

Optimal Placement and Sizing of Renewable Distributed Generation Using Hybrid Metaheuristic Algorithm

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Abstract—The problem of optimal placement and sizing (OPS) of renewable distributed generation (RDG) is followed by numerous technical, economical, geographical, and ecological constraints. In this paper, it is investigated from two viewpoints, namely the simultaneous minimization of total energy loss of a distribution network and the maximization of profit for RDG owner. The stochastic nature of RDG such as the wind turbine and photovoltaic generation is accounted using suitable probabilistic models. To solve this problem, a hybrid metaheuristic algorithm is proposed, which is a combination of the phasor particle swarm optimization and the gravitational search algorithm. The proposed algorithm is tested on an IEEE 69-bus system for several cases in two scenarios. The results obtained by the hybrid algorithm shows that it provides high-quality solution for all cases considered and has better performances for solving the OPS problem compared to other metaheuristic population-based techniques.

Index Terms—Wind turbine, photovoltaic generation, optimal placement, metaheuristic optimization.

I. INTRODUCTION

THE continuous increase in consumption, the need to reduce greenhouse gas emissions, the deregulation and liberalization of electricity market, and the privileged prices of green energy, have led to the rapid growth of renewable energy sources in the last two decades. It seems that the wind and solar energy are the best alternatives to fossil fuels for power generation. The rapid growth of wind and photovoltaic (PV) power installation has been enabled by the technology improvement on wind turbine (WT) and PV generation systems as well as the reduction in total installation costs [1]. Moreover, it can be argued that the WT and PV generation systems are well established and standardized technologies. As reported in [2], the electricity from renewable dis-

tributed generation (RDG) units such as WT and PV will soon be consistently cheaper than that from fossil fuels.

In principle, there are three ways to use the WT and PV sources: ① as large wind farms and PV arrays integrated into the power system; ② as RDG units constituting essential part of active distribution networks (DNs) and microgrids; ③ as power resources in small stand-alone hybrid power systems.

The integration of RDG units such as WT and PV leads to major challenges due to its uncertain power generation characteristics. Generally, the task of optimal planning of RDG is to determine its optimal location and rated power in order to minimize or maximize a desired objective function, considering different technical, economic and environmental constraints. In mathematical formulation, this is a large-scale, nonlinear, probabilistic constrained optimization problem with both continuous and discrete control variables. The general framework for defining and solving this problem must include the following aspects: ① the significance and context of this issue; ② the modeling of RDG units, e.g., the modeling of WT and PV output power due to uncertain characteristics of wind speed and solar irradiation; ③ the modeling of load uncertainties; ④ the choice of objective functions; ⑤ the definition of technical constraints, control variables and dependent variables; ⑥ the method for solving the optimization problem.

So far, many studies have dealt with the problem of optimal placement and sizing (OPS) of RDG focusing on some of the tasks above. References [3]-[6] give the comprehensive state-of-the-art reviews in this area.

References [7]-[10] use Weibull and Beta probability distribution functions (PDFs) to model the stochastic behavior of the wind speed and solar irradiance at a specific location. References [11], [12] take into account different types of loads such as linear and nonlinear loads as well as load growth.

As noted in [5], the objectives for OPS of distributed generation (DG) can be summarized in three groups: technical objectives, financial objectives, and multi-objectives. Technical objectives are the base objectives and include the energy loss minimization [8]-[10], [13] and the improvement of voltage conditions [14]-[17] in DNs. Financial objectives are related to the minimization of investment cost, operation cost and maintenance cost for DGs [11] as well as the maximization of the profit of DG owner [18]. Multi-objective func-

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tions with various combinations of objectives have also been implemented. One such case is the simultaneous minimization of annual average power loss, maximization of voltage stability index and minimization of DN security index [7]. In [19], the multi-objective optimization consists of the minimization of power loss, the total electrical energy cost, the pollutant emission, and the improvement of voltage stability. References [12], [20] define a multi-objective function based on the total active power loss and the voltage deviation. The multi-objective optimization in [18] is considered from the operation aspects such as improving voltage profile and power loss reduction. Moreover, an economic analysis is performed based on the viewpoints of distribution companies and DG owners.

Any optimal solution, which implies the OPS of a DG, must meet different technical and economic constraints to ensure standardized operation or design conditions, regardless of the type of an objective function [5]. These constraints can be classified into: ① the power system conservation constraints which include power flow balance, bus voltage limits, branch current limits, short circuit level, power quality limits, etc.; ② the DG limitations which include power factor of DG units, penetration level of DG, number of DG units, size of DG units, type of DG units, contract price limits between the DG owner and the distribution company, capitalization constraints of DG owner, etc.

Different approaches for solving the problem of OPS of DG can be classified into three main groups: analytical techniques, classical optimization methods, and metaheuristic optimization algorithms. References [3]-[5], [21] present a comprehensive overview of these approaches.

In recent research, some of metaheuristic population-based methods are used. In [7], a weighted aggregation particle swarm optimization (PSO) is proposed to find the optimal mix of RDG units in DNs with multi-objectives such as the minimization of power loss and the improvement of voltage stability and network security. In [11] and [13], the PSO is used to determine the OPS of RDG units in a DN considering technical, economic and environmental constraints. In [18], a multi-objective PSO (MPSO) algorithm is used to find the OPS of RDG units, in addition to determining their optimal prices of generated electricity in a competitive market. In [8], an evolutionary programming (EP) based approach is used for solving the problem of optimal locations of RDG such as PV and WT units in a DN. In [14] and [15], the application of ant lion optimization algorithm (ALOA) to solve the OPS of RDG units in DNs is proposed. In [16], the differential evolution (DE) is proposed to evaluate the optimal RDG capacity for minimizing power losses in sub-transmission systems. In [17] and [20], a well-established meta-heuristic optimization method, namely genetic algorithm (GA), is used to solve the problem of optimal planning of RDG in DNs considering multiple aspects of DN operation. In [19], a hybrid optimization algorithm consisting of ant colony optimization (ACO) algorithm and artificial bee colony (ABC) algorithm is proposed for solving probabilistic OPS of RDG units in DNs.

The main contribution of this paper is the application of

an efficient hybrid metaheuristic algorithm to solve the problem of OPS of RDG in DNs, observing the problem from the viewpoints of the DN operator and the RDG owners.

The rest of this paper is organized as follows. Section II presents the probabilistic models of RDG and load. The problem of OPS of RDG is mathematically formulated in Section III. The proposed algorithm and its application are explained in Section IV. The simulation results are discussed in Section V, and the conclusions are drawn in Section VI.

