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Voltage Profile Improvement through Optimal Placement of Distributed Generation in a Radial Distribution System Using Metaheuristic Algorithms

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Abstract

The radial distribution system (RDS) carries the bulk of consumer load and, owing to its topology and high R/X ratio, suffers from significant active power loss and a poor voltage profile that degrades toward the feeder ends. Maintaining an acceptable voltage profile is therefore a primary concern for distribution utilities. This paper presents the analysis and improvement of the voltage profile of a standard IEEE 33-bus RDS through optimal placement and sizing of distributed generation (DG). A single-objective optimization problem is formulated by combining active power loss and a voltage stability index into one objective through weighting factors, subject to voltage-limit and DG-size constraints, with a Gauss–Seidel load flow used to evaluate candidate solutions. Seven metaheuristic algorithms—Particle Swarm Optimization (PSO), Ant Lion Optimization (ALO), Whale Optimization Algorithm (WOA), Moth Flame Optimization (MFO), Marine Predator Algorithm (MPA), Sine Cosine Algorithm (SCA) and Gold Rush Optimization (GRO)—are implemented and compared. With a single 2000 kW DG placed at bus 7, the minimum bus voltage rises from 0.9131 p.u. to about 0.943–0.963 p.u. and the total active power loss falls from 202.66 kW to 107.95 kW. Most algorithms converged to highly similar near-optimal solutions but differ in accuracy and computation time; WOA and SCA demonstrated competitive solution quality with favourable computational performance.

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1. Introduction

Electricity demand continues to rise worldwide as population and industrial activity grow, forcing utilities to increase generation and to deliver power to consumers through transmission and distribution networks. Most distribution feeders are radial in structure because of their simplicity and low cost. However, the radial distribution system (RDS) is characterized by a high resistance-to-reactance ratio, which makes it prone to substantial active power loss, phase unbalance, voltage fluctuation and a progressively declining voltage profile toward the feeder ends.

Several techniques are available to improve the voltage profile of a distribution system, including the application of capacitor banks, load balancing among the three phases, reconductoring, feeder bifurcation, distributed energy storage, network reconfiguration [1], the deployment of flexible AC transmission system (FACTS) devices, and the application of distributed generation (DG) [2]. Among these, DG has become particularly attractive in modern distribution networks because of its favourable effect on overall network performance and security.

There is no single universally accepted definition of DG; it is generally described on the basis of its location and size, and sometimes by its characteristics such as renewable (photovoltaic, wind turbine, hydro turbine) or non-renewable (fuel cells, combustion turbines, diesel generators, gas turbines) sources [3]. The size attributed to DG varies between agencies, ranging from a few kilowatts to tens of megawatts. Installing DG in an RDS reduces line losses and improves the system voltage profile, although improper placement may cause reverse power flow, protection mal-operation and harmonic injection from asynchronous sources. The benefits therefore depend strongly on the optimal location and size of the DG units.

For optimal placement and sizing of DG, analytical methods, numerical methods, metaheuristic algorithms, artificial neural networks and hybrid methods have all been reported [14]. Metaheuristic methods are particularly suitable for this high-dimensional, non-linear problem because they are model-free, require few assumptions, perform global exploration of the search space, avoid entrapment in local minima during exploitation, and are not problem-specific. This paper formulates a single-objective placement problem for a single DG unit in the standard IEEE 33-bus RDS and compares seven metaheuristic algorithms for solving it: PSO, ALO, WOA, MFO, MPA, SCA and GRO.

2. Related Work

The optimal placement of DG to mitigate the problems of radial feeders has received considerable attention. Several authors have addressed power-loss reduction and voltage-profile enhancement together. Ant Lion Optimization has been applied to the IEEE 33- and 69-bus systems for simultaneous voltage-profile improvement and loss reduction, using a forward–backward sweep load flow and a voltage deviation index to quantify the improvement for single- and double-DG scenarios weighted by a factor [17]. Reliability-oriented binary programming formulations have also been proposed for distribution feeders [4]. An improved binary PSO has been reported to minimize losses and enhance the voltage profile while satisfying operational constraints [7], and PSO has likewise been used to optimize network reconfiguration for loss reduction [12].

