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A Solution to the Optimal Power Flow Problem Considering WT and PV Generation

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ABSTRACT This paper proposes a combination of phasor particle swarm optimization (PPSO) and a gravitational search algorithm, namely a hybrid PPSOGSA algorithm, for optimal power flow (OPF) in power systems with an integrated wind turbine (WT) and solar photovoltaic (PV) generators. The OPF formulation includes the forecasted active power generation of WT and PV as dependent variables, whereas the voltage magnitude at WT and PV buses is considered as control (decision) variables. Forecasting the output power of WT and PV generators is based on the real-time measurements and the probabilistic models of wind speed and solar irradiance. The proposed OPF approach and the solution method are verified on the IEEE 30-bus test system. The robustness and efficiency of the proposed PPSOGSA algorithm in solving the OPF problem are evaluated by comparing with 20 well-established metaheuristic optimization methods under the same system data, control variables, and constraints. The statistical features of the OPF results are estimated by using the Monte Carlo method.

INDEX TERMS Heuristic algorithms, load flow, optimization, wind power generation, solar power generation, power systems.

I. INTRODUCTION

The continuous increase in consumption, the need to reduce greenhouse gas emissions (COx, NOx and SOx), deregulation and liberalization of the electricity market, and privileged prices of green energy, have led to the rapid growth of renewable energy sources (RES) in the last two decades. It seems that the wind and solar energy are the best alternatives to fossil fuels for power generation. The fast-growing RES utilization has been enabled by using the enhanced technology of WT and PV generation systems that results to reduce the cost of system installations. Furthermore, it may be argued that the wind turbine and solar photovoltaic generation systems are proven and standardized technologies. As reported in [1], electricity from RES such as WT and PV will shortly be low-priced than from fossil fuels.

Depending on size, locations and technical characteristics of WT and solar PV generators they may have a significant impact on performances of power system operation in terms of economic indicators such as fuel cost in thermal power plants, power quality indicators and power losses. The optimal power flow (OPF) means an economical and stable operation of the power system, which is achieved by appropriate settings of the system's control variables. In the mathematical formulation, this is a large-scale, nonlinear, nonconvex, static, constrained problem with both continuous and discrete control variables. The integration of multiple WT and PV arrays into power system escalates the complexity of the OPF problem due to its intermittent power generation characteristics [2], [3].

The general framework for defining and solving the OPF considering WT and PV generation must include the following aspects: (i) the significance and context of this issue; (ii) modeling WT and PV output powers due to uncertain characteristics of wind speed and solar irradiation; (iii) choice of objective functions; (iv) defining technical constraints, control variables and dependent variables, and (v) OPF problem solution methodology. Recently, several researchers have dealt with the OPF problem focusing on some of the above tasks.

To model the stochastic behavior of wind speed at a specific location most authors [3]–[10] use Weibull

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probability distribution functions (PDFs), whereas the stochastic nature of solar irradiance can be described by lognormal PDF [3], [11] or Beta PDF [12] .

Different solution techniques towards OPF problem have been presented in the literature, as well as various ways of inclusion of WT and PV generation in the OPF model. In recent research works, most of the researchers considered metaheuristic population-based methodology for the OPF problem solution.

The authors in [3] used an adaptive differential evolution (SHADE) technique to minimize total generation cost which includes over and underestimation of stochastic sources - WT and PV taking into account as a reserve and penalty costs. A self-adaptive evolutionary programming (SAEP) method is proposed for solving OPF problem in power systems with integrated WT farms, where the main objective function includes the shortage and surplus power of WT with associated opportunity costs. A modified version of the bacteria foraging algorithm (BFA) is employed in [5] and [6] to solve the OPF problem the considered objective function includes the cost of thermal generation and the cost of purchase from wind power generation, the penalty costs corresponding to surplus and deficit of wind generation, and the cost corresponding to reactive power management of DFIG in WT. Chang *et al.* [7] proposed an evolutionary particle swarm optimization (EPSO) technique to solve the OPF in a wind-thermal generation system, considering up-spinning reserves, down-spinning reserves and the operational constraints of the generators. Roy and Jadhov [8] implemented the Gbest guided artificial bee colony (ABC) algorithm for OPF problem with multiple cost components including thermal generators fuel cost, probable cost of WT power to be purchased, expected penalty cost while none utilization of available WT power due to network congestion, expected reserve cost due the deficiency of WT power, and emission cost. Biogeography-based optimization (BBO) algorithm is used in [9] to solve probabilistic multi-objective OPF problem in a power system with WT generation taking into account the relationship in wind speed and the load. The hybridization of genetic algorithm and teaching-learning optimization (G-TLBO) technique is proposed in [10] to simultaneous minimization of the fuel cost for thermal units and the penalty costs for not using available power and required reserve of wind generation. The authors in [13] applied an improved differential evolution algorithm indicated as DEa-AR for solving the OPF problem considering RES i.e. WT, PV and mini-hydro generator units. Kotur and Stefanov [14] proposed the OPF methodology using optimal control of power converters for the minimization of power losses in the system with offshore wind power plants. For real time OPF in every 5-15 min intervals, the authors [15] proposed the valuation 'best-fit' involvement factors by considering the minute-to-minute variability of WT and PV generation.

In this paper, a novel hybrid PPSOGSA algorithm is proposed to solve the OPF problem in power systems with integrated WT and solar PV generators. The main contributions of this work are:

- Application of a novel hybrid PPSOGSA algorithm to solve the OPF problem
- The OPF formulation includes the forecasted active power generation of WT and PV as dependent variables; whereas the voltage magnitude at WT and PV buses are considered as control (decision) variables
- Forecasting the output power of WT and PV generators based on real time measurements and probabilistic models of wind speed and solar irradiance.

The rest of this paper is organized as follows: Section II presents the OPF problem formulation. The probabilistic models of WT and PV generation and calculation of their forecasted output powers are explained in Section III. The proposed hybrid PPSOGSA algorithm and its application on the OPF problem are explained in Section IV. The simulation results are presented in Section V, and the conclusions are listed in Section VI.