II. MODELING OF RDG AND LOAD

A. WT Generation Modeling

The output power of a WT for a given wind speed v is calculated using the power characteristic of the WT, which is a nonlinear function of wind speed [9]:

$$P_{WT}(v) = \begin{cases} 0 & v \leq v_{ci} \\ \frac{v^2 - v_{ci}^2}{v_{nom}^2 - v_{ci}^2} P_{nom} & v_{ci} < v \leq v_{nom} \\ P_{nom} & v_{nom} < v \leq v_{co} \\ 0 & v > v_{co} \end{cases} \quad (1)$$

where P_{nom} , v_{nom} , v_{ci} , and v_{co} are the nominal power, nominal wind speed, cut-in wind speed, and cut-out wind speed of the WT, respectively. These data and the experimentally determined power curve are given by the WT manufacturers.

The stochastic nature of wind speed in a predefined time period t at a certain location can be generally described by Weibull PDF [7], [9]:

$$f_v(v) = \frac{k^t}{C^t} \left(\frac{v}{C} \right)^{k^t-1} e^{-\left(\frac{v}{C} \right)^{k^t}} \quad (2)$$

where $f_v(v)$ is the Weibull PDF for wind speed data collected during time period t ; and C and k^t are the scale and shape parameters of the Weibull distribution at time period t , respectively.

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

$$F_v(v) = 1 - e^{-\left(\frac{v}{C} \right)^{k^t}} \quad (3)$$

The CDF with its inverse has been utilized to calculate the wind speed:

$$v = C^t \left(-\ln(r) \right)^{\frac{1}{k^t}} \quad (4)$$

where r is a random number uniformly distributed on $[0, 1]$.

In practice, parameters C^t and k^t can be calculated approximately using mean value μ_v^t and standard deviation σ_v^t of wind speed at time period t [7], [9]:

$$k^t = \left(\frac{\sigma_v^t}{\mu_v^t} \right)^{-1.086} \quad (5)$$

$$C^t = \frac{\mu_v^t}{\Gamma(1 + 1/k^t)} \quad (6)$$

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

t . In the problem of OPS of WTs, it is necessary to collect the wind speed data from the site under study for a time period of at least one year. Based on these historical data, the parameters of Weibull PDF can be calculated.

The yearly measured weather data is classified by seasons, i. e., spring, summer, autumn and winter. Each season consists of a number of days corresponding to the months of the season. The days are divided into hours, which are the elemental time segments. For a given season, a typical day is defined consisting of 24 characteristic hours. The sampling time for wind speed measurements is 1, 5 or 10 min during the entire considered period [22]. This means six to sixty readings of the wind speeds at each hour over the year. Therefore, a characteristic hour in a typical day of a season can be represented by the mean value and the standard deviation of wind speed calculated from measured data corresponding to this hour in all days within the season. By calculating the mean value and the standard deviation of wind speed for each of the 24 hours, a typical day of the considered season is obtained.

Based on the mean value and the standard deviation of wind speed described above, the shape parameter k and the scale index C of Weibull PDF can be calculated for each hour of the typical day by using (5) and (6). To realize the Weibull PDF for each hour in discrete form, hour t is divided into N_v states, where the corresponding wind speed and probability for each state g are calculated by using (4) and (2), respectively. Figure 1 shows the discrete Weibull PDF of wind speed corresponding to an hour with $\mu_v = 9$ m/s, $\sigma_v = 3$ m/s, and $N_v = 60$. The power output of WT is dependent on the probability of all possible states during hour t .

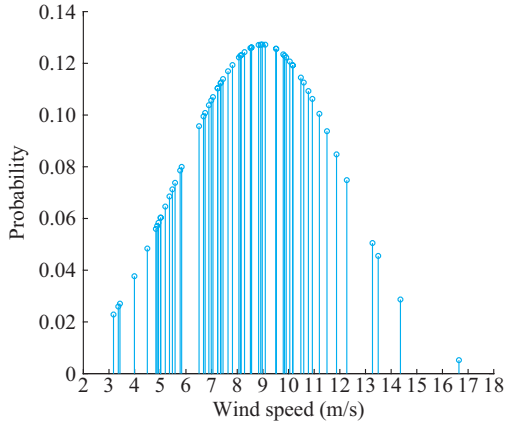


Fig. 1. Discrete Weibull PDF of wind speed during an hour.

Accordingly, the power generation of WT considering the probability of wind speed for each state during hour t can be calculated as follows:

$$P_{WT}^t = \frac{\sum_{g=1}^{N_v} P_{WTg} f_v(v_g^t)}{\sum_{g=1}^{N_v} f_v(v_g^t)} \quad (7)$$

where v_g^t is the wind speed of state g at hour t ; P_{WTg} is the power generation of WT calculated using (1) for $v = v_g^t$; and

$f_v(v_g^t)$ is the probability of the wind speed for state g during hour t .

B. PV Generation Modeling

The power output of the PV module with given technical characteristics is dependent on the solar irradiance and ambient temperature [23]:

$$P_{PV}(s, T_c) = P_{STC} \frac{s}{1000} \left[1 + \gamma(T_c - 25) \right] \quad (8)$$

where P_{STC} is the maximum power of PV module at standard test condition (STC); s is the solar irradiance on the PV module surface; γ is the temperature coefficient of PV module for power; and T_c is the temperature of PV cell (module).

The temperature of PV module can be calculated as a function of solar irradiance and ambient temperature based on the nominal operation cell temperature (NOCT) of modules. The equation of NOCT model is [24]:

$$T_c = T_a + \frac{s}{800} (T_{NOCT} - 20) \quad (9)$$

where T_a is the ambient temperature; and T_{NOCT} is the NOCT of the module. Beta PDF is suitable to describe the stochastic nature of solar irradiance [7], [9]:

$$f_s(s) = \begin{cases} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{\alpha-1} (1-s)^{\beta-1} & 0 \leq s \leq 1, \alpha \geq 0, \beta \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where $f_s(s)$ is Beta PDF of s ; and α and β are the shape parameters of Beta PDF. Shape parameters of Beta PDF can be obtained based on the mean value μ_s and the standard deviation σ_s of solar irradiance for the corresponding time period:

$$\beta = (1 - \mu_s) \left[\frac{\mu_s (1 + \mu_s)}{\sigma_s^2} - 1 \right] \quad (11)$$

$$\alpha = \frac{\mu_s \beta}{1 - \mu_s} \quad (12)$$

Based on the mean value and the standard deviation of solar irradiance determined in analogous manner for the wind speed, the shape parameters of Beta PDF (α and β) can be calculated for each hour of typical days using (11) and (12). To realize Beta PDF for each hour in discrete form, hour t is divided into N_s states, where the corresponding solar irradiance and probability for each state g are calculated using (10). Figure 2 shows the discrete Beta PDF of solar irradiance related to an hour with $\mu_s = 436$ W/m², $\sigma_s = 295$ W/m², and $N_s = 60$. The power output of PV module is dependent on the probability of all possible states for that hour t .

