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Optimal Placement and Sizing of Renewable Distributed Generators for Power Loss Reduction in Microgrid using Swarm Intelligence and Bio-inspired Algorithms

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Abstract

To responsibly fulfill the world's expanding electrical energy needs, renewable energy sources are now essential. Future energy policies must include these sources—like solar and wind energy—because they lower carbon emissions and save the environment. The optimal location and sizing of renewable distributed generators (OLSRDG) in the microgrid are determined in this study by applying one of the universal bio-inspired techniques and one of the swarms' algorithms. With lower power losses, an improved voltage profile, increased dependability, and stability, the goal is to improve energy efficiency and lessen reliance on the main grid while also enhancing the grid's overall performance and stability. The acquired results are promising and show the efficacy and resilience of the suggested technique in solving OLSRDG problems compared to recently published results. The results showed that the optimization process led to loss reduction, with the percentage of power loss reduction ranging from 45.387% to 73.89% using the PSO. While the percentage of loss reduction using the BAT ranged from 51.78% to 71.57%.

Keywords: *bat algorithm, distributed generators, micro-grids, optimal placement and sizing, particle swarm optimization, renewable energy sources*

1. Introduction

The most important concern in today's life is to meet the increased demand for electricity with effective utilization of existing networks. Numerous issues pertaining to the optimization process arise in energy supply systems [1]. One of the most significant issues with the system's operation, control, and administration is power system scheduling.

Distributed generation (DG) is the integration of multiple relatively small-power electrical energy sources into a local distribution network (DN). Due to ongoing increases in demand, the liberalization and deregulation of the electrical power market, restrictions on pollutant emissions, and other factors, DG units have become increasingly popular in recent decades. In general, the technological consequences of integrating DG units into a DN are favorable, as the installation of DG sources reduces power losses (PLR), improves voltage quality, increases the reliability and efficiency of consumer supplies, and reduces pollutant emissions. The capacity, type, and location of DG units affect the efficient operation and effectiveness of the distribution network (DNO) [1]. The goal of optimally positioning and sizing DG units is to maximize their benefits and minimize their negative impacts on the DN. Consequently, the choice of objective function depends on the desired goal.

DG units are categorized based on the flexibility of their location and size. The first type, such as wind turbines and small hydro plants, depends on climatic,

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hydrological, and geographic conditions, with connection points optimized within specified network busses. When designing new or revamped networks in defined areas, optimal placement is feasible. The second type, including diesel generators, fuel cells, and microturbines, can be installed anywhere in the network with steady power output [2].

Distributed generation (DG) units are integrated into power systems for their technical, economic, and environmental advantages. Technically, they reduce system losses, enhance voltage and frequency stability, improve energy efficiency, strengthen system reliability and power quality, and ease congestion in transmission and distribution networks. Economically, DG units lower facility upgrade costs, fuel expenses, reserve requirements, and operational costs, while ensuring critical load security and optimal energy pricing [2], [3]. Environmentally, they minimize pollutant emissions, reduce waste generation, and limit water discharge [4].

Nomenclature and Abbreviations

BAT	BAT algorithm
BLC	Bus location coefficients
DG	Distributed generation
DN	Distribution network
DNO	Distribution network operator
LSI	Loss sensitivity index
NB	Total number of buses
NDG	Total number of DGs
NG	Total number of generators
OLSRDG	Optimal location and sizing of RDG
PL	Powers losses
PSO	Particle swarm optimization
PV	Photovoltaic systems
RDG	Renewable distributed generators
WT	Wind turbines
B_{ij}	Susceptance of the network
G_{ij}	Conductance of the network
$i_{\max}$	Maximum number of iterations
J	Jaconian matrix
n_s	Total number of swarms
P, Q	Injecting active and reactive powers
P_{loss}	Active power loss
P_{Di}	Active power load at bus i
$P_{DG}^{\min}$, $P_{DG}^{\max}$	Minimum and maximum sizes of a DG
P_{gi}	Active power generation at bus i
V	Magnitude voltages
$V_i^{\max}$, $V_i^{\min}$	Minimum and maximum limits of voltage
v, $v_{\max}$	Velocity and Maximum limits of velocity
R	Line resistance
x	Position
w	Weight factor
θ	Angle voltages

Installing DG units in optimal locations helps minimize losses. Renewable DG sources like photovoltaic systems (PV) and wind turbines (WT) are often located in remote areas, necessitating seamless integration into transmission and distribution networks. The primary goal of DG is to unify all generation sources to lower losses, reduce costs, and decrease greenhouse gas emissions [2].

2. Literature Review

Various strategies have been proposed for optimizing DG placement and sizing, including analytical methods, programming techniques, and modern metaheuristic approaches inspired by natural processes [4]. Numerous mathematical and intelligent methods have been developed and implemented to address the OPSDG problem.

Several analytical methods have been proposed for determining the optimal location and size of DGs. Elsaiah et al. [5] introduced a power flow-based formulation for DG placement and sizing. Similarly, Naik et al. [6], Hung and Mithulanantha [7] developed analytical expressions to optimize DG placement by minimizing losses from active and reactive branch currents. A linear programming approach in [8] addresses optimal DG location to maximize capacity while adhering to voltage and current constraints.