II. PROBLEM FORMULATION

The integration of WT and PV makes the OPF problem more complex due to their uncertain power generation characteristics. The OPF problem incorporating the uncertainties of WT and PV generation is formulated in this paper under several practical assumptions, as follows.

- The active power generations of WT and PV are non-dispatchable, and accounts in the OPF problem as forecasted values.
- The OPF is performed sequentially in predefined time intervals t of 10 min [15]. Considering the sampling time in wind speed and solar irradiance measurements of 1 min, there are ten readings at the time interval t. Based on the measurement data, probabilistic models of wind speed and solar irradiance, and technical characteristics of WT and PV units the forecasted active power generation of WT and PV can be calculated.
- The WT and PV units are capable to produce reactive power in the range of -0.4 p.u. to 0.5 p.u. of their active power [3], [5], [11], [16]. Therefore, WT and PV buses voltage magnitudes can be considered as control variables in the OPF problem.

Mathematically, the OPF problem can be expressed as follows [17].

$$\min \ F(\mathbf{x}, \mathbf{y}) \tag{1}$$

$$\text{Subject to}: \ g(\mathbf{x}, \mathbf{y}) = 0 \tag{2}$$

$$h(\mathbf{x}, \mathbf{y}) \leq 0 \tag{3}$$

$$\mathbf{x} \epsilon \mathbf{X} \tag{4}$$

where: F is the objective function to be minimized; $\mathbf{x}$ shows vector of control variables, active power outputs of thermal units (P_G) excluding at the slack bus (assumed bus 1), generator voltages including WT and PV (V_G), tap settings of transformer (T), and (Q_C) is the shunt

VAR compensations:

$$\mathbf{x} = [P_{G2} \ldots P_{GNG}, V_{G2} \ldots V_{GNG}, V_{WT}, V_{PV}, T_1 \ldots T_{NT}, Q_{C1} \ldots Q_{CNC}] \quad (5)$$

NG, *NT* and *NC* indicate the number of thermal power plants, regulating transformer and VAR compensators, respectively. **y** is the vector of dependent variables consisting of slack bus power (P_{G1}), voltages at load bus (V_L), reactive power outputs of the generator(Q_G), and loads of transmission line (S_l):

$$\mathbf{y} = [P_{Gsl}, V_{L1} \ldots V_{LNL}, Q_{G1} \ldots Q_{GNG}, Q_{WT}, Q_{PV}, S_{l1} \ldots S_{lNTL}] \quad (6)$$

NL and *NTL* represent the number of load buses and transmission lines.

A. CONSTRAINTS

The equation (2) shows the equality constraints which are the classical nonlinear power flow equations.

$$P_i - V_i \sum_{j=1}^{NB} V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0 \quad (7)$$

$$Q_i - V_i \sum_{j=1}^{NB} V_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) = 0 \quad (8)$$

where, $i = 1, \ldots, NB$; *NB* represent the number of busses; P_i active power; Q_i reactive power injected at bus i; the voltage angle between i and j is denoted by θ_{ij}; G_{ij} is the real part and B_{ij} is the imaginary part of bus admittance matrix correlating to ith row and jth column, respectively.

The equation (3) shows the inequality constraints considering the functional operating factors, i.e. voltage magnitudes and their limits at load buses, reactive power output limits at the generator and branch flow limits.

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \quad i = 1, \ldots, NL \quad (9)$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad i = 1, \ldots, NG \quad (10)$$

$$S_{li} \le S_{li}^{\max} \quad i = 1, \ldots, NTL \quad (11)$$

Constraints (4) define the space of possible solutions for the OPF problem:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \quad i = 1, \ldots, N \quad (12)$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \quad i = 1, \ldots, NG \quad (13)$$

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1, \ldots, NT \quad (14)$$

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, \quad i = 1, \ldots, NC \quad (15)$$

It is pertinent to mention that the control variables i.e. (**x**) are self-constrained. Moreover, Inequality constraints of the dependent variables i.e. (**y**) are restricted by adding them as the quadratic penalty terms to the objective function [17].

B. OBJECTIVE FUNCTION

The main objective function F has considered in OPF problems is the total cost of fuel in thermal generating units ($Fcost$). The cost characteristics of a thermal generating unit can be express as a quadratic function of the output power of generator P_G:

$$\min_{\mathbf{x}} Fcost\,(\mathbf{x}, \mathbf{y}) = \min_{\mathbf{x}} \sum_{i=1}^{NG} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \quad (16)$$

where a_i, b_i and c_i are the cost coefficients of the ith thermal power plant, and P_{Gi} is the corresponding active power output.

The objective function for minimization of active power loss ($Ploss$) in the system has expressed as follow:

$$\min_{\mathbf{x}} Ploss\,(\mathbf{x}, \mathbf{y}) = \min_{\mathbf{x}} \sum_{L=1}^{NTL} g_{L,ij} \left[V_i^2 + V_j^2 - 2V_iV_j\cos\left(\theta_i - \theta_j\right)\right] \quad (17)$$

where $g_{L,ij}$ is the conductance of transmission line L connecting the ith and jth bus; V_i, V_j, θ_i, and θ_j are the voltage magnitudes and voltage angles at bus i and j, respectively.

The bus voltage is one of the most essential and significant safety and service quality indices. In this case the main objective is to minimize the load bus voltage deviations (VD) is expressed as follow:

$$\min_{\mathbf{x}} VD\,(\mathbf{x}, \mathbf{y}) = \min_{\mathbf{x}} \sum_{i=1}^{NL} \left|V_i - V_i^{ref}\right| \quad (18)$$

where V_i shows the voltage magnitude of the ith bus, and V_i^{ref} is the reference value of the voltage magnitude at bus i, which is generally considered as 1 p.u.