Network reconfiguration has also been combined with optimization to reduce losses and improve reliability [13], and a range of population-based methods—including binary PSO variants [1], topology-reconfiguration-based voltage optimization [11], genetic algorithms [13], teaching–learning-based optimization [9], [10], and bacterial foraging optimization [16]—have been applied to related distribution-system problems; power-loss minimization through reconfiguration has been demonstrated on radial feeders [15]. These studies confirm that metaheuristics consistently locate good DG placements, but they also show that the relative accuracy and computational effort of different algorithms vary, motivating the comparative study reported here. Table 1 summarizes the four conventional DG categories used in this work.

Table 1: Classification of DG types by power delivered

DG Type	Power Delivered	Power Factor
DG-I	Real power only	Unity
DG-II	Reactive power only	Zero
DG-III	Real and reactive	0.80–0.99 lag
DG-IV	Real power, absorbs reactive	0.80–0.99 lag

Note: Power-factor ranges follow the conventional four-type DG classification used for placement studies.

3. Problem Formulation

The objective is to improve the voltage profile of the RDS by inserting a single DG unit while reducing active power loss. A single-objective function is obtained by combining the active power loss and a voltage stability index (VSI) through weighting factors, subject to voltage-limit and DG-size constraints. The fitness function is:

$$F = \min\left(W_1 \Sigma\, I_x^2 R_x + W_2\, VSI^{-1}/VSI_{base}^{-1} \right) \quad (1)$$

where W_1 and W_2 are weighting factors, $I^2_x R_x$ represents the active power loss of branch x summed over all nb branches, and VSI is the voltage stability index of the receiving-end bus j of a branch, computed as:

$$VSI = V_i^4 - 4(P_j X_{ij} - Q_j R_{ij})^2 - 4(P_j R_{ij} - Q_j X_{ij}) V_i^2 \quad (2)$$

The optimization is subject to a bus-voltage limit and a DG-size limit:

$$V_{min} \le V \le V_{max}\ (0.9 \le V \le 1.05) \quad (3)$$

$$0.2 \le P_{DG} \le 2 \quad (4)$$

The fitness of each candidate solution is evaluated using a load-flow study, which yields the steady-state operating point of the network—the magnitudes and angles of the bus voltages and the real and reactive power flows [5]. In this work the Gauss–Seidel (GS) method is used; direct and sweep-based solvers are also widely adopted for radial networks [6]. GS is an iterative technique for solving the non-linear algebraic power-flow equations; with the slack-bus voltage specified, the voltage at the i-th bus is updated as:

$$V_i = (1/Y_{ii})[(P_i - jQ_i)/V_i^* - \Sigma Y_{ik} V_k] \quad (5)$$

for i = 2, 3, … n, with the load-bus voltage magnitudes and angles first assumed and then refined iteratively until convergence.

4. Optimization Algorithms

Seven metaheuristic algorithms were implemented to solve the formulated problem. Each is briefly described below.

4.1. Particle Swarm Optimization (PSO)

PSO [8] models the social behaviour of a bird flock or fish school. Each particle carries a position and a velocity and remembers its personal best, while the swarm shares the global best. The velocity is updated from an inertia (momentum) term, a cognitive term toward the personal best, and a social term toward the global best; the position is then updated by adding the new velocity. Acceleration coefficients and random numbers between 0 and 1 balance exploration and exploitation.

4.2. Moth Flame Optimization (MFO)

MFO [19] is inspired by the transverse-orientation navigation of moths, which fly at a fixed angle to the moon but spiral around artificial light. The moths are initialized randomly within the variable bounds, and each moth updates its position relative to a flame along a logarithmic spiral. The number of flames is reduced adaptively to shift the search from exploration to exploitation.

