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 distributed 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-
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]:

\[
P_{WT}(v) = \begin{cases} 
0 & v \leq v_{ci}, \\
\frac{3}{2} \frac{v^3 - v_{ci}^3}{v_{ci}^3 - v_{re}^3} P_{nom} & v_{ci} < v \leq v_{nom}, \\
P_{nom} & v_{nom} < v \leq v_{re}, \\
0 & v > v_{re}. 
\end{cases}
\]  

where \( P_{nom}, v_{nom}, v_{ci}, \) and \( v_{re} \) 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]:

\[
f_c(v) = \frac{k' C'}{c} \left( \frac{v}{c} \right)^{k'-1} e^{-\left( \frac{v}{c} \right)^k}
\]  

where \( f_c(v) \) is the Weibull PDF for wind speed data collected during time period \( t \); and \( C \) and \( k' \) 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:

\[
F_c(v) = 1 - e^{-\left( \frac{v}{c} \right)^k}
\]  

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

\[
v = C\left(-\ln(r)\right)^{\frac{1}{k'}}
\]  

where \( r \) is a random number uniformly distributed on [0, 1].

In practice, parameters \( C \) and \( k' \) can be calculated approximately using mean value \( \mu' \) and standard deviation \( \sigma' \) of wind speed at time period \( t \) [7], [9]:

\[
k' = \left( \frac{\sigma'}{\mu'} \right)^{-1.086}
\]

\[
C = \frac{\mu'}{\Gamma(1 + 1/k')}
\]  

where \( \Gamma() \) is the gamma function. Note that the \( \mu' \) and \( \sigma' \) are calculated from the wind speed measurements in time period...
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 $N_t$ 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 $\mu_t = 9$ m/s, $\sigma_s = 3$ m/s, and $N_s = 60$. The power output of WT is dependent on the probability of all possible states during hour $t$.

$$ f_s(v_s) $$ 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]:

$$ P_{PV}(s, T_s) = P_{STC} \frac{s}{1000} [1 + \gamma(T_s - 25)] $$

(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; $\gamma$ is the temperature coefficient of PV module for power; and $T_s$ 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]:

$$ T_s = T_o + \frac{s}{800}(T_{NOCT} - 20) $$

(9)

where $T_s$ 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]:

$$ f_s(s) = \frac{\Gamma(\alpha + \beta) s^{\alpha-1}(1-s)^{\beta-1}}{\Gamma(\alpha) \Gamma(\beta)} \quad 0 \leq s \leq 1, \alpha \geq 0, \beta \geq 0 $$

(10)

where $f_s(s)$ is Beta PDF of $s$; and $\alpha$ and $\beta$ are the shape parameters of Beta PDF. Shape parameters of Beta PDF can be obtained based on the mean value $\mu_s$ and the standard deviation $\sigma_s$ of solar irradiance for the corresponding time period:

$$ \beta = (1-\mu_s) \frac{\mu_s (1+\mu_s)}{\sigma_s^2} - 1 $$

(11)

$$ \alpha = \frac{\mu_s \beta}{1-\mu_s} $$

(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 ($\alpha$ and $\beta$) 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/m$^2$, $\sigma_s = 295$ W/m$^2$, 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:

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

(13)

where $s_g$ 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 \( t \).

\[
\begin{align*}
\text{Fig. 2. Discrete Beta PDF of solar irradiance during an hour.}
\end{align*}
\]

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.

\[
f_l(L) = \frac{1}{\sqrt{2\pi} \sigma_L} e^{-\frac{(L-\mu_L)^2}{2\sigma_L^2}} \tag{14}
\]

\[
f_l(L) = \frac{1}{2} \left[ 1 + \text{erf} \left( \frac{L-\mu_L}{\sqrt{2} \sigma_L} \right) \right] \tag{15}
\]

\[
L = \mu_L + \sqrt{2} \sigma_L \cdot \text{erf}^{-1} (2r-1) \tag{16}
\]

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

To realize the normal PDF for each hourly load in discrete form, hour \( t \) is divide into \( N_t \) 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., \( \sigma_L = 0.6 \) p.u., and \( N_t = 60 \).