Optimization of different objective functions is performed to achieve a compromise solution. The multi-objective OF problem can be solved by using a weighted sum method as follows:

$$\min_{\mathbf{x}} MOF\,(\mathbf{x}, \mathbf{y}) = \min_{\mathbf{x}}\{w_F \cdot Fcost(\mathbf{x}, \mathbf{y}) + w_P \cdot Ploss(\mathbf{x}, \mathbf{y}) + w_V \cdot VD(\mathbf{x}, \mathbf{y})\} \quad (19)$$

where w_F, w_P, and w_V are weighting coefficients.

III. MODELING OF WT AND PV GENERATION

A. WT POWER GENERATION

The output power of a WT, for given wind speed (v) can be analyzed as follow:

$$P_{WT}(v) = \begin{cases} 0 & v \le v_{ci} \\ \dfrac{v - v_{ci}}{v_n - v_{ci}} \cdot P_{wtn} & v_{ci} < v \le v_n \\ P_{wtn} & v_n < v \le v_{co} \\ 0 & v \ge v_{co} \end{cases} \quad (20)$$

where P_{wtn}, is the nominal power; v_n is nominal wind speed; v_{ci} is cut-in wind speed; and v_{co} is cut-out wind speed of the wind turbine.

The stochastic nature of wind speed in a predefined time period at a specific locality can be generally defined by Weibull PDF:

$$f_v(v) = \frac{k}{C} \cdot \left(\frac{v}{C}\right)^{k-1} \cdot e^{-\left(\frac{v}{C}\right)^k} \tag{21}$$

The cumulative density function (CDF) for the Weibull distribution is:

$$F_v(v) = 1 - \cdot e^{-\left(\frac{v}{C}\right)^k} \tag{22}$$

The CDF with its inverse has been considered for calculating the wind speed:

$$v = C \cdot (-\ln(r))^{\frac{1}{k}} \tag{23}$$

where $f_v(v)$ is Weibull PDF of wind speed; C and k are the scale and shape parameters of the Weibull distribution; r is a random number uniformly distributed on [0], [1].

In practice, parameters C and k can be calculated, approximately, using mean (μ_v^t) and standard deviation (σ_v^t) of wind speed at the tth time interval:

$$k^t = \left(\frac{\sigma_v^t}{\mu_v^t}\right)^{-1.086} \tag{24}$$

$$C^t = \frac{\mu_v^t}{\Gamma\left(1 + 1/k^t\right)} \tag{25}$$

where $\Gamma(x)$ is the gamma function. Note that the μ_v^t and σ_v^t are calculated from the wind speed measurements in considered time interval t.

The OPF is performed sequentially in predefined time intervals of 5 to 15 min [15]. In this work the time interval t is adapted to be 10 min. Considering the sampling time in wind speed measurements of 1 min, there are ten readings of the wind speeds at the time interval t. Therefore, the mean and standard deviation of wind speed can be calculated from measured data which correspond to this time interval. Based on mean and standard deviation of wind speed, the shape parameter (k) and the scale index (C) of Weibull PDF can be calculated by using (24) and (25). The measured wind speed data in the time interval t of 10 min are base for forecasting the wind speed and consequently output power of WT in the next time interval of 10 min.

To realize the Weibull PDF in discrete form, the tth time interval is divided into N_v states, where the corresponding wind speed and probability for each state $(g = 1 \div N_v)$ are calculated by using (21) and (23), respectively. The forecasted output power of WT is calculated based on the probability of all possible states for that time interval:

$$P_{WT} = \frac{\sum_{g=1}^{N_v} P_{WTg} \cdot f_v\left(v_g^t\right)}{\sum_{g=1}^{N_v} f_v\left(v_g^t\right)} \tag{26}$$

where v_g^t is the gth state of wind speed at the tth time interval; P_{WTg} is the power generation of WT calculated using (20) for $v = v_g^t$; $f_v\left(v_g^t\right)$ is the probability of the wind speed for state g during the specific interval t.

B. PV POWER GENERATION

The output power generated of a PV unit is dependent on the solar irradiance [3]:

$$P_{PV}(S) = \begin{cases} P_{pvn} \dfrac{S^2}{S_{stc} R_c} & \text{for } S < R_c \\ P_{pvn} \dfrac{S}{S_{stc}} & \text{for } S \geq R_c \end{cases} \tag{27}$$

where P_{pvn} is the nominal output power of the PV unit; $S$is the solar irradiance on the PV module surface (W/m^2); S_{stc} is the solar irradiance at standard test conditions; R_c is a certain irradiance point.

Beta PDF is suitable to model the stochastic nature of solar irradiance:

$$f_s(S) = \begin{cases} \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot S^{(\alpha+1)} \cdot (1-S)^{(\beta-1)}, \\ \quad \text{for } 0 \leq S \leq 1,\ \alpha \geq 0,\ \beta \geq 0 \\ 0, \quad \text{otherwise} \end{cases} \tag{28}$$

In the above equation the S represents the solar irradiance in kW/m^2; $f_s(S)$ is Beta distribution function of S and α, β shows its shape parameters; and Γ represents Gamma function.

Shape parameters of Beta PDF can be obtained based on the mean (μ_s) and standard deviation (σ_s) of solar irradiance calculated from measured data in a time interval t:

$$\beta^t = \left(1 - \mu_s^t\right) \cdot \left(\frac{\mu_s^t\left(1 + \mu_s^t\right)}{\left(\sigma_s^t\right)^2} - 1\right) \tag{29}$$

$$\alpha^t = \frac{\mu_s^t \cdot \beta^t}{1 - \mu_s^t} \tag{30}$$

The solar irradiance measurements are made available with the sampling time of 1 min. Therefore, the mean and standard deviation of solar irradiance can be calculated from measured data which correspond to the tth time interval of 10 min. Based on the mean and standard deviation of solar irradiance, the shape parameters of Beta PDF (α and β) can be calculated using (29) and (30).