Recently, population-based methods have been widely used for OLSDG optimization. Genetic algorithms (GAs) are frequently employed, as highlighted in [9]. A profit-maximizing approach was proposed in [10], while evolutionary programming in [11] focused on reducing power losses (PL) and improving efficiency across various load models.

Differential evolution algorithms (DEA) were proposed in [12] and [13] to optimize OLSDG and reduce PL. Similarly, backtracking search optimization (BTA) was applied in [14] and [15] for the same purpose.

Local swarm intelligence methods have been applied to OLSDG optimization. PSO [16] addresses OLSDG taking into account load variations in DN, while Artificial bee colony (ABC) [17], [18] focuses on loss reduction with multiple DG sources. ACO [19] and glowworm swarm optimization (GSO) [20] aim to minimize active PL and enhance voltage profile.

Gravitational search algorithms (GSA) [21], [22] address OLSDG by reducing PL, harmonic distortion, and gas emissions while improving power quality. Black hole optimization (BHO) [23] and wind driven optimization (WDO) [24] also target OLSDG for gas emission optimization in DN.

Nature-inspired and bio-inspired methods, including grey wolf optimization [25], [26], cuckoo search [27], [28], ant lion optimization [29], [30], whale optimization [31], [32], bacterial foraging [33], firefly algorithm (FFA) [34], [35], dragonfly algorithm (DFA) [36], and moth swarm algorithm [37], are used for minimizing the active PL and enhancing voltage in DN by optimize the placement and sizing DG.

Population-based algorithms like shuffled frog leaping (SFLA) [38], [39], teaching learning-based optimization (TLBO) [40], biogeography-based optimization (BG) [41], [42], league championship algorithm (LCA) [43], harmony search (HS) [44], [45], imperialistic competition (ICA) [46], [47], [48], and sine-cosine algorithm (SCA) [49], [50] are applied to OLSDG for various objectives such as PL reduction and voltage enhancement in DN.

In [51], [52], [53], authors combined GA with methods like PSO, FFA, and DFA to optimize OLSDG in DN networks. Similarly, [54] addressed OLSDG by merging fuzzy logic with GA, transforming the objective function with constraints into a multi-objective fuzzy model.

Hybrid optimization methods like PSO and GSA, GWO and PSO, and ACO and ABC have been proposed in [55], [56], [57] to optimize OLSDG units in power systems. These multi-objective approaches focus on minimizing costs, network losses, and improving the voltage profile.

Real-world distribution networks (DNs) can contain hundreds of buses. The variables requiring optimization fall into two categories: discrete/integer variables, such as bus slots and the number of distributed generation (DG) units, and continuous variables, such as voltages and power levels. Traditional optimization techniques—which often depend on differentiating an objective function—can struggle to address such complexity. To resolve this, so-called biologically inspired methods, grounded in principles of natural evolution, were applied in this work to explore a wide range of potential solutions. These methods are particularly suited to distribution network optimization (DNO) problems involving DG, as they inherently treat such challenges as combinatorial optimization problems due to the vast solution space.

3. Problem formulation

When accounting for all variables, the number of potential combinations requiring evaluation becomes exceedingly large—particularly in real-world distribution networks, which may encompass thousands of buses. However, this complexity can be significantly reduced by analyzing specific details of the network's configuration and operational parameters. Furthermore, through the methodology used to calculate bus location coefficients (BLCs), an initial prioritized list of advantageous installation sites can be generated.

3.1. Preliminary locations of DG

BLCs can be used to convey the favorability of connecting the DG [1], [58]. This method is centered on determining how a change in bus injection power affects a DN's overall PL. Power flows and PL are impacted by voltage variation and the calculation of PL is as follows.

$$\begin{bmatrix} \dfrac{\partial P_{gub}}{\partial P} \\ \dfrac{\partial P_{gub}}{\partial Q} \end{bmatrix} = J^{-1}. \begin{bmatrix} \dfrac{\partial P_{gub}}{\partial \theta} \\ \dfrac{\partial P_{gub}}{\partial V} \end{bmatrix} \;\&\; J = \begin{bmatrix} \dfrac{\partial \Delta P}{\partial \theta} & \dfrac{\partial \Delta P}{\partial V} \\ \dfrac{\partial \Delta Q}{\partial \theta} & \dfrac{\partial \Delta Q}{\partial V} \end{bmatrix} \tag{1}$$

The total amount of injected active power in each bus can be used to calculate total PL [58].

$$P_{gub} = \sum_{i=1}^{NB} P_i = \sum_{i=1}^{NB} \sum_{j \in a_i} V_i V_j \left[G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j) \right] \tag{2}$$

From Eq. (2), the PL derivation may be determined as

$$\frac{\partial P_{gub}}{\partial V_i} = \sum_{i=1}^{NB} P_i = \sum_{i=1}^{NB} \sum_{j \in a_i} V_i V_j \left[-G_{ij} \sin(\theta_i - \theta_j) + B_{ij} \cos(\theta_i - \theta_j) \right] \tag{3}$$

$$\frac{\partial P_{gub}}{\partial \theta_i} = \sum_{i=1}^{NB} P_i = \sum_{i=1}^{NB} \sum_{j \in a_i} V_j \left[G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j) \right] \tag{4}$$

Where P_i and Q_i are the injecting active and reactive powers at bus *i*; V_i θ_i, V_j and θ_j are the magnitude and angle voltages at bus *i* and *j,* respectively. a_i is the set of buses connected at bus *i*; G_{ij} and B_{ij} are the conductance and susceptance of the network, and NB is the total number of buses.