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:

\[
L_t = \sum_{g=1}^{N_t} f_s(s'_g) \frac{L_s'(g)}{f_s(L_s'(g))} \tag{17}
\]

where \( L_s'(g) \) is the load of state \( g \) at hour \( t \); \( L_s \) is the load level calculated using (16); and \( f_s(L_s'(g)) \) is the probability of the load level for state \( g \) during hour \( t \).

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:

\[
\min (F) = \min \left( w_1 F_1 + w_2 \frac{1}{F_2} \right) \tag{18}
\]

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

\[
F_1 = \frac{365}{4} \sum_{y=1}^{N_y} \sum_{t=1}^{N_t} P_{\text{loss},t} \tag{19}
\]

where \( P_{\text{loss},t} \) is the power loss for hour \( t \) in year \( y \) of considered time period of \( N_t \) years.

The objective function \( F_1 \) can be defined as the difference between the incomes and costs of RDG owners:
\[ F_2 = IN_{RDG} - C_{investment} - C_{oper,maint} \]  
(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]:

\[ C_{investment} = \sum_{i=1}^{N_{RDG}} P_{RDG} C_{inv} \]  
(21)

where \( P_{RDG} \) 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:

\[ C_{oper,maint} = \sum_{y=1}^{N_y} \sum_{i=1}^{N_{RDG}} P_{RDG} C_{om} \left( \frac{1 + INFR} {1 + INTR} \right)^y \]  
(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]:

\[ IN_{RDG} = \frac{365} {4} \sum_{y=1}^{N_y} \sum_{i=1}^{N_{RDG}} P_{RDG} C_{om} \left( \frac{1 + INFR} {1 + INTR} \right)^y \]  
(23)

where \( P_{RDG,i} \) is the generated active power of RDG unit \( i \) at hour \( t \) of year \( y \); and \( C_{om} \) 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:

\[ P_{RDG} = N_{RDG} P_{RDG} \]  
(24)

where \( P_{RDG} \) 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 \( P_{RDG} \) 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:

\[ P_{grid} = \sum_{i=1}^{N_b} P_{li} - \sum_{i=1}^{N_{RDG}} P_{RDG,i} + \sum_{i=1}^{N_{bus}} P_{busi} \]  
(25)

where \( N_b \) is the number of buses in the network; \( N_{RDG} \) is the number of RDG farms; \( N_{bus} \) 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; \( P_{RDG,i} \) is the active power of load at bus \( i \); \( Q_{li} \) is the reactive power of load at bus \( i \); and \( P_{busi} \) and \( Q_{busi} \) 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:

\[ V_{i}^{min} \leq V_{i} \leq V_{i}^{max} \]

\[ i = 1, 2, \ldots, N_{b} \]  
(27)

\[ S_{l}^{min} \leq S_{l} \leq S_{l}^{max} \]

\[ i = 1, 2, \ldots, N_{b} \]  
(28)

where \( V_{i}^{min} \) and \( V_{i}^{max} \) are the minimum and maximum allowable values of voltage magnitude of bus \( i \), respectively; and \( S_{l}^{max} \) 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 \( P_{RDG} \) as:

\[ P_{RDG} \leq P_{RDG}^{max} \]

\[ i = 1, 2, \ldots, N_{RDG} \]  
(29)

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

\[ N_{RDG} P_{RDG} \leq N_{max} P_{RDG} \]  
(30)

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

IV. SOLUTION METHOD

An improved PSOGSA [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 PSOGSA 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 \( x_i \) 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 \( x_i(t) \) can be represented as \( x_i(t) = [x_i^1(t), \ldots, x_i^d(t), \ldots, x_i^n(t)] \), 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 \( \text{POP} \) 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., \( \text{POP}(t)=[x_1(t),\ldots,x_i(t),\ldots,x_N(t)]^T \). 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 \( F(x_i) \) 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 \( \text{POP}(t) \).