To realize Beta PDF in discrete form, the tth time interval is divided into N_s states, where the corresponding solar irradiance and probability for each state $(g = 1 \div N_s)$ calculated using equation (28). The forecasted output power of PV is evaluated considering the probabilities of all solar irradiance states in the observed time interval.

$$P_{PV} = \frac{\sum_{g=1}^{N_s} P_{PVg} \cdot f_s\left(S_g^t\right)}{\sum_{g=1}^{N_s} f_s\left(S_g^t\right)} \tag{31}$$

where S_g^t is the gth state of solar irradiance at the tth time interval; P_{PVg} is the power generation of PV calculated using (27) for $S = S_g^t$; $f_s\left(S_g^t\right)$ is the probability of the solar irradiance for the state g during the specific time interval t.

IV. SOLUTION METHOD

An improved hybrid PSOGSA [18], namely hybrid PPSOGSA algorithm, is proposed in this paper to solve the OPF problem. The hybrid PPSOGSA algorithm is a combination of phasor particle swarm optimization (PPSO) [19] and gravitational search algorithm (GSA) [20]. The improvement of the proposed PPSOGSA algorithm in relation to the original PSOGSA algorithm is based on modeling the particle control parameters with a phase angle (θ). In the new hybrid PPSOGSA algorithm the periodic nature of trigonometric sine and cosine functions is utilized to represent the particle control parameters (c_1 and c_2) through phase angles θ.

Our proposed algorithm is a type of hybrid metaheuristic optimization technique applied in optimization problems. PPSOGSA algorithm involves a stochastic search method based on population, where the size of the population is defined by a number of search agents (N). We represent these agents by a vector ($\mathbf{x}_i$) as in (5) whose entries correspond to the control variables of the specific optimization problem at hand. The search space dimension (n) is defined by the number of control variables involved. The techniques essentially generate a new population in an iterative successive correction mechanism by the application of stochastic search operators on the current population [17]. Below we expand upon the general structure of a hybrid PPSOGSA algorithm in detail.

Initialization

1. The objective function $F(\mathbf{x_i})$ and space of possible solutions **X;**
2. Generate an initial population size, where the starting positions of N agents are randomly selected between the minimum and maximum values of the control variables. Set the iteration counter: *iter*=1

   Iterative procedure and calculation
3. The fitness value for each agent in the current population **POP**(*iter*).
4. Generate new population **POP**(*iter*+1) by placing the algorithmic operators on search agents from the **POP**(*iter*). For the proposed PPSOGSA algorithm the operators for updating the current velocity and the current position of agents are as follows:

$$\begin{aligned} \mathbf{v}_i(iter+1) = r_1 \cdot \mathbf{v}_i(iter) &+ r_2 \cdot |\cos\theta_i(iter)|^{2\cdot\sin\theta_i(iter)} \cdot \mathbf{a}_i(iter) \\ &+ r_3 \cdot |\sin\theta_i(iter)|^{2\cdot\cos\theta_i(iter)} \\ &\cdot (\mathbf{gbest}(iter) - \mathbf{x}_i(iter)) \end{aligned} \tag{32}$$

$$\mathbf{x}_i(iter+1) = \mathbf{x}_i(iter) + \mathbf{v}_i(iter+1) \tag{33}$$

   The phase angle (θ) is updated using the following equation:

$$\begin{aligned} \theta_i(iter+1) = \theta_i(iter) + |\cos\theta_i(iter) \\ + \sin\theta_i(iter)| \cdot 2\pi \end{aligned} \tag{34}$$

   Initial positions of N agents (initial population) are randomly generated in the search space of the problem with their own phase angle θ_i through uniform distribution U (0, 2π).
5. Repeat the iterative procedure until the stop criteria is reached.
6. Report best solution. End.

In (32) **gbest** denotes the best solution (position) among all agents best positions achieved so far. The **gbest** is calculated in each iteration within the above iterative procedure. The acceleration of agents, $\mathbf{a}_i$, is updated using the equations given in [20]. r_1, r_2, and r_3 are random numbers in the range of [0], [1].

A. APPLICATION OF PPSOGSA FOR OPF

The proposed hybrid PPSOGSA approach has been applied to solve the OPF problem. Application of the proposed PPSOGSA approach in solving the OPF problem considering WT and PV generation can be described in the following steps:

Step 1: Read the input data including the power system configuration, lines data, transformers data, shunt VAR compensators data, loads data, and generation units data.

Step 2: Specify the control variables and their limits; Specify the dependent variables and their limits; Specify the objective function to be optimized.

Step 3: Calculate the forecasted output power of WT and PV units, as described in Section III.

Step 4: Set the algorithmic parameters, such as the population size and the maximum number of iterations; Generate an initial random population of N search agents.

Step 5: Run the power flow program for each agent from the current population and calculate the corresponding values of the objective function (fitness values).

Step 6: Apply the PPSOGSA operators to create a new population of agents (i.e. improved solutions of the problem).

Step 7: Repeat steps 5-6 until the stop criteria is reached, i.e. the max number of iterations.

Step 8: Report the optimal results.

V. SIMULATION RESULTS

The OPF simulations are performed on the IEEE 30-bus test system with the total active and reactive loads of 283.4 MW and 126.2 MVAr, respectively. The basic IEEE 30-bus test system consists of 41 transmission lines, six thermal generators at the buses 1, 2, 5, 8, 11 and 13, four transformers with off-nominal tap ratio at lines 6-9, 6-10, 4-12 and 28-27, and nine shunt VAR compensators at the buses 10, 12, 15, 17, 20, 21, 23, 24 and 29. The limits of the transformer tap settings, the shunt VAR compensations, and the generator voltages are considered to be (0.9, 1.1) p.u., (0, 5) MVAr, and (0.95, 1.1) p.u., respectively. The voltage magnitude at the load buses are constrained in the range (0.95 ÷ 1.05) p.u. The system branch, bus, and thermal generator data are taken from reference [17].

A. DETERMINISTIC OPF

In order to prove the efficiency of the proposed hybrid PPSOGSA algorithm, the deterministic OPF cases for the

TABLE 1. OPF results obtained by proposed hybrid PPSOGSA algorithm.