3.2. Loss sensitivity index

The Loss Sensitivity Index (LSI) identifies optimal locations for distributed generation (DG) deployment by evaluating power losses at network buses and their sensitivity to compensation. To determine these sites, active and reactive power losses (PL) are calculated for each bus, with priority given to buses exhibiting the highest losses. Integrating DG units at high-loss buses maximizes loss reduction. LSI quantifies the relationship between loss variation and the compensation provided by DG placement, effectively ranking locations based on their potential to improve efficiency. By narrowing the search to the most impactful buses, LSI streamlines the optimization process, reducing computational effort and DG implementation costs while minimizing overall system losses [2]. Additionally, LSI values act as Bus Location Coefficients (BLCs), serving as indicators of favorable DG connection points [1], [59].

$$BLC_i = LSI_i = \omega \frac{\partial P_{gub}}{\partial P_i} + (1-\omega)\frac{\partial P_{gub}}{\partial Q_i} \tag{5}$$

ω is the weight factor that depends on the network's (r/x). There is a wide range in the resistance and reactance (r/x) ratio of feeders and transformers in DN. The method used here suggests that the weight factor w is calculated for each bus separately in DNs with a wide variety of r/x ratio. The PL in the corresponding line are greatly affected by changes in the injection power in a given bus due to the radial topology of the network as well as the relatively small power [1].

3.3. Objective function

The objectif taken in this paper is the active PL in (MW), it can be expressed as follows

$$P_{loss} = \sum_{i=1}^{NB} R_i I_i^2 \tag{6}$$

In equation (6), I_i , and R_i are, respectively the current and the line resistance.

3.4. Constraints

• *Voltage constraints*

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{7}$$

Where V_i , $V_i^{\min}$ and $V_i^{\max}$ are respectively, the bus voltage, upper and lower limits of voltage at bus *i*.

• *Power balance constraints*

$$\sum_{i=1}^{NG} P_{gi} + \sum_{k=1}^{NDG} P_{DG} = P_{Di} + P_{Loss} \tag{8}$$

Where P_{gi}, P_{DG}, P_{Di} and P_{loss} are respectively, the active power generation, the active power of DG, the power load and active PL.

• *DG limits*

$$P_{DG}^{\min} \le P_{DG} \le P_{DG}^{\max} \tag{9}$$

Where $P_{DG}^{\min}$ and $P_{DG}^{\max}$ are, respectively, upper and lower limits of DG sizes.

3.5. DGs types

DG are primarily classified based on the used fuel type, the energy source (renewable or non-renewable), the generation capacity, the electrical output, etc. [60]. DGs are divided into four main kinds according on their ability to supply both reactive and active power.

Type 1: DGs with the ability to exclusively produce active power.

Type 2: DGs with the ability to produce both reactive and active power.

Type 3: DGs with the sole ability to produce reactive power.

Type 4: DGs that can produce active power but also use reactive power [60], [61].

4. Optimization methods

4.1. Particle swarm optimization

Kennedy and Eberhart created the novel optimization technique known as PSO [62]. This algorithm, which is essentially an evolutionary computation technique, is based on the social behavior processes found in a flock of birds. It makes use of several particles that come together as a swarm. In quest of the global minimum, each particle moves across the search space (or maximum). Particles go through a multidimensional search space in a PSO system. During flight, each particle adjusts its location based on its own experience and that of its nearby particles, utilizing the best position that both it and its neighbors have found. A particle's swarm orientation is determined by the surrounding particles, the particle itself, and its past experiences [63]. A particle's best previous position is saved and expressed as. Among all the particles, the best particle's position is indicated by. The position and velocity of each particle can be computed using

$$v_j^{(i+1)} = k\begin{bmatrix} w.v_j^{(i)} + c_1 rand_1.(pbest_j - x_j^{(i)}) \\ + c_2 rand_2.(gbest_j - x_j^{(i)}) \end{bmatrix} \tag{10}$$

$$x_j^{(i+1)} = x_j^{(i)} + v_j^{(i+1)} \quad \forall\ j = 1, 2, 3, ...n_S \tag{11}$$

Where w represents the factor of inertia weight and v_j and x_j represent the particle velocity and current position, respectively, at the generation. The number of swarms is indicated by n_S and $rand$ are random numbers between 0 and 1. The acceleration constants are denoted by c_1 and c_2. In general, w is represented by [64]:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{i_{\max}}.i \tag{12}$$

where i denotes the current iterations and $i_{\max}$ denotes the maximum number of iterations. The weight of inertia, denoted by $w_{\max}$ and $w_{\min}$, drops linearly from 0.9 to 0.4 in each run. k is a factor restriction that is obtained from the stability analysis of equation (11). In terms of mathematics, k is represented by

$$k = \frac{2}{\left|2 - c - \sqrt{c^2 - 4c}\right|} \quad \text{where} \quad c = c_1 + c_2 \quad \text{and } c < 4 \tag{13}$$

In the above procedures, the particle velocity is limited by a maximum value $v_{\max}$ [64], [65].