Accordingly, the power generation of PV module considering the probability of solar irradiance for each state during hour t can be calculated as:

$$P_{PV}^t = \frac{\sum_{g=1}^{N_s} P_{PVg} f_s(s_g^t)}{\sum_{g=1}^{N_s} f_s(s_g^t)} \quad (13)$$

where s_g^t is the solar irradiance state g at hour t ; P_{PVg} is the

power generation of PV module calculated using (8) for $s=s'_g$; and $f_s(s'_g)$ is the probability of the solar irradiance for state g during hour t .

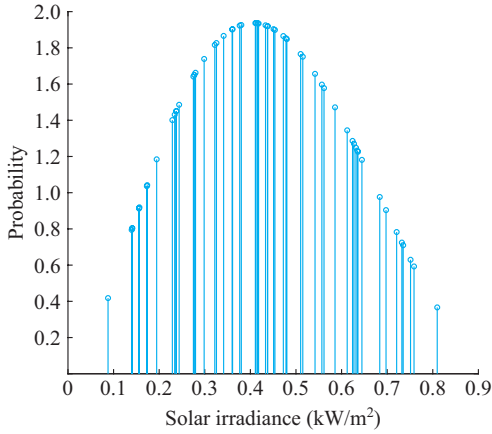


Fig. 2. Discrete Beta PDF of solar irradiance during an hour.

C. Load Modeling

It is assumed that the load profiles are the same for both active and reactive power. The random nature in the load change is modeled by the normal PDF. Generally, the load is assumed to be a random variable L following the same PDF within each hour of a given diagram of daily load.

$$f_L(L) = \frac{1}{\sqrt{2\pi}\sigma_L} e^{-\frac{(L-\mu_L)^2}{2\sigma_L^2}} \quad (14)$$

$$f_L(L) = \frac{1}{2} \left(1 + \operatorname{erf} \left(\frac{L-\mu_L}{\sqrt{2}\sigma_L} \right) \right) \quad (15)$$

$$L = \mu_L + \sqrt{2}\sigma_L \cdot \operatorname{erf}^{-1}(2r-1) \quad (16)$$

where μ_L and σ_L are the mean value and standard deviation of L , respectively; r is a random number in $[0, 1]$; and $\operatorname{erf}(\cdot)$ and $\operatorname{erf}^{-1}(\cdot)$ are the error function and inverse error function, respectively.

To realize the normal PDF for each hourly load in discrete form, hour t is divided into N_L states, where the corresponding load and probability for each state g are calculated using (16) and (14), respectively. Figure 3 shows the discrete normal PDF for the hourly load level with $\mu_L = 0.7$ p.u., $\sigma_L = 5\%$, and $N_L = 60$.

Load level related to a time segment is determined by the probability of all possible states for that hour. Accordingly, considering the probability of load for each state during hour t , the load level can be calculated as:

$$L^t = \frac{\sum_{g=1}^{N_L} L_g f_L(L_g^t)}{\sum_{g=1}^{N_L} f_L(L_g^t)} \quad (17)$$

where L_g^t is the load of state g at hour t ; L_g is the load level calculated using (16); and $f_L(L_g^t)$ is the probability of the load level for state g during hour t .

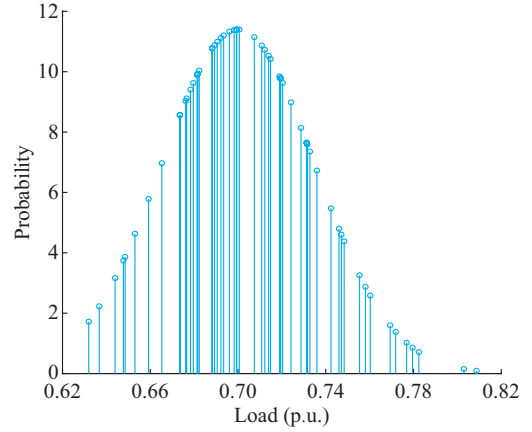


Fig. 3. Discrete normal PDF of load during an hour.

III. PROBLEM FORMULATION

The problem of OPS of RDG is considered as a constrained nonlinear combinatorial optimization planning problem with two objectives: ① minimizing the total energy loss in DNs; ② maximizing the profit of RDG owners. Several practical assumptions have been adopted which are necessary for the proper definition of this problem. The same or similar assumptions used by most authors to deal with this problem are as follows:

- 1) There are no geographic limitations to install various RDG technologies within DNs [18].
- 2) All buses in the DN under study are subjected to the same wind profile and solar irradiance [9], [10], [13].
- 3) Only one type of RDG can be connected to the same bus in DNs [9], [10].
- 4) All the RDG units are modelled as negative loads with unity power factor, i.e., producing active power only, as recommended by the IEEE 1547 standard [9], [13], [25].
- 5) The maximum penetration of RDG is assumed to be equal to the maximum load of DNs [26].

A. Objective Function

Two conflicting objectives are considered: the minimization of total energy loss of DNs and the maximization of profit of RDG owners in a given planning horizon of N_y years. The multi-objective optimization problem can be converted to a single-objective optimization problem by weighted aggregation method. Therefore, the multi-objective function for simultaneously minimizing the total energy loss and maximizing the profit can be formulated as:

$$\min(F) = \min \left(w_1 F_1 + w_2 \frac{1}{F_2} \right) \quad (18)$$

where w_1 and w_2 are the weight coefficients. The total energy loss is calculated as:

$$F_1 = \frac{365}{4} \sum_{y=1}^{N_y} \sum_{t=1}^{96} P_{loss,t}^y \quad (19)$$

where $P_{loss,t}^y$ is the power loss for hour t in year y of considered time period of N_y years.

The objective function F_2 can be defined as the difference between the incomes and costs of RDG owners:

$$F_2 = IN_{RDG} - C_{investment} - C_{oper,maint} \quad (20)$$

where IN_{RDG} is the income of DG owners; $C_{investment}$ is the investment cost; and $C_{oper,maint}$ is the operation and maintenance cost.

The investment cost $C_{investment}$ contains different initial costs such as the amount of money spent on unit construction, installation, and essential equipment for each RDG unit. This cost can be formulated as [18]:

$$C_{investment} = \sum_{i=1}^{N_{RDG}} P_{RDGi} C_{inv} \quad (21)$$

where P_{RDGi} is the rated power of RDG unit i ; N_{RDG} is the number of RDG units; and C_{inv} is the investment cost of RDG unit i .