	Base	Case 1	Case 2	Case 3	Case 4
P_{G1}	99.22227	177.11	45.297	140.01	124.524
P_{G2}	80	48.579	80.000	49.036	52.6563
P_{G5}	50	21.367	49.999	44.741	31.7298
P_{G8}	20	21.437	35.000	18.405	34.9427
P_{G11}	20	11.935	30.000	24.134	25.2781
P_{G13}	20	12.002	39.999	14.496	20.3795
V_{G1}	1.05	1.0842	1.0620	1.0109	1.0349
V_{G2}	1.04	1.0652	1.0577	1.0007	1.0220
V_{G5}	1.01	1.0339	1.0377	1.0193	1.0008
V_{G8}	1.01	1.0379	1.0444	1.0092	1.0054
V_{G11}	1.05	1.0934	1.0605	1.0027	1.0117
V_{G13}	1.05	1.0433	1.0544	1.0242	1.0098
$T_{11(6\text{-}9)}$	1.078	1.0242	1.0240	1.0156	1.0268
$T_{12(6\text{-}10)}$	1.069	0.9533	0.9439	0.9045	0.9064
$T_{15(4\text{-}12)}$	1.032	0.9637	0.9924	1.0117	0.9818
$T_{36(28\text{-}27)}$	1.068	0.9786	0.9787	0.9572	0.9695
Q_{C10}	0	0.7220	3.8438	4.5929	4.9973
Q_{C12}	0	1.3816	2.1119	3.5656	1.0531
Q_{C15}	0	4.5110	4.7997	4.9957	4.6921
Q_{C17}	0	4.9959	4.9572	0.3245	0.7150
Q_{C20}	0	3.9825	4.4559	5.0000	4.9997
Q_{C21}	0	4.9908	4.9923	4.9964	4.9678
Q_{C23}	0	3.8007	3.4984	4.9676	4.9993
Q_{C24}	0	4.9889	4.9915	4.9928	4.9997
Q_{C29}	0	3.3442	2.7125	1.2979	2.9358
Fcost	901.949	**800.528**	967.669	849.613	**829.598**
Ploss	5.82225	9.02665	**3.10327**	7.41951	**6.11036**
VD	1.14966	0.91136	0.89050	**0.08986**	**0.11039**

original system configuration (without WT and PV) are considered first. Four cases are considered here, with the objective functions described in Section II, namely: Case 1 – minimization of fuel cost; Case 2 – minimization of active power loss; Case 3 – voltage profile improvement; Case 4 simultaneous minimization of fuel cost, power loss and voltage deviation. The optimal results obtained by the proposed hybrid PPSOGSA algorithm, shown in Table 1, are the best values obtained over 30 consecutive test runs for each case examined. These results are in accordance with the considered objective functions, and all the specified constraints are met. The optimal settings of control variables highly reduced the total fuel cost in Case1 compared to the initial (Base) case. Optimization of the total fuel cost in Case 1 causes the maximum power loss and voltage deviation in relation to other optimization cases. In Case 2, the minimum power loss is achieved, but the total fuel cost is higher even in relation to the initial (base) case. The constant PQ models of loads require increasing voltages at load buses to minimize branch power losses in Case 2. This is the reason for the relatively high value of voltage deviation in Case 2. As can be seen in Figure 1, the optimal voltage profile is obtained in Case 3. However, a compromise solution is obtained in Case 4. The performance of the system is significantly improved by simultaneous minimization of total fuel cost, power loss and voltage deviation.

To achieve a fair comparison with other solution techniques, the OPF for Case 1 is solved by 20 different population-based metaheuristic algorithms (including proposed PPSOGSA and original PPSO and GSA) under

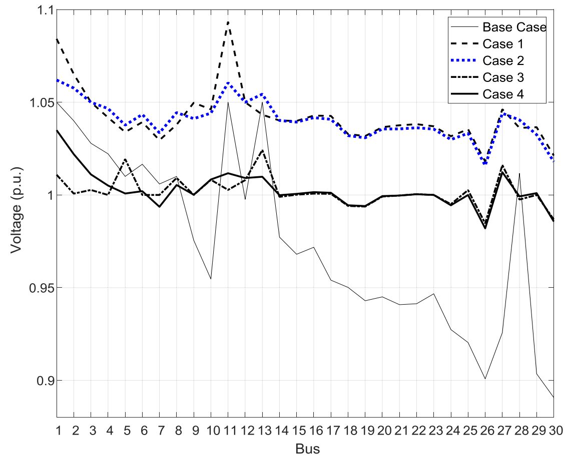

FIGURE 1. Voltage profiles for deterministic OPF cases.

the same system data, control variables, and constraints. These algorithms are as follows: particle swarm optimization (PSO) [21], moth-flame optimization algorithm (MFO) [22], genetic algorithm (GA) [23], differential evolution (DE) [24], teaching-learning-based optimization (TLBO) [25], artificial bee colony (ABC) [26], moth swarm algorithm (MSA) [27], harmony search (HS) [28], wind-driven optimization (WDO) [29], cuckoo search (CS) [30], backtracking search optimization algorithm (BSA) [31], swarm robotics search & rescue (SRSR) [32], imperialist competitive algorithm (ICA) [33], firefly algorithm (FFA) [34], biogeography-based optimization (BBO) [35], multi-verse optimizer (MVO) [36], grey wolf optimizer (GWO) [37], and ant colony optimization (ACO) [38].

The statistical indicators obtained over 30 runs for each of optimization methods are shown in Table 2. The parameters such as population size (50), max iteration number (200), and a number of runs (30) are the same for each algorithm. Other algorithmic parameter settings are adopted as default values proposed by the authors of these algorithms. The results given in Table 2 clearly shows that the proposed PPSOGSA provides high quality and stable solutions in comparison with other metaheuristic methods.

Moreover, the convergence characteristics of these methods are shown in Figure 2. Clearly, the proposed PPSOGSA achieves better solutions and converges to the global best solution with less iterations compared to the other methods. These facts prove the ability of PPSOGSA to solve the OPF problems with high level of complexity; taking into account stochastic variables such as WT and PV generation.