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

\[
v_i(t+1)=r_1v_i(t)+r_2\cos\theta_i(t)g_{best}(t)-x_i(t)
\]

\[
x_i(t+1)=x_i(t)+v_i(t+1)
\]

where \( g_{best}(t) \) is the best solution (position) among all the best positions of agents achieved so far; \( a_i(t) \) 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).

\[
\theta_i(t+1)=\theta_i(t)+2\pi\cos\theta_i(t)+\sin\theta_i(t)
\]

Initial positions of \( N \) agents (initial population) are randomly generated in the search space of the problem with their own phase angle \( \theta_i \) 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, \( x_i \) can be written as:

\[
x_i = [\text{Bus}_1^d \ldots \text{Bus}_N^d \text{P}_1^d \ldots \text{P}_N^d]
\]

where \( n=2N_{RDGF}^d \). \( \text{Bus}_N^d \) is the position of the \( N^d \) RDG in the potential solution \( i \); and \( \text{P}_N^d \) 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 \( N_{RDGF}^d \) 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 \( x_i(t) \) from the current population \( \text{POP}(t) \).
- **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 \( x_i \) 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.

---

**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
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 $P_{\text{RDG}}$ is 200 kW whereas the maximum size of RDG farms $N_{\text{max_RDG}}$ is 10 for both WT and PV generation. The commercial data of the RDG units are given in Table I. The installed cost $C_{\text{inv}}$, the operation and management (O&M) cost $C_{\text{O&M}}$ and the contract price of electricity selling $C_{\text{PDG}}$ are adopted based on the report of International Renewable Energy Agency (IRENA) [2]. The planning horizon is $N_{\text{y}} = 10$ years.

### TABLE I

**COMMERCIAL DATA OF RDG UNITS**

| Type | $C_{\text{inv}}$ ($$/kW$$) | $C_{\text{O&M}}$ ($$/kW$$) | $C_{\text{PDG}}$ ($$/kW$$) | INFRA (%) | INTR (%) | $N_{\text{y}}$ (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 $P_{\text{STC}} = 250$ W, $\gamma = -0.0045$ °C$^{-1}$, and $T_{\text{NOCT}} = 46$ °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.

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) | Spring $\mu_1$ | Spring $\sigma_1$ | Summer $\mu_2$ | Summer $\sigma_2$ | Autumn $\mu_3$ | Autumn $\sigma_3$ | Winter $\mu_4$ | Winter $\sigma_4$ |
|------------|----------------|------------------|---------------|------------------|----------------|------------------|----------------|------------------|
| 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.

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.

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.
Figure 12. Convergence characteristics in Case 2.

TABLE VI

| Case     | Method    | Optimal result Bus | Size (MW) | Total DG power (MW) | Power loss (kW) |
|----------|-----------|--------------------|-----------|---------------------|-----------------|
| 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         |
|          | 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         |
| 1 DG     | ACO-ABC   | 18                 | 0.5309    | 0.7818              | 71.6570         |
|          | MTLBO     | 17                 | 0.5197    | 1.7320              | 71.7760         |
|          | GA        | 11                 | 0.5550    | 1.7770              | 71.7910         |
|          | PPSO      | 17                 | 0.5312    | 1.7815              | 71.6460         |
|          | GSA       | 12                 | 0.7851    | 1.7058              | 72.1330         |
|          | PPSOGSA   | 17                 | 0.5312    | 1.7815              | 71.6460         |
| 2 DG     | ACO-ABC   | 11                 | 0.5597    | 0.3468              | 69.4290         |
|          | MTLBO     | 11                 | 0.4938    | 1.6725              | 69.5390         |
|          | SOS       | 11                 | 0.5267    | 1.7190              | 69.4270         |
|          | PPSO      | 11                 | 0.4668    | 1.7184              | 69.4870         |
|          | GSA       | 17                 | 0.5309    | 0.7931              | 70.1350         |
|          | PPSOGSA   | 11                 | 0.5270    | 1.7189              | 69.3980         |
| 3 DG     | ACO-ABC   | 11                 | 0.5270    | 0.7189              | 69.3980         |
|          | MTLBO     | 11                 | 0.4668    | 0.7189              | 69.4870         |
|          | SOS       | 11                 | 0.5267    | 0.7190              | 69.4270         |
|          | PPSO      | 11                 | 0.4668    | 1.7184              | 69.4870         |
|          | GSA       | 17                 | 0.5309    | 0.7931              | 70.1350         |
|          | PPSOGSA   | 11                 | 0.5270    | 1.7189              | 69.3980         |