How to apply the proposed approach to solving OLSDG is shown in the following steps:

Step 1: Input the microgrid data (line and bus), and bus voltage limits.

Step 2: Using the load flow equation, calculate the total PL;

Step 3: Randomly generates an initial population (array) of particles with random positions and velocities on dimensions in the solution space and set the iteration counter $i = 0$.

Step 4: If the bus voltage is within the limits, for each particle, calculate the total loss using equation (1). Otherwise, that particle is infeasible.

Step 5: For each particle, compare its objective value with the individual best. If the objective value is lower than P_{best}, set this value as the current P_{best}, and record the corresponding particle position.

Step 6: Choose the particle associated with the minimum individual best P_{best} of all particles, and set the value of this P_{best} as the current overall best G_{best}.

Step 7: Using (6) and (7), respectively, to update the velocity and position of particle.

Step 8: If the iteration number reaches the maximum limit, go to Step 9. Otherwise, set iteration index $i = i + 1$, and go back to Step 4.

Step 9: Print out the optimal solution to the target problem. The best position includes the optimal locations and size of DG, and the corresponding fitness value representing the minimum PL.

4.2. BAT algorithm

BAT algorithm is a bio-inspired algorithm proposed it in 2010 by Xin-She Yang [60], [66], [67]. This method takes advantage of the bats' echolocation behavior. The microbat is the most frequent user of echolocation among all bat species. A bat will use sonar to locate prey, identify objects, and steer clear of obstacles. When these sonar signals strike an item, they bounce back and produce echoes. Bats use the time difference between an echo signal's emission and its detected position to estimate an object's size [60], [66]. Additionally, bats adjust the intensity and pulse rate of their signal based on how close their prey is. When utilizing the bat algorithm, the following idealized guidelines should be followed:

- ✓ To locate obstacles and distinguish between them and potential food, all BATs use the echolocation.
- ✓ Bats have a random velocity v_i at position x_i initially, with frequency fixes at f_{imin}, loudness (A_0) variable, and wavelength λ fluctuating. Depending on how close the prey is, they automatically modify their loudness and pulse rate.
- ✓ A_0 it goes from a high value to a fixed minimum value A_{min}. The steps below illustrate the Bat algorithm [60], [67], [68].

Step 1. Population

In the search space, the bat population is initialized at random. A good population range is from 10 to 40. The objective function is used to determine fitness, and changes in loudness, heart rate, and velocity are used to update these values. The population in this simulation is assumed to be 20.

Step 2. Movement of bats

The parameters of bats are updated to reflect the current state of the search spaces

$$f_1 = f_{min} + (f_{max} - f_{min})rand \quad (14)$$

$$v_i^t = v_i^{t-1} + (x^t - x_*)f_i \quad (15)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (16)$$

Where x_i^t and v_i^t are current position and velocity of i^{th} bat. x_* is the current gbest position.

Step 3. Local search by random walk

In the local search phase, one of the best solutions is chosen at random, and a random walk is then used to create a new solution locally centered around that solution using (10) [60].

$$x_{new} = x_{old} + \varepsilon A^t \quad (17)$$

ε denotes a random number between [-1, 1] and $A^t$is the mean of loudness of all bats at present iteration.

Step 4. The pulse emission and loudness

Typically, when a Bat finds its prey or is close to it, its loudness (A_i) decreases and its pulse emission rate (r_i) increases. Every iteration updates A_i and r_i using (18) and (19). The values of α and γ in this simulation are assumed to be α = γ = 0.9 [60], [68].

$$A_i^{t+1} = \alpha A_i^t \quad (18)$$

$$r_i^{t+1} = r_i^0[1 - exp(-\gamma t)] \quad (19)$$

Step 5.Optimal solution

Sort the answer based on the fitness values of each person; the best fitness value is updated as *gbest*. The steps involved using Bat algorithm to determine the DG size and placement are described below [66], [67], [68].

1. Lire the networks line and bus data's.
2. Select the DG number to be placed.
3. Establish the DG's voltage and powers limits.
4. Use equation (17) LSI for the base case and run power flow to determine the total active loss;
5. Set the frequency (f), velocity, loudness (A), pulse rate (r), and total number of iterations.
6. Choose the best current solution from the minimum or objective functions.
7. For each iteration, the DGs position and size are chosen at random. Eq. (14), (15), and (16) are used to update position, frequency, and velocity.
8. Use (18) and (19) to update the loudness and rate of pulse emission.
9. Until the maximum repetition is achieved, repeat steps 6 through 9 one again.
10. Among all the solutions, choose the best (minimum) goal function. The DGs' size and matching position are then regarded as optimal.
11. The basic case is compared with the optimal objective function. The minimum LSI and loss reduction are computed.

5. Simulation & results

Figure 1 illustrates the single-line diagram of the IEEE 33-bus distribution system. Bus Location Coefficients (BLCs) were selected as the criterion for identifying initial network sites for distributed generation (DG). These BLCs were computed at five distinct load levels—20%, 40%, 60%, 80%, and 100% of the rated power—based on the load profile depicted in Figure 2. The results, shown in Figure 3, indicate that lower load levels yield slightly higher BLC values. Notably, buses 23 and 24 exhibit the highest BLC values across all load levels, whereas bus 10 consistently shows the lowest value.