B. PROBABILISTIC OPF

The IEEE 30-bus test system is modified by introducing two renewable energy sources, ie. the wind farm (WT) and the solar PV generator as shown in Figure 3. The WT farm connected at bus 19 has rated power of 50 MW, and consisting of 25 turbines of 2 MW each with a nominal wind speed of 10 m/s, cut-in wind speed of 2.7 m/s, and cut-out wind speed of 25 m/s. The rated power of the solar PV generator

TABLE 2. Statistical indicators of the OPF results for case 1 obtained with different methods.

	Min	Max	Mean	Std.
PPSOGSA	800.53	800.65	800.58	0.03
PPSO	800.93	802.55	801.48	0.44
GSA	800.70	800.99	800.82	0.08
PSO	800.83	808.32	802.99	2.40
PSOGSA	800.78	807.30	803.57	2.45
MFO	800.55	801.84	800.81	0.38
GA	800.62	801.89	801.01	0.44
DE	800.66	801.18	800.91	0.17
TLBO	800.63	802.67	801.25	0.73
ABC	800.72	801.20	800.91	0.14
MSA	800.74	801.05	800.87	0.10
HS	800.78	802.49	801.29	0.53
WDO	800.86	801.21	801.04	0.12
CS	800.91	801.07	800.98	0.05
BSA	801.31	802.67	801.79	0.39
SRSR	801.18	803.37	801.86	0.67
ICA	801.18	806.06	802.98	1.52
FFA	801.43	808.83	804.25	2.47
BBO	801.86	810.31	806.00	2.47
MVO	802.54	810.65	805.55	2.56
GWO	802.78	819.49	809.04	5.89
ACO	805.69	820.07	810.88	4.89

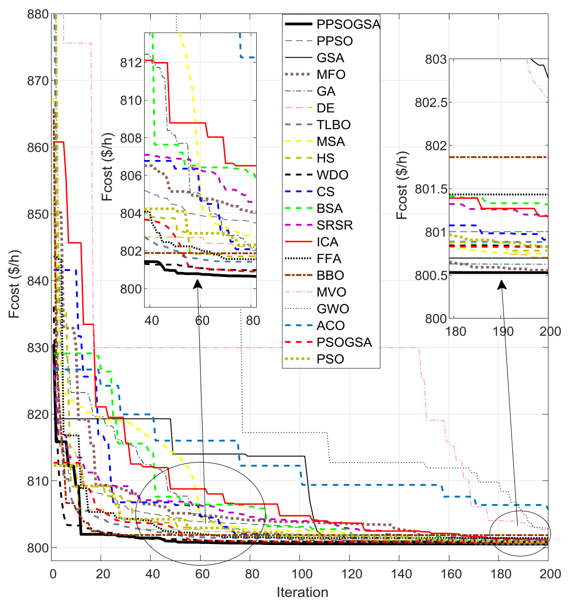

FIGURE 2. Comparison of convergence characteristics.

connected at bus 30 is 25 MW. To calculate the output power of PV generator using (27), the solar irradiance at standard test condition (S_{stc}) is set as 1000 W/m^2 and certain irradiance point (R_c) is set as 120 W/m^2.

As mentioned above, the OPF is performed sequentially in predefined time intervals of 10 min. To calculate the forecasted output power of WT and PV generators the wind speed and solar irradiance data are adopted from NREL [39]. Figure 4 presents the measured values of wind speed and solar irradiance with a sampling time of 1 min for the considered period of 10 min. Based on these measured data, the mean values and standard deviations of wind speed and solar irradiance are calculated, and appropriate PDFs of wind speed and solar irradiance are determined, as illustrated in Figure 4. Finally the forecasted output powers of WT and PV can be calculated using (26) and (31), respectively.

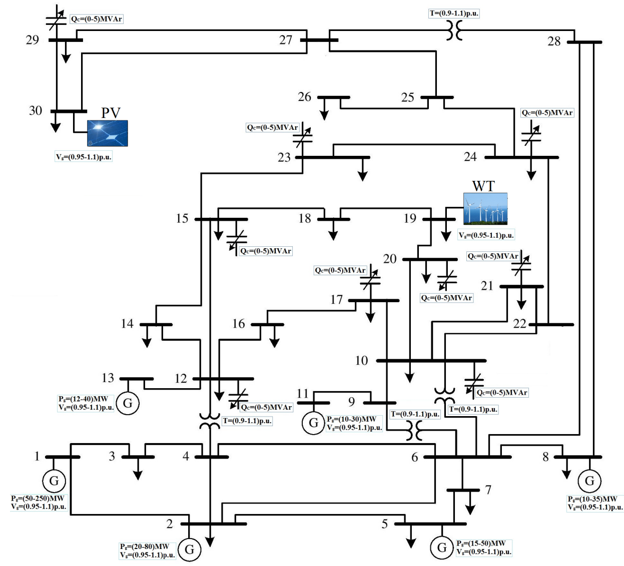

FIGURE 3. Modified IEEE 30-bus test system.

TABLE 3. OPF results considering WT and PV generation.