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..

![Figure 13. Voltage profiles of IEEE 69-bus test system.](image)

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

| Case     | Method    | Min (kW) | Max (kW) | Mean (kW) | Std (kW) |
|----------|-----------|----------|----------|-----------|----------|
| 1 DG     | GSA       | 83.1790  | 83.1790  | 83.1790   | 0        |
|          | PPSOGSA   | 83.1790  | 83.1790  | 83.1790   | 0        |
| 2 DG     | GSA       | 71.6460  | 72.4840  | 71.8610   | 0.3598   |
|          | PPSOGSA   | 71.6460  | 71.6460  | 71.6460   | 0        |
| 3 DG     | 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.

REFERENCES

[1] M. Xu and X. Zhuang, “Identifying the optimum wind capacity for a power system with interconnection lines,” International Journal of Electrical Power & Energy Systems, vol. 51, no. 1, pp. 82-88, Jan. 2013.

[2] International Renewable Energy Agency. (2018, Jan.). Renewable power generation costs in 2017. [Online]. Available: http://www.irena.org/-/media/IRENA/Agency/Publication/2018/Jan/IRENA_2017_Power_Costs_2018.pdf

[3] W.-S. Tan, M. Y. Hassan, M. S. Majid et al., “Optimal distributed renewable generation planning: a review of different approaches,” Renewable and Sustainable Energy Reviews, vol. 18, pp. 626-645, Feb. 2013.

[4] P. Prakash and D. K. Khatod, “Optimal sizing and siting techniques for distributed generation in distribution systems: a review,” Renewable and Sustainable Energy Reviews, vol. 57, pp. 111-130, May 2016.

[5] H. A. Mahmoud, P. D. Huy, and V. K. Ramachandaramurthy, “A review of the optimal allocation of distributed generation: objectives, constraints, methods, and algorithms,” Renewable and Sustainable Energy Reviews, vol. 75, pp. 293-312, Aug. 2017.

[6] A. Adel-Abady and R. C. Bansal, “Integration of renewable distributed generators into the distribution system: a review,” IET Renewable Power Generation, vol. 10, no. 7, pp. 873-884, Mar. 2016.

[7] P. Kayal and C. K. Chanda, “Optimal mix of solar and wind distributed generations considering performance improvement of electrical distribution network,” Renewable Energy, vol. 75, pp. 173-186, Mar. 2016.

[8] D. K. Khatod, V. Pant, and J. Sharma, “Evolutionary programming based optimal placement of renewable distributed generators,” IEEE Transactions on Power Systems, vol. 28, no. 2, pp. 683-695, May 2013.

[9] Y. M. Arwa, E. F. El-Saadany, M. M. A. Salama et al., “Optimal renewable resources mix for distribution system energy loss minimization,” IEEE Transactions on Power Systems, vol. 25, no. 1, pp. 360-370, Feb. 2010.