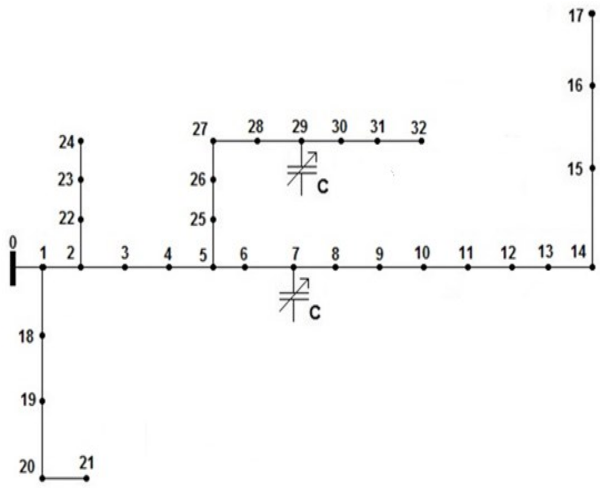

Figure 1. IEEE-33 bus test system [1].

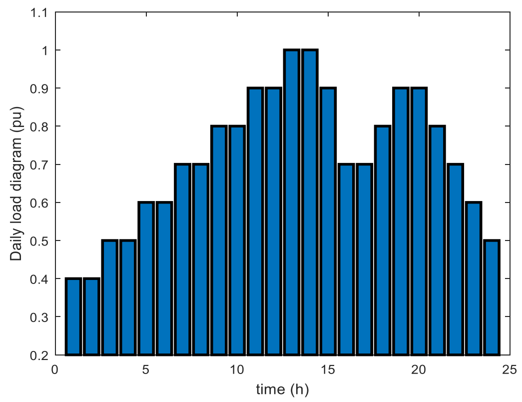

Figure 2. Daily load diagram.

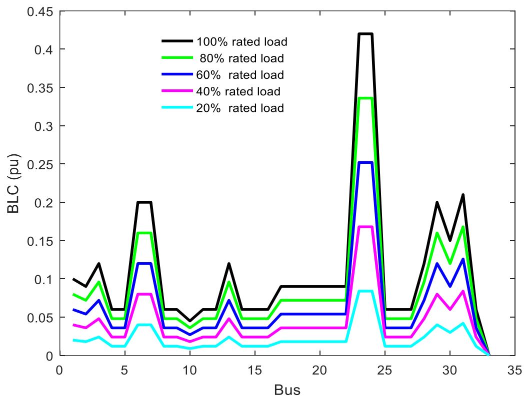

Figure 3. BLC test system for 5 load levels.

The proposed algorithms implemented and the computations were performed using MATLAB software, R2021a and all cases were run on a desktop computer Windows-10, 64-bit, Intel(R) Core(TM) i5-6500 CPU, 3.20 GHz processing frequency and 8.0 GB RAM.

Notably, the ranking of buses based on BLC values remains independent of the load level at which they are calculated. As demonstrated in Figure 3, buses located at the network periphery exhibit significantly higher BLC values compared to those in central positions.

5.1. Optimal placement & sizing of DGs by PSO

In this study, four cases are considered.

Case 1: One DGs are to be placed and sized optimally in the distribution network.

Case 2: Two DGs are to be placed and sized optimally in the distribution network.

Case 3: Three DGs are to be sited and sized optimally in the test systems.

Case 4: Four DGs are to be placed and sized optimally in the test systems.

In all cases, PSO parameters have been taken as follows: Population size = 50, $i_{max} = 200$ $w_{min} = 0.4$ and $w_{max} = 0.9$. The voltage limits are taken as 0.95 and 1.05.

Simulation results for all cases are illustrated in Figures 4 through 7. The objective function (Loss) serves as the optimal criterion for determining distributed generation (DG) placement. Table 1 summarizes the optimal DG locations, corresponding DG sizes, and total active and reactive power losses across the four cases.

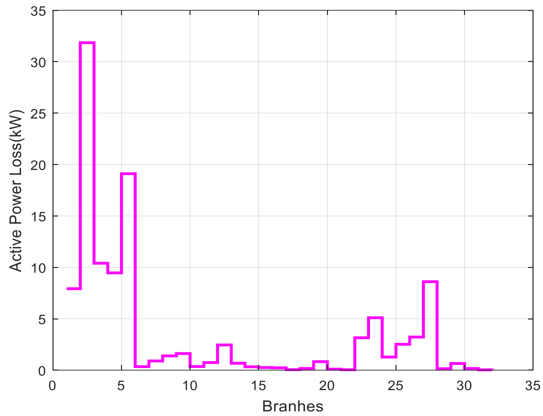

Figure 4. Power losses for 2 DG.

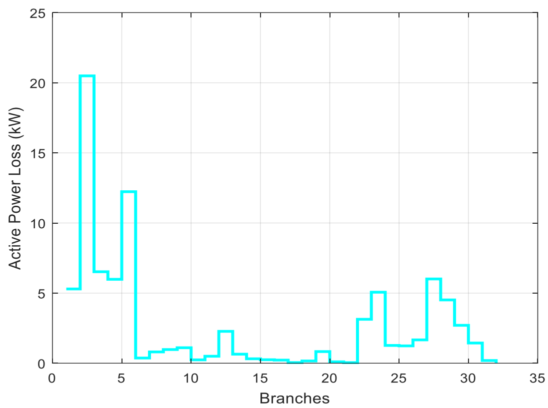

Figure 5. Power losses for 2 DG.