	Case 1	Case 2	Case 3	Case 4
P_{G1}	147.151	50.502	105.560	104.907
P_{G2}	39.2754	32.6402	44.5566	42.4504
P_{G5}	18.1741	49.3669	29.4222	28.2935
P_{G8}	10.6609	34.9432	18.5736	21.9672
P_{G11}	10.0697	27.1924	19.1721	21.9130
P_{G13}	12.0088	38.7387	19.4943	15.4843
P_{wt}	33.4943	32.3803	32.2454	33.4315
P_{pv}	19.7815	19.7813	19.7817	19.7789
V_{G1}	1.0751	1.0550	1.0224	1.0291
V_{G2}	1.0519	1.0466	1.0137	1.0185
V_{G5}	1.0192	1.0265	1.0167	0.9987
V_{G8}	1.0290	1.0449	1.0069	0.9997
V_{G11}	0.9930	1.0726	1.0304	1.0569
V_{G13}	0.9646	1.0442	1.0007	1.0050
V_{G19}	0.9946	1.0502	1.0013	1.0080
V_{G30}	0.9811	1.0506	0.9898	1.0059
$T_{11(6\text{-}9)}$	1.0311	0.9878	1.0354	1.0185
$T_{12(6\text{-}10)}$	1.0126	1.0071	0.9008	0.9407
$T_{15(4\text{-}12)}$	1.0798	1.0151	0.9358	0.9603
$T_{36(28\text{-}27)}$	1.0047	1.0050	0.9404	0.9784
Q_{C10}	2.2164	4.6501	1.6523	2.3314
Q_{C12}	1.8537	2.0971	1.5316	1.5964
Q_{C15}	2.7664	2.4491	1.7593	1.9211
Q_{C17}	2.5633	1.8439	3.4470	1.7137
Q_{C20}	2.5473	1.4828	0.1861	1.9552
Q_{C21}	2.9162	2.6635	4.7931	4.8933
Q_{C23}	1.4139	4.0290	4.8840	3.6552
Q_{C24}	2.5253	3.4665	4.4738	4.9966
Q_{C29}	3.6863	3.7062	1.8624	1.3849
Fcost	**618.017**	765.562	647.079	**640.844**
Ploss	7.21532	**2.14466**	5.40586	**4.82648**
VD	0.68295	0.74108	**0.08016**	**0.11510**

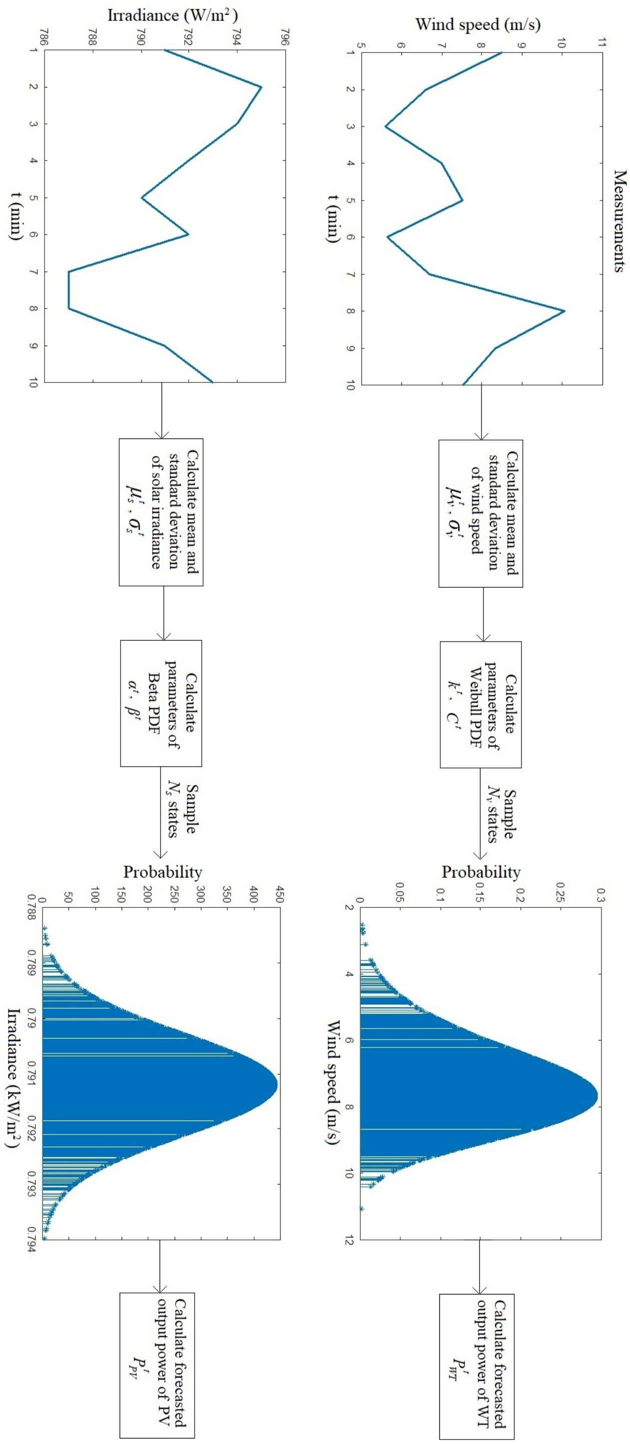

FIGURE 4. Flowchart for calculation of forecasted output powers of WT and PV.

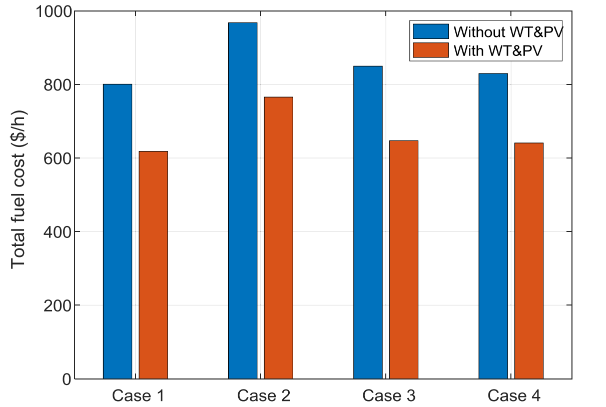

FIGURE 5. Comparison of the OPF results.

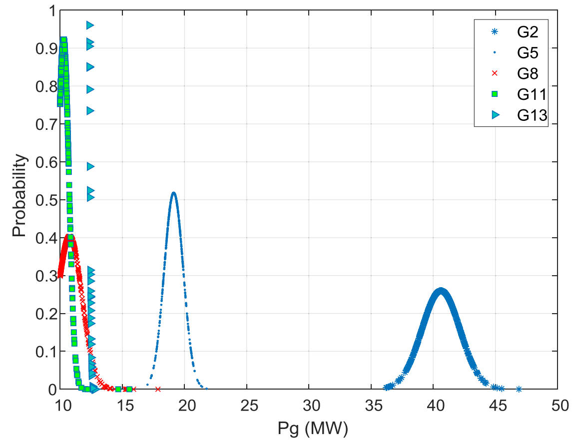

FIGURE 6. PDF for output power of generators.