[10] A. Y. Abdelaziz, Y. G. Hegazy, W. El-Khattam et al., “Optimal allocation of stochastically dependent renewable energy based distributed generators in unbalanced distribution networks,” Electric Power System Research, vol. 119, pp. 34-44, Feb. 2015.

[11] H. H. Fard and A. Jalilian, “Optimal sizing and location of renewable energy based DG units in distribution systems considering load growth,” Electrical Power and Energy Systems, vol. 101, pp. 356-370, Oct. 2018.

[12] S. Barik and D. Das, “Determining the sizes of renewable DGs considering seasonal variation of generation and load and their impact on system load growth,” IET Renewable Power Generation, vol. 12, no. 10, pp. 1101-1110, Aug. 2018.

[13] A. Nasri, M. E. H. Golshan, and S. M. S. Najed, “Optimal planning of dispatchable and non-dispatchable distributed generation units for minimizing distribution system’s energy loss using particle swarm optimization,” International Transactions on Electrical Energy Systems, vol. 24, no. 4, pp. 504-519, Apr. 2014.

[14] E. S. Ali, S. M. Abd-Elazim, and A. Y. Abdelaziz, “Ant lion optimization algorithm for optimal location and sizing of renewable distributed generations,” Renewable Energy, vol. 101, pp. 1311-1324, Feb. 2017.

[15] E. S. Ali, S. M. Abd-Elazim, and A. Y. Abdelaziz, “Optimal allocation and sizing of Renewable distributed generation using ant lion optimization algorithm,” Electrical Engineering, vol. 100, pp. 99-109, Dec. 2016.

[16] D. Arya, A. Koshi, and S. C. Choube, “Distributed generation planning using differential evolution accounting voltage stability consideration,” International Journal of Electrical Power & Energy Systems, vol. 42, no. 1, pp. 196-207, Nov. 2012.

[17] S. Biswas, S. K. Goswami, and A. Chatterjee, “Optimal distributed generation placement in shunt capacitor compensated distribution systems considering voltage sag and harmonics distortions,” IET Generation, Transmission & Distribution, vol. 8, no. 5, pp. 783-797, May 2014.

[18] A. Ameli, S. Bahrabi, F. Khazaee et al., “A multiobjective particle swarm optimization for sizing and placement of DGs from DG owner’s and distribution company’s view points,” IEEE Transactions on Power Delivery, vol. 29, no. 4, pp. 1831-1840, Aug. 2014.

[19] M. Kefayat, N. L. A. K. M. Shariff, and S. A. N. Niaki, “A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources,” Energy Conversion and Management, vol. 92, pp. 149-161, Mar. 2015.

[20] M. Saric, J. Hivziefendic, T. Konjic et al., “Distributed generation allocation considering uncertainties,” International Transactions on Electrical Energy Systems. DOI: 10.1002/ett.2585

[21] J. Radosavljević, Metaheuristic Optimization in Power Engineering. London: The Institution of Engineering and Technology, 2018.

[22] IEEE PES. (2018, Oct.). Open data sets. [Online]. Available: http://sites.ieee.org/pest-iss-data-sets/wset

[23] G. N. Tiwari and S. Dubey, Fundamentals of Photovoltaic Modules and Their Applications. Cambridge: RSC Energy Series, 2010, p. 422.

[24] Design Qualification Type Approval of Commercial PV Modules, IEC 61215, 2005.

[25] P. Kayal and C. K. Chanda, “Placement of wind and solar based DGs in distribution system for power loss minimization and voltage stability improvement,” Electrical Power and Energy Systems, vol. 53, pp. 795-809, Dec. 2013.

[26] K. D. Mistry and R. Roy, “Enhancement of loading capacity of distribution system through distributed generator placement considering techno-economic benefits with load growth,” International Journal of Electrical Power & Energy Systems, vol. 54, pp. 505-515, Jan. 2014.

[27] S. Mirjalili and S. Z. M. Hashim, “A new hybrid PSOGA algorithm for function optimization,” in Proceedings of International Conference on Computer and Information Application, Tanjin, China, Dec. 2010, pp. 374-377.