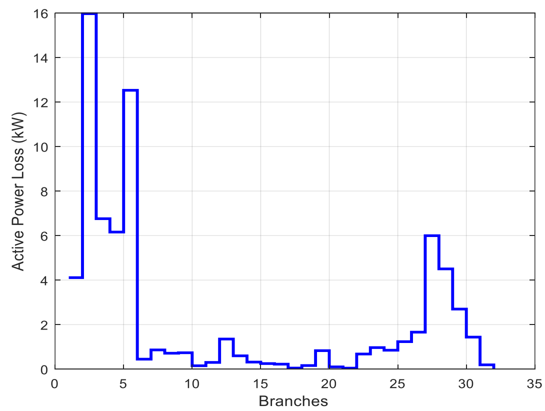

Figure 6. Power losses for 3 DG.

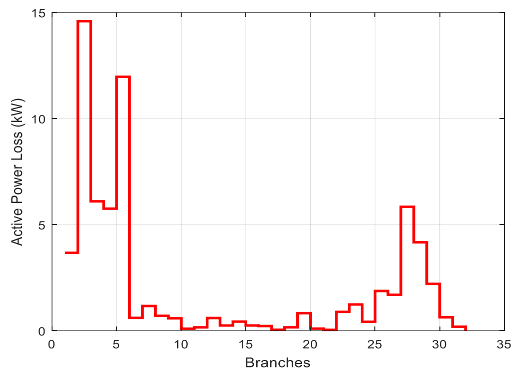

Figure 7. Power losses for 4 DG.

We note that the PL reduces from 202.67 kW to 114.89 (kW), 86.647 (kw), 72.414 (kw) and 66.398 (kw), respectively which are about 47.39 %, 47.39 %, 47.39 %, and 47.39 %, of without DG. While the reactive power decreased from 135.14 (kV) to 73.89 (kV), 58.676 (kV), 49.809 (kV) and 45.387 (kV) which represents 43.70%, 47.39% 47.39%, and 47.39% without DG. The magnitudes voltages for all cases are shown in Figure 8.

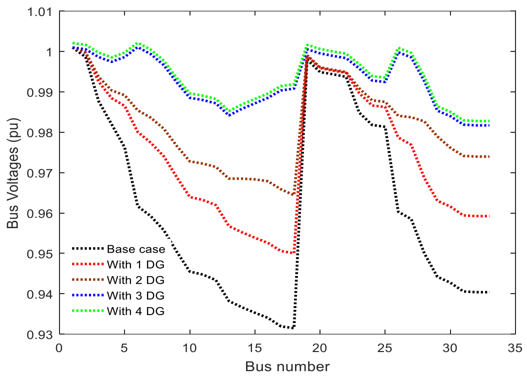

Figure 8. Magnitude voltages for all cases using PSO.

As shown in the Table 1, we notice that as the number of distributed generators increased, the losses were less. It is noticeable from the results that the size of the distributed generators obtained is higher when using a larger number of generators compared to the size obtained from a single generator. This is due to the fact that the losses in the reactive power were also reduced and thus the reactive power available from the main station was reduced.

5.2. Optimal placement & sizing of DGs using BAT

Table 2 lists the BAT parameters that were used to solve the OLSDG problem. As seen in section 2.5, DGs are divided into 4 categories according to their potential to generate both reactive and active power. In this simulation, the following parameter ranges are taken into consideration: pulse rate (r) [0, 1], frequency (f) [0, 2], and loudness (A) [2, 0]. Depending on the DG type, two instances are examined in this work.

Table 2. BAT parameters.

Parameters	Iterations	Particles	Loudness	Frequency
Values	250	25	0.9	0.9

Case 1: Only active power is delivered by DG.

Case 2: DG is capable of producing or absorbing reactive power in addition to providing active power. Two scenarios are constructed based on various combinations of the objective functions.

Table 1. Location and optimal size of DGs obtained by PSO.

Cases	DG N°	Optimal placement DGs	Optimal placement bus	Optimal size of DG (MW)	Efficiency %	Active loss (KW)	Reactive loss (kVAr)
With 1 DGs		DG_1	12	1.000	43.70	114.89	73.890
With 2 DGs		DG_1	30	1.000	43.70	86.647	58.676
		DG_2	13	0.893			
With 3 DGs		DG_1	30	1.000	43.70	72.414	49.809
		DG_2	25	0.837			
		DG_3	14	0.791			
With 4 DGs		DG_1	7	0.869	43.709	66.398	45.387
		DG_2	14	0.582			
		DG_3	31	0.710			
		DG_4	25	0.719			

Table 3. Location and optimal size of DGs obtained by BAT.