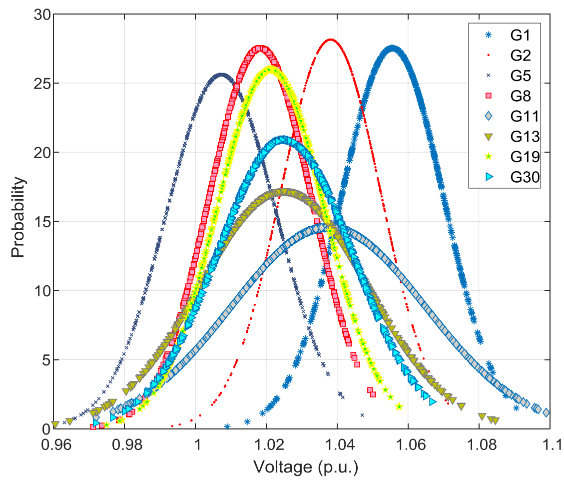

FIGURE 7. PDF for voltage magnitudes of generators.

Estimated OPF results based on the forecasted WT and PV generation are presented in Table 3. The results obtained using the proposed hybrid PPSOGSA are in line with the objectives. Figure 5 presents a comparison of the OPF results with those obtained for the original system configuration (Table 1). Obviously, WT and PV generation significantly affects on the reduction of the total fuel cost compared to the original system configuration - without WT and PV.

Note that the output powers of WT (P_{wt}) and PV (P_{pv}) are not the control (decision) variables in the OPF problem. The values of P_{wt} and P_{pv} are different for different cases (Case 1-4) because these are considered as stochastic variables. Therefore, the results in Table 3 can be considered as expected OPF results.

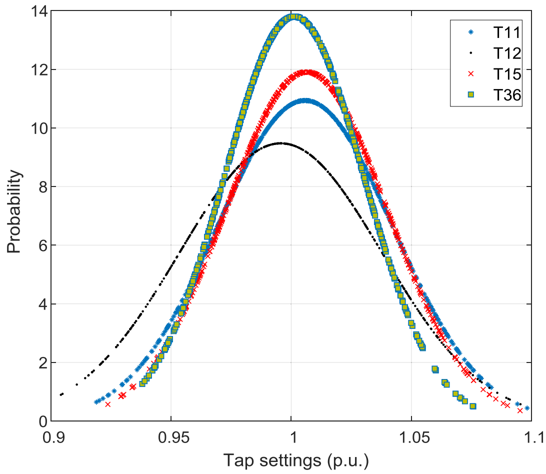

FIGURE 8. PDF for transformer tap settings.

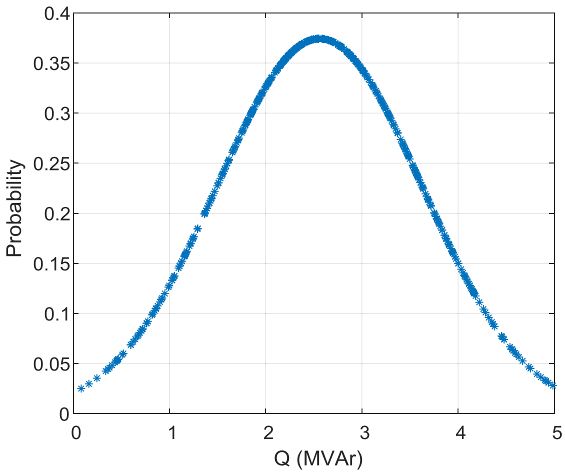

FIGURE 9. PDF for reactive power of shunt VAR compensator at bus 10.

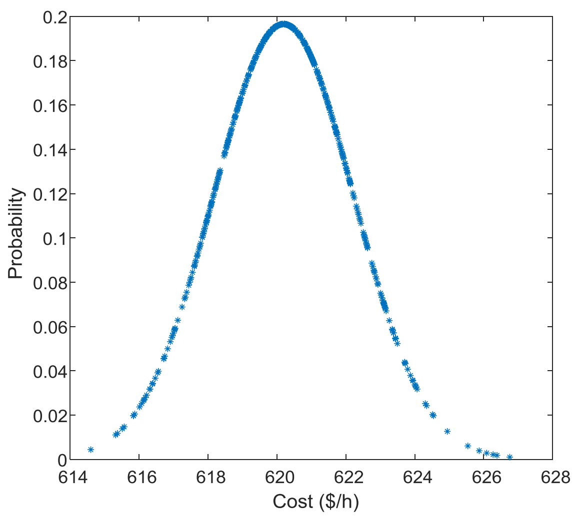

FIGURE 10. PDF for total fuel cost of thermal generators in Case 1.

Due to the probabilistic nature of the WT and PV generation the OPF results should be considered as random variables also. Monte Carlo simulation (MSC) is used to evaluate the statistical features of the OPF results in Case 1.

Figure 6-9 shows the PDFs of the optimum control variables, and Figure 10 presents the PDF for the total fuel cost obtained with 500 sample MCS.

VI. CONCLUSION

In this paper, a novel hybrid PPSOGSA algorithm has been applied to solve the OPF problem in power systems with integrated WT and solar PV generators. The proposed approach has been tested on the IEEE 30-bus test system. The simulation results refer to conclusions which can be summarized as follows:

- The proposed PPSOGSA approach provides robust and high-quality OPF solutions both in the case single-objectives, and in the case multi-objectives, such as minimization of total fuel costs, minimization of active power loss, and minimization of voltage deviation.
- The proposed hybrid PPSOGSA achieves better OPF solutions and converges to global optimum with less iterations compared to the original PPSO and GSA algorithms, as well as compared to 20 other well-known metaheuristic techniques reported in the literature.
- The model for forecasting of active power outputs enables efficient inclusion of WT and PV in the OPF model, and evaluation of deterministic and probabilistic OPF results.
- Positive effects of WT and PV on the performance of the system, such as reducing the fuel costs of thermal generators, as well as reducing power losses and voltage deviations in the system are demonstrated.

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