady and fast convergence curve as compared to PSO, GWO and SHADE-SF algorithms. It was further concluded that the emissions were reduced by 0.00104 ton/h after imposing a carbon tax on emission from TGs, while penetration from SPV and WE sources increased. A solution to the OPF problem by combining the SPV, WE and hydro energy sources for other IEEE test systems is a potential subject of future research work.

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Nomenclature

		Abbreviations	
OPF	Optimal power flow	K_{Rs}	Reserve cost coefficient for SPV source
PSO	Particle swarm optimization	K_{Ps}	Penalty cost coefficient for SPV source
GWO	Gray wolf optimization	K_{gw}	Direct cost coefficient for WE source
HPS-GWO	Hybrid particle swarm gray wolf optimizer	K_{Rw}	Reserve cost coefficient for WE source
RES	Renewable energy sources	K_{Pw}	Penalty cost coefficient for WE source
PDF	Probability density function	$f_G(s)$	Probability of solar irradiance (W/m^2)
p.u.	Per unit	$f_U(w)$	Probability of wind speed(m/s)
SPV	Solar photovoltaic	σ	Lognormal PDF standard deviation
WE	Wind energy	μ	Lognormal PDF mean
	Symbols	G	Solar irradiance in W/m^2
P_{TG}	Thermal generator real power	k	Weibull PDF shape parameter
P_{WG}	Wind energy source real power	c	Weibull PDF scale parameter
P_{SPV}	Solar photovoltaic source real power	P_{loss}	Power losses in the network
P_{sr}	Rated power output of SPV source	V.D	Cumulative voltage deviation
P_{wr}	Rated power output of WE source	C_{emi}	Emission cost
SHADE	Success history based adaptive differential evolution	SF	Superiority of feasible solutions
K_{hs}	Direct cost coefficient for SPV source		

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