Cases	DG N° DGi	optimal placement bus	optimal DG Size (MW)	optimal DG Size (kVAr)	Efficiency %	Time (s)	Active loss (KW)	Reactive loss (kVAr)
without DG	-	-	-	-	-	0.114	202.67	135.14
With 1 DG	DG_1	33	1.492	-	0.933	46.87	97.728	66.166
With 2 DGs	DG_1	7	0.378	0.496	0.817	49.96	88.005	60.3086
	DG_2	15	0.484	0.597	0.467			
With 3 DGs	DG_1	33	0.336	0.448	0.770	46.68	67.75	45.620
	DG_2	8	0.374	0.498	0.514			
	DG_3	31	0.219	0.260	0.754			
With 4 DGs	DG_1	17	0.432	0.65	0.220	46.68	57.61	38.50
	DG_2	5	0.116	0.195	0.260			
	DG_3	29	0.478	0.436	0.581			
	DG_4	12	0.193	0.270	0.360			

Scenario 1 employs a single-objective optimization focused on minimizing active PL. In contrast, Scenario 2 incorporates a multi-objective framework that balances PL reduction with DG installation costs.

Scenario 2 involves a multi-objective optimization to minimize active power losses (PL) and associated costs. Figures 9 through 12 compare the ideal voltage profiles across two cases for each scenario: systems without distributed generation (DG) and those with one, two, three, or four DG units installed. The results demonstrate that DGs supplying both active and reactive power significantly improve voltage profiles compared to units delivering only active power. The global optimal solution, derived from successive executions of the BAT algorithm, is presented in Table 3.

We observe that without DG, the active and reactive PL are 202.67 kW and 135.14 kVAr, respectively. The active and reactive PL with 1 DG are 97.728 kW and 66.166 kVAr, respectively. The active and reactive PL with 2 DG are 88.005 kW 60.3086 kVAr, respectively. The active and reactive PL with 3 DG are 67.758 kW and 45.62 kVAr, respectively. The active and reactive PL with 4 DG are 57.61 kW and 38.50 kVAr, respectively.

The results demonstrate that increasing the number of DG units enhances PL reduction. When active losses are prioritized, the percentage reductions compared to a DG-free system are 51.78%, 56.58%, 66.57%, and 71.57% for one to four DG units, respectively. However, this improvement comes at the expense of higher investment costs, underscoring the need for further research to optimize DG deployment for maximum cost-effectiveness. Table 4 show the comparison of obtained and literature results.

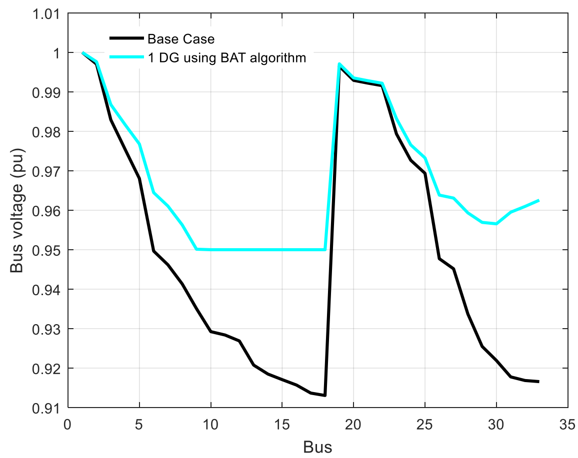

Figure 9. Optimal bus voltages when connecting 1 DGs by BAT algorithm.

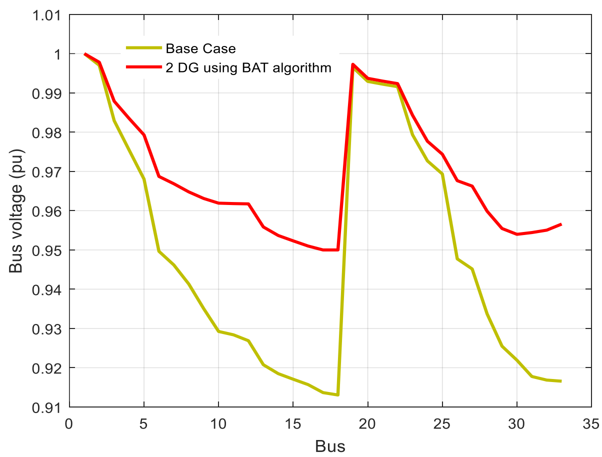

Figure 10. Optimal bus voltages when connecting 2 DGs by BAT algorithm.

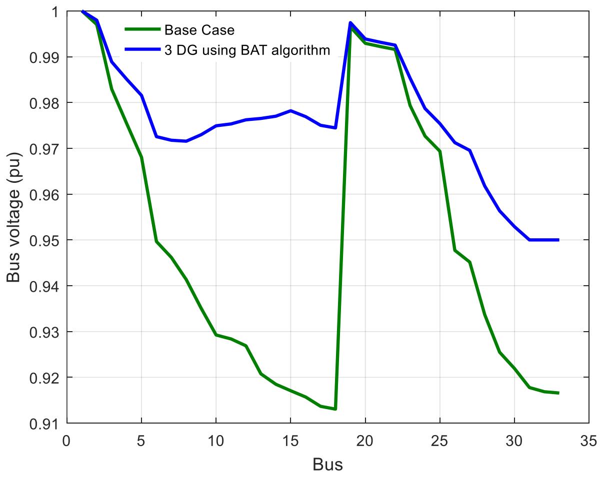

Figure 11. Optimal bus voltages when connecting 3 DGs by BAT algorithm.