4.3. Ant Lion Optimization (ALO)

ALO [17] mimics the hunting mechanism of antlions, which dig conical pits to trap ants. It models random walks of ants, sliding of ants toward the pit centre, entrapment within a trap, roulette-wheel trap building proportional to fitness, and the catching of prey followed by trap rebuilding. Elitism preserves the best antlion found so far.

4.4. Whale Optimization Algorithm (WOA)

WOA [18] is based on the bubble-net feeding behaviour of humpback whales. It comprises encircling the prey by moving toward the current best solution; a bubble-net attack combining a shrinking encircling movement with a logarithmic spiral, chosen with equal probability; and a search-for-prey (exploration) phase in which agents move relative to a randomly chosen agent when the coefficient magnitude exceeds unity.

4.5. Gold Rush Optimization (GRO)

GRO [22] is inspired by the decision-making of a group of gold prospectors (operators) within a search space. Each operator perceives detector loudness—attenuated by distance, fatigue and metal-type error—and decides, with a probability, whether to move toward or away from the loudest signal. Successful operators that find optimal locations are recorded and guide the search.

4.6. Marine Predator Algorithm (MPA)

MPA [20] emulates predator–prey movement using Lévy and Brownian strategies over three iteration phases: in the first third the prey moves by Brownian motion while the predator is stationary; in the second third the population is split between Brownian and Lévy movement; and in the final third the predator adopts Lévy motion. A prey matrix and an elite matrix are maintained, and a step-size control factor governs the phase transitions.

4.7. Sine Cosine Algorithm (SCA)

SCA [21] generates a set of random candidate solutions and updates them toward the best (goal) position using sine and cosine functions. A switching parameter selects between the sine and cosine update rules, while an adaptive parameter decreasing linearly with iteration count guides the balance between exploration and exploitation.

5. Results and Discussion

The methodology was applied to the standard IEEE 33-bus radial distribution system shown in Fig. 1, comprising 33 buses and 32 branches at a base voltage of 12.66 kV, with a total load of 3.715 MW and 2.3 MVAr. The line and load data of the standard test system were used. For all population-based runs the maximum number of iterations was 200 and the number of search agents 50; statistics were collected over 30 independent trials.

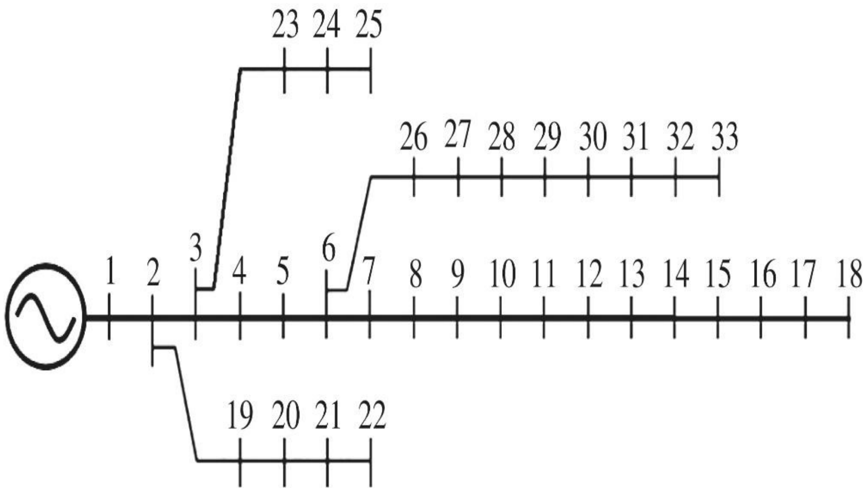

Fig 1: Single-line diagram of the IEEE 33-bus radial distribution system

5.1. Voltage profile without DG

In the base case (no DG), the voltage profile declines steadily along the feeders, with the lowest voltages at the feeder-end buses. The minimum voltage was 0.9131 p.u. at bus 18 and 0.9166 p.u. at bus 33, both below the desirable band, while the total active power loss was 202.66 kW. These violations confirm the need for voltage-profile improvement.