The operation and maintenance cost $C_{oper,maint}$ includes cost of generation, renewing, repairing, and restoring unit equipment in case necessity. The equation for modeling the present worth of this cost is:

$$C_{oper,maint} = \sum_{y=1}^{N_y} \sum_{i=1}^{N_{RDG}} P_{RDGi} C_{OM} \left(\frac{1+INFR}{1+INTR} \right)^y \quad (22)$$

where C_{OM} is the operation and maintenance cost of RDG units per year; and $INFR$ and $INTR$ are the inflation rate and interest rate, respectively.

The RDG owner earns a profit by selling the generated energy to the distribution company at the contract price. The present worth of the income of DG owners IN_{RDG} is [18]:

$$IN_{RDG} = \frac{365}{4} \sum_{y=1}^{N_y} \sum_{i=1}^{N_{RDG}} \sum_{t=1}^{96} P_{RDGi,t}^y \cdot CP_{RDGi} \cdot \left(\frac{1+INFR}{1+INTR} \right)^y \quad (23)$$

where $P_{RDGi,t}^y$ is the generated active power of RDG unit i at hour t of year y ; and CP_{RDGi} is the contract price of electricity selling between the RDG owner and the distribution company.

B. Control Variables

The control variables in this optimization problem are locations, i.e., indexes of connecting buses, and numbers of elementary RDG units which should be connected at these buses. Thus, the optimal rated power of the RDG farms can be obtained as:

$$P_{RDGF} = N_{RDG} P_{RDGi} \quad (24)$$

where P_{RDGF} is the total rated power of the RDG farms; N_{RDG} is the number of elementary RDG units which form an RDG farm (WT farm or PV farm); and P_{RDGi} is the rated power of an elementary RDG unit.

C. Constraints

The optimization problem is subjected to various technical constraints which are described below.

1) Power Flow Constraints

The power flow constraints in DN with RDG units operating with unity power factor are the equality constraints represented by the power balance equations:

$$P_{grid} = \sum_{i=1}^{N_B} P_{Li} - \sum_{i=1}^{N_{RDGF}} P_{RDGF_i} + \sum_{i=1}^{N_{Br}} P_{loss_i} \quad (25)$$

$$Q_{grid} = \sum_{i=1}^{N_B} Q_{Li} + \sum_{i=1}^{N_{Br}} Q_{loss_i} \quad (26)$$

where N_B is the number of buses in the network; N_{RDGF} is the number of RDG farms; N_{Br} is the number of branches in the network; P_{grid} is the active power injected to substation; Q_{grid} is the reactive power injected to substation, P_{RDGF_i} is the active power generation of RDG farm i ; P_{Li} is the active power of load at bus i ; Q_{Li} is the reactive power of load at bus i ; and P_{loss_i} and Q_{loss_i} are the active and reactive power losses in branch i , respectively.

The backward/forward sweep algorithm [21] is suitable to solve the above power balance equations for radial DNs.

2) Bus Voltage and Branch Load Constraints

The OPS of RDG should be determined in such a way that bus voltages and branch loads remain in standard intervals in all normal operation states of DNs. These constraints can be defined as:

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad i = 1, 2, \dots, N_B \quad (27)$$

$$S_{li} \leq S_{li}^{\max} \quad i = 1, 2, \dots, N_{Br} \quad (28)$$

where V_i^{\min} and V_i^{\max} are the minimum and maximum allowable values of voltage magnitude of bus i , respectively; and S_{li}^{\max} is the maximum load of branch i of the network.

3) RDG Capacity Constraints

The active power capacity of each RDG farm is limited to a specific maximum $P_{RDGF_i}^{\max}$ as:

$$P_{RDGF_i} \leq P_{RDGF_i}^{\max} \quad i = 1, 2, \dots, N_{RDGF} \quad (29)$$

According to the relation (24), the constraint of RDG capacity can be expressed as:

$$N_{RDGi} P_{RDGi} \leq N_{RDGi}^{\max} P_{RDGi} \quad (30)$$

where N_{RDGi} is the number of elementary RDG units which comprises the RDG farm at location i ; P_{RDGi} is the rated power of elementary RDG unit at location i ; and N_{RDGi}^{\max} is the maximum number of elementary RDG units at location i .

IV. SOLUTION METHOD

An improved PSO [27], namely PPSOGSA is proposed to solve the optimization problem. The PPSOGSA is the combination of phasor PSO (PPSO) [28] and gravitational search algorithm (GSA) [29]. The improvements of PPSOGSA in relation to PSO are transforming standard PSO to a self-adaptive and parametric independent algorithm based on modeling the particle control parameters with a phase angle. Since the proposed algorithm belongs to metaheuristic population-based optimization techniques, it will be explained here through a general metaheuristic framework [21].

Metaheuristic optimization methods are the population-based stochastic search techniques. In general, a search agent can be represented as vector \mathbf{x}_i whose elements are the values of the control variables of the optimization problem. The number of control variables n is the search space dimension of the optimization problem. At time (iteration) t , the agent $\mathbf{x}_i(t)$ can be represented as $\mathbf{x}_i(t) = [x_i^1(t), \dots, x_i^d(t), \dots, x_i^n(t)]$, where $x_i^d(t)$ is the position of the agent i with respect to the dimension d , i.e., the values of the control variable d in the candidate

solution i . The population POP is defined by a set of search agents which represent potential solutions of the optimization problem. The number of agents N is defined as the size of the population, i. e., $POP(t)=[\mathbf{x}_1(t), \dots, \mathbf{x}_i(t), \dots, \mathbf{x}_N(t)]^T$. The essence of metaheuristic methods is the iterative correction of the solution, i.e., generating a new population by applying algorithmic operators with stochastic search mechanism on agents from the current population.

The general structure of the proposed algorithm can be described as follows.

1) Initialization.

Step 1: define the objective function $F(\mathbf{x}_i)$ and the space of possible solutions X .

Step 2: generate an initial population of N agents, where the initial positions of agents are randomly selected between minimum and maximum values of the control variables. Set the iteration counter $t=1$.

2) Iterative procedure.

Step 3: calculate the fitness value for each agent in the current population $POP(t)$.