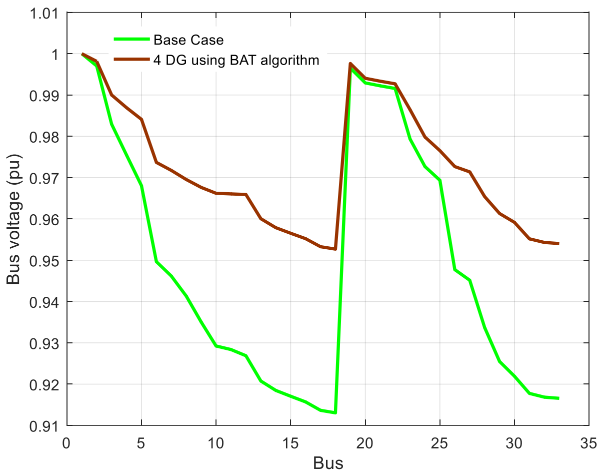

Figure 12. Optimal bus voltages when connecting 4 DGs by BAT algorithm.

The numerical and graphical results clearly indicate that, prior to DG installation; the base case exhibited significantly poor LSI values and voltage profiles. Both metrics improved markedly after DG implementation, with voltage profiles and LSI trends aligning closely across scenarios. In summary, the optimal DG allocation and sizing achieved through PSO and BAT algorithms resulted in substantial reductions in active PL, near-ideal voltage profiles, and enhanced LSI values. Simulation outcomes consistently demonstrate that PSO and BAT algorithms produce higher-quality solutions compared to conventional methods. Furthermore, the findings confirm that DGs supplying both active and reactive power exhibit superior capability in minimizing system losses.

Table 4. Comparison of obtained and literature results.

Method	**DG N°**	Power loss	Optimal location	Optimal size	loss reduction %
Proposed PSO	2 DG	86.64	30 13	1.000 0.893	57.25
	3 DG	72.41	30 25 14	1.000 0.837 0.791	64.27
Proposed BAT	1 DG	46.87	33	1.492	51.78
	2 DG	88.005	7 15	0.484 0.336	56.58
	3 DG	67.75	33 8 31	0.336 0.374 0.219	66.57
IA [7]	1 DG	111.1	6	0.260	47.39
	2 DG	91.63	6 14	0.252	65.61
	3 DG	81.05	6 12 31	0.252	61.62
GA [9]	1 DG	70.5	15	0.214	68.56
	2 DG	87.0	33 2	0.395 1.125	91.57
	3 DG	64.7	17 20 2	0.418 0.895 0.991	71.15
PSO [16]	1 DG	111.03	6	0.259	47.38
	2 DG	87.17	13 30	0.201	58.68
	3 DG	72.79	13 24 30	0.647	65.50
PSO [20]	1 DG	186.7	6	0.039	7.66
	2 DG	186.7	6 3	0.037 0.032	8.16
	3 DG	183.6	6 3 28	0.036 0.037 0.039	9.41
GSO [20]	1 DG	16	6	0.022	7.66
	2 DG	185.7	6 3	0.023 0.022	8.11
	3 DG	182.8	6 3 28	0.032 0.039 0.039	9.79
TLBO [20]	1 DG	188.4	6	0.022	5.82
	2 DG	187.6	6 3	0.023 0.022	6.64
	3 DG	182.8	6 3 28	0.032 0.039 0.039	6.98
Hybrid PSO-IA [52]	1 DG	111.17	6	0.260	47.31
	2 DG	87.28	33 2	0.194	58.64
	3 DG	72.89	17 20 2	0.287	65.45

6. Conclusion

This study presents a comprehensive methodology for optimizing the sizing and placement of distributed generation (DG) units using Particle Swarm Optimization (PSO) and BAT algorithms. By minimizing active power losses (PL), these methods enhance energy efficiency, reduce electricity costs, and lower the environmental impact of power generation. Optimal DG integration also promotes renewable energy adoption, aligning with global sustainability objectives. Improved system performance further decreases operational expenses and incentivizes investment in distributed power infrastructure. Notably, the approach demonstrates robust performance even with high numbers of DG units and bus location coefficients (BLCs).

The efficacy of the proposed approaches was validated using the IEEE 33-bus test system, a widely recognized benchmark for distribution networks. Results indicate significant success in addressing optimal DG placement challenges, achieving PL reductions ranging from 51.78% to 71.5%—a marked improvement over conventional techniques. These outcomes provide a critical foundation for advancing cost optimization and renewable integration in power systems, bridging the gap between theoretical research and practical implementation to benefit both academia and society.

However, the study is limited by its reliance on the IEEE 33-bus system, which simplifies real-world network complexities. Fixed parameters were assumed, neglecting dynamic factors such as demand variability, renewable energy intermittency, and equipment reliability—key considerations for practical deployment.

Future work will extend these methods to larger, diverse networks and real-world smart grids, incorporating energy storage, demand response strategies, and advanced communication protocols. Collaboration with industry stakeholders will ensure economic viability and adaptability to uncertainties like load fluctuations, renewable intermittency, and grid failures. This expansion aims to enhance the robustness and applicability of the approches for complex, real-world energy systems.

Competing Interest Statement

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

No data or additional materials were utilized for the research described in the article.

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