5.2. Voltage profile with DG

Each algorithm was used to determine the optimal location and size of a single DG unit. For five of the seven algorithms, the optimal placement converged to bus 7 with a DG size of 2000 kW, whereas PSO and ALO converged to buses 10 and 26, respectively. With DG installed, the voltage at bus 18 improved from 0.9131 p.u. to 0.9454 p.u. for WOA, MFO, MPA and GRO, 0.9429 p.u. for ALO, 0.9520 p.u. for PSO and 0.9627 p.u. for SCA. Similarly, the end-node voltage at bus 33 improved from 0.9166 p.u. to values ranging between 0.9433 p.u. and 0.9716 p.u. The total active power loss decreased from 202.66 kW to 107.95 kW for most algorithms, corresponding to a reduction of approximately 47%, while PSO achieved a loss of 114.09 kW. Fig. 2 compares the resulting voltage profiles, and Table 2 summarizes the algorithm-wise results before and after DG placement.

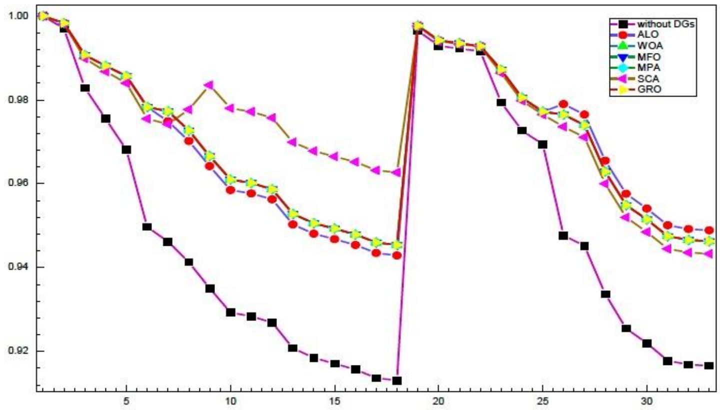

Fig 2: Comparison of bus voltage profiles without DG and with DG for each algorithm

Table 2: Comparison of algorithms before and after DG placement

Algorithm	Bus	Size (kW)	Loss (kW)	Min V (p.u.)
PSO	10	1660.6	114.09	0.9520
ALO	26	2000	107.95	0.9429
WOA	7	2000	107.95	0.9454
MFO	7	2000	107.95	0.9454
MPA	7	2000	107.95	0.9454
SCA	7	2000	107.95	0.9627
GRO	7	2000	107.95	0.9454

Note: "Without DG" power loss is 202.66 kW with minimum voltage 0.9131 p.u. for all algorithms.

The fitness, average, worst and standard-deviation statistics over the 30 independent trials indicate that most algorithms converged to highly similar near-optimal solutions for this single-DG placement problem. However, minor differences were observed in the final DG location, size and power-loss values, particularly for PSO. The algorithms differed mainly in computational efficiency. Based on the observed execution times, WOA and SCA demonstrated a favourable balance between solution quality and computational speed, while MPA required comparatively higher computation time.

Overall, optimal placement of a single 2000 kW DG unit at bus 7 substantially flattens the voltage profile of the IEEE 33-bus system and roughly halves the active power loss. The choice of algorithm had limited influence on the final solution quality but affected computational efficiency and convergence consistency.

6. Conclusion

This paper analyzed the voltage profile of a radial distribution system and improved it through the optimal placement of distributed generation, formulated as a single-objective optimization of active power loss and voltage stability index combined through weighting factors, with voltage-limit and DG-size constraints and a Gauss–Seidel load flow. Seven metaheuristic algorithms—PSO, ALO, WOA, MFO, MPA, SCA and GRO—were implemented and compared on the standard IEEE 33-bus test system. After DG placement the voltage profile of every bus improved and the total active power loss fell from 202.66 kW to 107.95 kW, with the optimal DG of 2000 kW located at bus 7. Most algorithms converged to a common near-optimal solution, while PSO produced a slightly different DG placement and higher power loss. Future work may extend the formulation to multiple DG units, multi-objective optimization, and reactive-power-capable and renewable DG with uncertainty modelling.

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