Step 4: generate the new population $POP(t+1)$ by applying the algorithmic operators on search agents from the current population $POP(t)$. For the proposed algorithm, the operators for updating the current velocity and the current position of agents are as follows:

$$\mathbf{v}_i(t+1) = r_1 \mathbf{v}_i(t) + r_2 \left| \cos \theta_i(t) \right|^{2 \sin \theta_i(t)} \mathbf{a}_i(t) + r_3 \left| \sin \theta_i(t) \right|^{2 \cos \theta_i(t)} (\mathbf{g}_{best}(t) - \mathbf{x}_i(t)) \quad (31)$$

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \quad (32)$$

where $\mathbf{g}_{best}(t)$ is the best solution (position) among all the best positions of agents achieved so far; $\mathbf{a}_i(t)$ is the acceleration of agents, which is updated using the equations given in [29]; r_1 , r_2 , and r_3 are the random numbers in the range of $[0, 1]$; and $\theta_i(t)$ is the phase angle, which is updated using (33).

$$\theta_i(t+1) = \theta_i(t) + 2\pi \left| \cos \theta_i(t) + \sin \theta_i(t) \right| \quad (33)$$

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 $U(0, 2\pi)$.

Step 5: repeat the iterative procedure until the stop criteria is met.

Step 6: report the best solution.

In this case, a potential solution can be presented by a vector consisting of a combination of locations and rated power of RDG farms, i.e., the number of elementary RDG units at these locations. Thus, \mathbf{x}_i can be written as:

$$\mathbf{x}_i = \left[Bus_1^1 \quad \dots \quad Bus_{N_{RDGF}}^d \quad P_1^{d+1} \quad \dots \quad P_{N_{RDGF}}^n \right] \quad (34)$$

where $n=2N_{RDGF}$; $Bus_{N_{RDGF}}^d$ is the position of the N^{th} RDGF in the potential solution i ; and $P_{N_{RDGF}}^n$ is the rated power, i.e., the number of elementary RDG units of the RDGF at this position.

A general procedure of applying the proposed optimization algorithm to solve the problem of OPS of RDG units (WT and PV) in DNs can be described as follows.

Step 1: define the DN configuration, the line data, the transformer data, and the load data.

Step 2: define the technical and commercial data about the elementary RDG units such as the rated power and other manufacturer specifications, the installation costs, the operation and maintenance costs, the contract power of selling power, the interest rate, the inflation rate, and the total number of years in the planning horizon.

Step 3: define the total number of RDG farms N_{RDGF} to be connected in DNs, and the maximum number of each type of elementary RDG units which can be connected at a bus of the network.

Step 4: define the typical daily diagrams of output power for WT and PV, and the typical daily load profiles for each of season, as described in Section II.

Step 5: set the algorithmic parameters such as the population size and the maximum number of iterations, and generate an initial random population of N agents.

Step 6: calculate the objective function (18) for each agent $\mathbf{x}_i(t)$ from the current population $POP(t)$.

Step 7: apply the PPSOGSA operators (31)-(33) to create a new population of agents, i.e., the potential solutions of the problem.

Step 8: repeat *Step 6* and *Step 7* until the stop criteria, i.e., the max number of iterations, is reached.

Step 9: report the best \mathbf{x}_i from the last iteration, i.e., the optimal locations (list of buses) and rated power (number of elementary RDG units at each of these buses).

The general flowchart of the proposed algorithm is presented in Fig. 4.

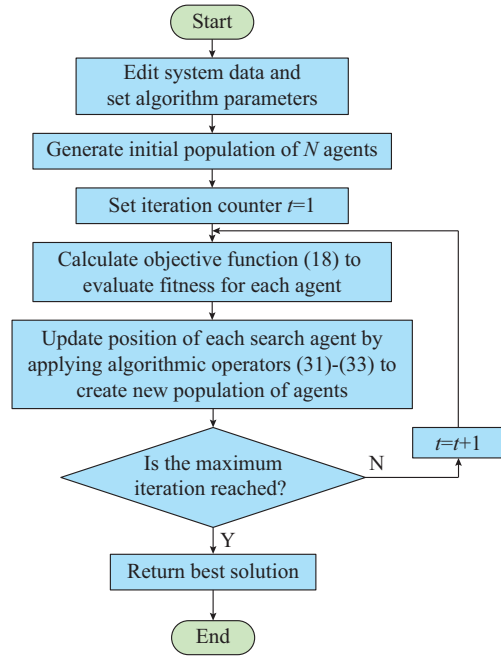


Fig. 4. Flowchart of proposed algorithm.

V. SIMULATION RESULTS

The proposed algorithm is applied on the IEEE 69-bus test system with the nominal voltage of 12.66 kV, and the total active and reactive loads of 3791.89 kW and 2694.10

kvar, respectively. The total power loss in the original system without any DG shown in Fig. 5 is 224.946 kW. The system data can be found in [30].

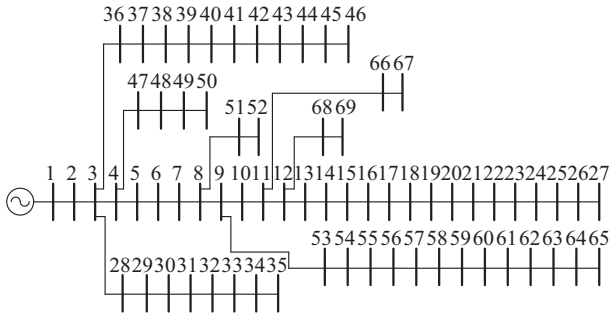


Fig. 5. Single-line diagram of IEEE 69-bus test system.

The task is to determine the optimal placement and sizing for one WT farm and one PV farm in the IEEE 69-bus system. The rated power of elementary RDG units P_{RDG1} is 200 kW whereas the maximum size of RDG farms N_{RDG}^{\max} is 10 for both WT and PV generation. The commercial data of the RDG units are given in Table I. The installed cost C_{inv} , the operation and management (O&M) cost C_{OM} and the contract price of electricity selling CP_{DG} are adopted based on the report of International Renewable Energy Agency (IRENA) [2]. The planning horizon is $N_y = 10$ years.

TABLE I
COMMERCIAL DATA OF RDG UNITS

Type	C_{inv} (\$/kW)	C_{OM} (\$/kW)	CP_{DG} (\$/kWh)	$INFR$ (%)	$INTR$ (%)	N_y (year)
WT	1100	16	0.10	2	1.25	10
PV	1000	10	0.15	2	1.25	10

The WT units used in this simulation have rated power of 200 kW, 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 PV has rated power of 200 kW and consists of 800 PV modules with $P_{STC} = 250$ W, $\gamma = -0.0045$ °C⁻¹, and $T_{NOCT} = 46$ °C.

The measured wind speed and solar irradiance data are taken from [22]. The wind speed and solar irradiance data are recorded with sampling period of 10 min and 5 min during the entire year of 2013, respectively. The period of one year is divided into four seasons, i.e., spring (March, April, May), summer (June, July, August), autumn (September, October, November), and winter (December, January, February), and a typical day for each season is obtained, as explained in Section II. Based on the measured data, the mean values and standard deviations of wind speed and solar irradiance are calculated for each hour of the typical days, as given in Tables II and III, respectively. Using these data, the discrete PDFs of wind speed and solar irradiance for each hour can be determined, as illustrated in Figs. 1 and 2.