[28] M. Ghasemi, E. Akbari, A. Rahimnejad et al., “Phasor particle swarm optimization: a simple and efficient variant of PSO,” Soft Computing, vol. 23, pp. 9701-9718, Sept. 2018.

[29] E. Rashidi, H. Nezamabadi-Pour, and S. Saryazdi, “GSA: a gravitational search algorithm,” Information Sciences, vol. 179, no. 13, pp. 2233-2248, Jun. 2009.

[30] N. Ranjan, B. Venkatesh, and D. Das, “Voltage stability analysis of radial distribution networks,” Electric Power Components and Systems, vol. 23, no. 2, pp. 129-135, Feb. 2001.

[31] Power Systems Test Case Archive. (2018, Aug.). Reliability test system. [Online]. Available: https://www2.ee.washington.edu/research/pstca/pg_testcases.htm

[32] F. S. Abu-Mouti and M. E. El-Hawary, “Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm,” IEEE Transactions on Power Delivery, vol. 26, no. 4, pp. 2090-2101, Oct. 2011.

[33] A. Hassan, F. Fahmy, N. Nafeh et al., “Genetic single objective optimization for sizing and allocation of renewable DG systems,” International Journal of Sustainable Energy, vol. 36, no. 6, pp. 545-562, Nov. 2017.

[34] T. Shukla, S. Singh, V. Srinivasarao et al., “Optimal sizing of distributed generation placed on radial distribution systems,” Electric Power Components and Systems, vol. 38, no. 3, pp. 260-274, Jan. 2010.

[35] M. M. Aman, G. B. Jasmon, A. H. A. Bakar et al., “A new approach for optimal DG placement and sizing based on voltage stability maximization and minimization of power losses,” Energy Conversion and
Jordan Radosavljević received the B.Sc. degree from the Faculty of Electrical Engineering, University of Priština, Kosovska Mitrovica, Serbia, in 1998, the M.Sc. degree from the Faculty of Electrical Engineering, University of Belgrade, Belgrade, Serbia, in 2003, and the Ph.D. degree from the Faculty of Technical Sciences, University of Priština, Priština, Serbia, in 2009, all in electrical engineering. Currently, he is a full professor with the Faculty of Technical Sciences, University of Priština, Kosovska Mitrovica, Serbia. His main research interests include power system analysis and control, power system optimization, renewable energy, distributed generation, and microgrids.

Nebojša Arsić received the B.Sc. degree in 1983 from the Technical Faculty, University of Priština, Kosovska Mitrovica, Serbia, and the M.Sc. and Ph.D. degrees in 1989 and 1994 from the Faculty of Electrical Engineering, University of Belgrade, Belgrade, Serbia. Currently, he is a full professor with the Faculty of Technical Sciences, University of Priština, Priština, Serbia. His main research interests include high voltage techniques, high voltage measurement techniques, modern energy technologies and materials, and renewable energy.

Miloš Milovanović received the B.Sc. and M.Sc. degrees in electrical engineering and computer science from the Faculty of Technical Sciences, University of Priština, Kosovska Mitrovica, Serbia, in 2013 and 2015, respectively, and is currently pursuing the Ph.D. degree in electrical engineering and computer science at the same faculty. His research interests include power system analysis, power quality and distributed power generation.

Aphrodite Ktena holds the Ph.D. and M.Sc. degrees (1993) in electrical and computer engineering from Carnegie Mellon University, Pittsburgh, USA, and a B.Sc. degree (1989) in electrical engineering from the University of Bridgeport, Bridgeport, USA. She is a tenured professor and member of the Energy Systems Laboratory of the National and Kapodistrian University of Athens, Greece. Her research interests include RES microgrids, sensor development and measurement technology, hysteresis modeling, system optimization, magnetic nondestructive testing.