By using the typical day models for seasons, the predicted power of WT and PV is calculated for each year in the planning horizon of 10 years. The normalized output power of WT and PV shown in Figs. 6 and 7 is given relative to their rated power.

TABLE II
MEAN VALUES AND STANDARD DEVIATIONS OF WIND SPEED

Time (hour)	m/s							
	Spring		Summer		Autumn		Winter	
	μ_v	σ_v	μ_v	σ_v	μ_v	σ_v	μ_v	σ_v
1	8.188	5.271	7.253	5.039	12.342	7.009	8.189	6.509
2	8.269	5.622	7.517	5.090	12.049	6.929	8.451	5.928
3	8.678	5.526	7.118	4.839	11.981	6.871	8.792	5.735
4	9.053	5.820	7.238	4.893	11.897	7.035	8.989	5.984
5	8.927	5.549	7.219	4.851	12.258	7.361	9.015	6.056
6	9.056	5.889	7.491	4.725	12.140	6.948	8.899	5.895
7	8.616	5.492	7.695	4.750	11.677	6.836	8.499	5.791
8	8.248	5.523	7.568	4.460	12.076	7.288	9.038	6.221
9	8.684	5.679	8.430	4.875	12.341	7.086	9.554	5.901
10	9.259	6.401	8.801	4.904	12.774	7.203	9.930	6.049
11	9.110	6.258	9.036	5.029	12.745	7.342	10.332	5.896
12	9.043	6.132	9.185	5.194	12.845	6.633	9.879	6.038
13	9.111	6.072	9.099	5.095	13.123	6.607	9.866	5.674
14	9.099	6.285	8.625	4.619	13.505	6.789	10.101	5.957
15	9.202	5.906	8.519	4.948	13.313	6.922	10.362	6.049
16	9.123	5.508	8.328	5.215	12.991	6.742	10.157	5.565
17	8.732	5.191	8.174	5.324	12.514	6.423	10.112	5.977
18	8.519	5.228	7.864	4.949	12.136	6.498	9.644	6.015
19	8.468	5.037	7.523	4.869	11.624	6.072	9.022	5.647
20	7.849	4.998	7.483	4.618	11.582	5.789	8.676	5.715
21	7.806	5.184	7.535	4.606	11.467	6.138	8.136	5.554
22	7.544	4.859	7.566	4.758	11.442	6.771	8.219	5.922
23	7.984	4.972	7.653	4.820	11.325	6.709	8.229	6.019
24	8.391	5.167	7.383	4.778	11.848	6.916	8.306	6.549

A typical daily load profile is assumed for each season according to the IEEE RTS system [31]. Figure 8 shows seasonal variations of load levels with standard deviation of 5%. The mean hourly load levels are given relative to the peak load.

In the system under study, two different cases (Cases 1 and 2) are considered in determining OPS of WT and PV farms, along with an extra reference case (Case 3) for comparison.

1) Case 1: consider the simultaneous minimization of total energy loss and the maximization of profit of RDG owners, i.e., (18).

2) Case 2: consider the minimization of total energy loss only, i.e., (19).

3) Case 3: compare the total energy loss without RDG integrated into system.

The optimal results are shown in Tables IV and V. The total energy loss for considered period of 10 years calculated for Case 3 amounts to 7251.311 MWh.

The optimal solutions in Case 1 and Case 2 indicate a huge reduction in total energy losses in relation to Case 3. The total energy loss is only 3.5% higher for Case 1 than that in Case 2, but the profit of RDG owners is 20.1% higher in Case 1 than that in Case 2.

TABLE III
MEAN VALUES AND STANDARD DEVIATIONS OF SOLAR IRRADIANCE

Time (hour)	W/m ²							
	Spring		Summer		Autumn		Winter	
	μ_s	σ_s	μ_s	σ_s	μ_s	σ_s	μ_s	σ_s
1	0.031	0.109	0	0.001	0.017	0.058	0.131	0.547
2	0.023	0.076	0.009	0.039	0.006	0.027	0.363	1.435
3	0.027	0.099	0.003	0.021	0.019	0.076	0.139	0.598
4	0.033	0.116	0.001	0.006	0.032	0.123	0.305	1.426
5	0.028	0.083	0.015	0.051	0.038	0.109	0.048	0.134
6	0.047	0.161	0.023	0.080	0.021	0.089	0.173	0.841
7	3.706	5.895	7.433	7.809	0.036	0.139	0.150	0.453
8	137.600	132.400	157.700	120.400	23.790	32.180	2.159	4.574
9	360.100	265.800	385.900	248.500	241.900	186.400	97.780	124.800
10	535.600	316.700	538.200	276.600	437.700	282.200	254.400	234.200
11	655.700	314.400	668.500	261.400	553.100	306.500	363.600	279.400
12	670.200	322.100	747.800	241.900	606.900	319.900	435.400	294.800
13	728.800	313.500	818.400	221.200	612.300	329.600	419.100	288.700
14	740.100	307.200	862.200	207.100	629.700	317.900	398.800	286.700
15	715.900	337.400	869.700	196.500	610.300	312.000	332.500	258.700
16	689.400	347.300	853.300	205.400	555.900	316.200	287.800	233.700
17	640.400	351.600	778.900	237.300	420.900	315.100	145.900	163.100
18	534.800	348.900	699.600	257.800	276.800	311.200	33.430	78.990
19	364.300	325.200	571.600	262.700	135.200	194.900	1.321	3.960
20	183.300	200.800	356.900	205.700	22.000	47.780	0.134	0.729
21	26.340	44.010	89.040	79.090	0.045	0.151	0.197	0.806
22	0.040	0.109	0.877	1.344	0.010	0.052	0.117	0.534
23	0.012	0.042	0.007	0.036	0.025	0.089	0.231	1.140
24	0.026	0.071	0.001	0.013	0.007	0.038	0.359	1.929

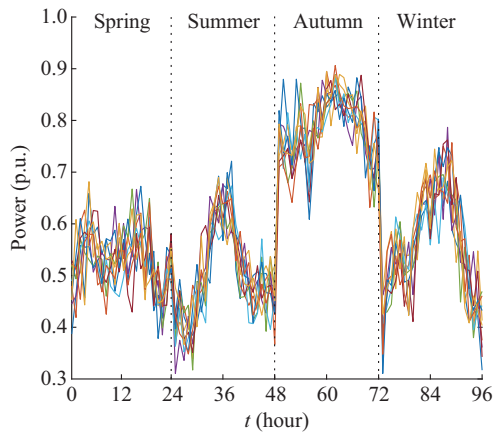


Fig. 6. Prediction of WT generation.

These ratios show that the solution obtained in Case 1 is satisfactory from the viewpoints of both distribution company and the RDG owners. For at least one third of the year (at night), the energy produced by the PV farm is zero, thus the total generation (and profit) from the PV farm is considerably lower than the total generation (and profit) from the WT farm.

The power losses in Case 2 and Case 3 are shown in Fig. 9. The results reveal that the OPS of WT and PV leads to

significant reduction of power losses in the whole period. As shown in Fig. 10, the power loss reduction is more in periods with higher power generation of WT and PV farms. As expected, the power loss reduction is less in periods without PV generation.

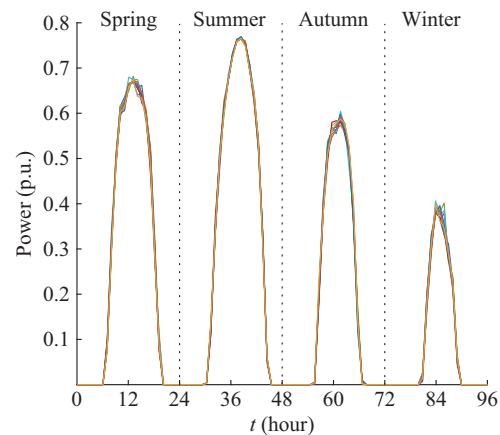


Fig. 7. Prediction of PV generation.

The convergence profiles of the PPSO [28], GSA [29] and the proposed hybrid algorithm in solving the OPS of WT and PV for Cases 1 and 2 are shown in Figs. 11 and 12, respectively. It is clear that the proposed hybrid algorithm

achieves better solutions and converges to an optimal solution with less number of iterations compared to the PPSO and GSA.

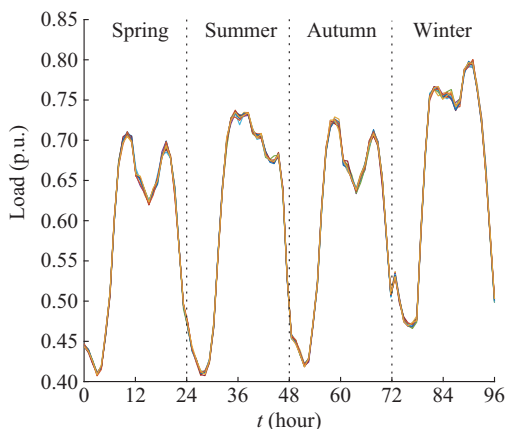


Fig. 8. Prediction of load levels.

TABLE IV
OPTIMAL RESULTS OF WT AND PV FARMS

Case	Farm	Location bus	N_{RDG}	P_{RDGF} (MW)
1	WT	61	10	2.0
	PV	11	8	1.6
2	WT	61	9	1.8
	PV	16	4	0.8

TABLE V
OPTIMAL RESULTS OF ECONOMIC AND TECHNICAL INDICES FOR
CONSIDERED PERIOD OF 10 YEARS

Index	Case 1	Case 2
Total energy loss F_1 (MWh)	2975.7	2871.4
Profit of RDG owners F_2 (M\$)	11.168	8.923
Profit from WT (M\$)	8.289	7.484
Profit from PV (M\$)	2.879	1.438
Total investment cost (M\$)	3.800	2.780
Investment cost of WT (M\$)	2.200	1.980
Investment cost of PV (M\$)	1.6	0.8
Total O&M cost (M\$)	0.500	0.383
O&M cost of WT (M\$)	0.333	0.300
O&M cost of PV (M\$)	0.167	0.083
Income of RDG owners (M\$)	15.468	12.086
Income from WT (M\$)	10.822	9.764
Income from PV (M\$)	4.645	2.322
Total generation of WT (MWh)	103896.5	93738.8
Total generation of PV (MWh)	29730.1	14857.7

In order to verify the efficiency of the proposed algorithm in comparison with other optimization algorithms such as ACO-ABC [19], ABC [32], GA [33], [34], PSO [35], modified teaching-learning based optimization (MTLBO) [36], big bang-big crunch (BB-BC) [37], and symbiotic organism search (SOS) [38], the problem of OPS of DG is considered for dispatchable DG units operating at the unity power factor.

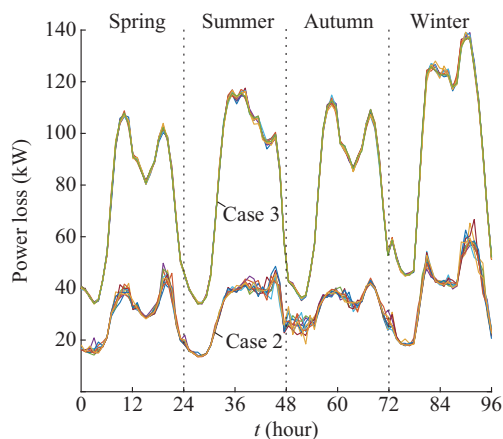


Fig. 9. Power losses for Cases 2 and 3.

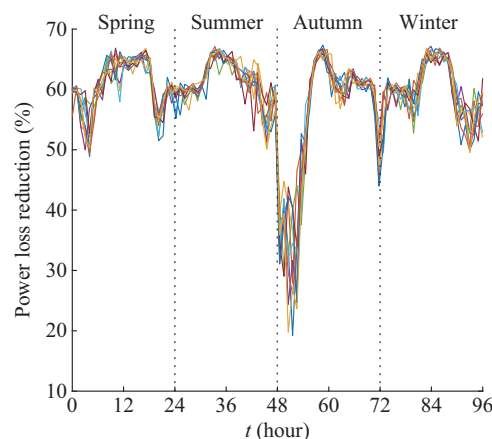


Fig. 10. Power loss reduction in Case 2.

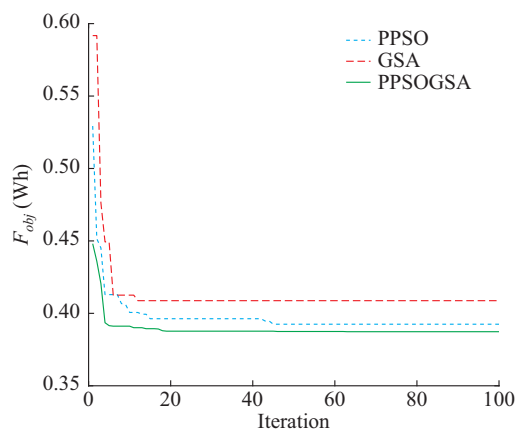


Fig. 11. Convergence characteristics in Case 1.

The objective function is the minimization of total power loss with nominal loads on all buses. The results presented in Table VI shows that the optimal DG placement highly reduces the total power losses compared to the case without DG integrated in the system. The reduction of power losses is more pronounced with increasing DG units at different locations in the network. This implies that the optimal allocation of multiple DG units with low rated power is more effective compared to optimal integration of one DG with high capacity.

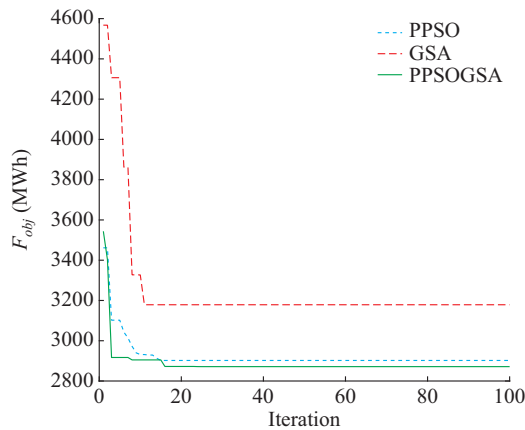


Fig. 12. Convergence characteristics in Case 2.

TABLE VI
OPTIMAL RESULTS FOR DISPATCHABLE DG UNITS

Case	Method	Optimal result		Total DG power (MW)	Power loss (kW)
		Bus	Size (MW)		
No DG					
	ACO-ABC	61	1.8726	1.8726	83.1890
	ABC	61	1.9000	1.9000	83.3100
	GA	61	1.8720	1.8720	83.1800
	PSO	61	2.0264	2.0264	84.0400
1 DG					
	MTLBO	61	1.8197	1.8197	83.3230
	BB-BC	61	1.8725	1.8725	83.2246
	PPSO	61	1.8726	1.8726	83.1790
	GSA	61	1.8743	1.8743	83.1790
	PPSOGSA	61	1.8726	1.8726	83.1790
2 DG					
	ACO-ABC	18	0.5309	2.3127	71.6570
		61	1.7818		
	MTLBO	17	0.5197	2.2517	71.7760
		61	1.7320		
	GA	11	0.5550	2.3320	71.7910
		61	1.7770		
	PPSO	17	0.5312	2.3127	71.6460
		61	1.7815		
	GSA	12	0.7851	2.4116	72.1330
		61	1.7058		
	PPSOGSA	17	0.5312	2.3127	71.6460
		61	1.7815		
3 DG					
	ACO-ABC	11	0.5597	2.6224	69.4290
		21	0.3468		
		61	1.7159		
	MTLBO	11	0.4938	2.5447	69.5390
		18	0.3787		
		61	1.6725		
	SOS	11	0.5267	2.6262	69.4270
		18	0.3805		
		61	1.7190		
	PPSO	11	0.4668	2.5938	69.4870
		17	0.4086		
		61	1.7184		
	GSA	17	0.5309	3.1052	70.1350
		49	0.7931		
		61	1.7812		
	PPSOGSA	11	0.5270	2.6260	69.3980
		17	0.3801		
		61	1.7189		

Figure 13 shows the effect of DG with optimal locations and sizes on the profile of network voltage. It is evident that the voltage deviation is significantly reduced with optimal connection of DG units, where the voltage magnitude on each bus is within permissible limits of 0.95-1.05 p.u..

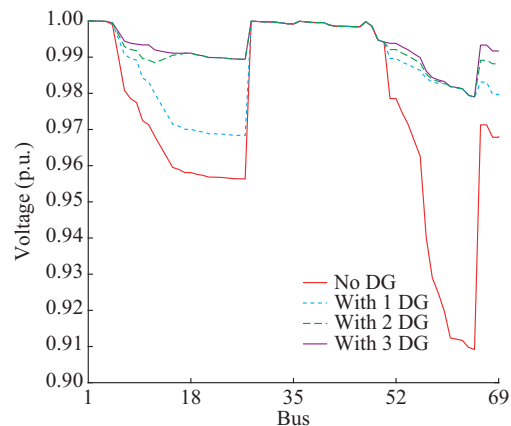


Fig. 13. Voltage profiles of IEEE 69-bus test system.

It can be seen from Table VI that the proposed algorithm leads to the lowest value of active power loss in all considered cases, which confirms its excellent performances in solving the problems of optimal DG planning. Moreover, the comparison of minimum value *Min*, maximum value *Max*, mean value *Mean*, and standard deviation *Std* of the results obtained by PPSO, GSA and proposed algorithm over 20 runs is presented in Table VII. These statistical indicators as well as the convergence profiles in Figs. 11 and 12 clearly show that the proposed algorithm provides better and more stable solutions than PPSO and GSA.

TABLE VII
STATISTICS OF PPSO, GSA AND PPSOGSA

Case	Method	<i>Min</i> (kW)	<i>Max</i> (kW)	<i>Mean</i> (kW)	<i>Std</i> (kW)
1 DG	PPSO	83.1790	83.1790	83.1790	0
	GSA	83.1790	83.2020	83.1821	0.0071
	PPSOGSA	83.1790	83.1790	83.1790	0
2 DG	PPSO	71.6460	72.4840	71.8610	0.3598
	PPSOGSA	71.6460	71.6460	71.6460	0
3 DG	PPSO	69.4870	74.6090	70.8308	1.6377
	GSA	70.1460	78.0880	73.9546	2.7664
	PPSOGSA	69.3970	70.1460	69.6444	0.3477

VI. CONCLUSION

In this paper, a hybrid algorithm is proposed and successfully applied to solve the problem of OPS of RDG with objectives to minimize the total energy loss in DNs and maximizing the profit of RDG owners. The proposed algorithm has been tested on the IEEE 69-bus test system considering the probabilistic models for WT, PV and loads based on the typical daily diagrams representing the seasons of years. The conclusions can be summarized as follows.

1) The proposed algorithm provides the results that are quite satisfactory from the viewpoints of both distribution company and RDG owners. There is a significant reduction of total energy losses in the case of both simultaneous minimization of total energy loss and maximization of profit of RDG owners as well as minimization of total energy loss only.

2) The proposed algorithm provides robust and high-quality solutions in the case of both simultaneous minimization of total energy loss and maximization of profit of RDG owners as well as minimization of the total energy loss.

3) The proposed algorithm enables better solutions and converges to an optimal solution with less number of iterations compared to PPSO and GSA algorithms in the case considering RDG units with stochastic nature of power outputs as well as in the case considering dispatchable DG units.

4) The proposed algorithm leads to better results in solving the problem of OPS of DG units than other metaheuristic population-based algorithms reported.

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