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Cuckoo search algorithm approach for optimal placement and sizing of distribution generation in radial distribution networks

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ABSTRACT

Radial distribution networks (RDNs) often experience power loss due to improper distribution generation (DG) allocation. Strategic DG placement can reduce power loss, minimize costs, and improve voltage profiles and stability. This research optimizes DG placement and sizing in RDNs using the cuckoo search algorithm (CSA). The objective function considers losses across all network branches, and CSA identifies optimal DG locations and sizes. Tested on IEEE 33-bus, IEEE 69-bus, and Nigeria's Imalefalafia 32-bus RDN, the Cuckoo Search technique results in optimal DG locations at buses 6, 50, and 18 with corresponding sizes of 2.4576, 1.852, and 2.718 MW, respectively. Voltage improvements are 0.9509, 0.9817, and 0.9821 p.u, while total active and reactive power losses for IEEE 33-bus are reduced by 49.03% and 45.00%, and for IEEE 69-bus by 63.67% and 61.14%. The CSA approach significantly enhances voltage profiles and reduces power losses in these networks.

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1. INTRODUCTION

The efficiency of radial distribution networks (RDNs) is significantly hampered by active power losses occurring across all branches [1]. These losses stem primarily from a high resistance-to-reactance ratio in distribution branches, exacerbated by increasing load demand [2]. To mitigate these losses and enhance network efficiency, researchers have implemented diverse techniques, including deploying capacitors, reconfiguring the network, and integrating distribution static synchronous compensators [3], [4]. However, among these approaches, deploying distribution generators (DGs) has emerged as the most effective. DGs offer the unique capability to contribute both active and reactive power to distribution networks [5]. Notably, type 1 DGs provide these advantages without generating harmful emissions, contributing to environmental sustainability [6]. Yet, optimal planning of DGs is essential to harnessing the full benefits of their deployment in distribution networks. The strategic determination of DG locations and sizes is crucial [7]. Poor planning can adversely affect network functionality. Various planning methods for DGs have surfaced, often utilizing optimization techniques due to the complexity inherent in the configuration of distribution networks with multiple buses and branches [8]. The optimization problems associated with DG planning involve formulating an objective function aimed at minimizing the active power losses and reactive power compensation subject to the operating constraints while adhering to network constraints in RDNs. Solving these problems yields optimal DG locations and sizes, ensuring smooth and efficient RDNs operation [9]–[12]. For voltage profile and voltage stability index improvement, power factor correction, power quality improvement, and a decrease in total voltage harmonic distortion (THD), DG must be positioned correctly in RDN [13].

The literature has documented a variety of optimization techniques, especially metaheuristic approaches, for the purpose of properly sizing and positioning DG in distribution networks. The goal is to lower the total active power loss in the networks while simultaneously improving their voltage profiles, which will increase their efficiency [14]–[16]. Reddy *et al.* [17] used the whale optimization algorithm (WOA) to determine where DGs should be placed in distribution networks in order to minimize power losses, improve voltage profiles, and increase system dependability. Applying WOA to several IEEE test systems, such as 15-bus, 33-bus, 69-bus, and 85-bus configurations, was motivated by the distinctive hunting behavior of humpback whales. Comparative analyses were performed, comparing WOA to several DGs and evolutionary algorithms. The findings showed that WOA and the index vector methods performed better than other strategies, particularly when contrasted with the voltage sensitivity index method. Notably, the study discovered that Type III DGs running at a power factor of 0.9 produced the best results. Understanding the limits of analytical approaches when dealing with numerous DG placements, Kansal *et al.* [18] employed a hybrid strategy in their work to address the best placement of several DGs. The goal of the study was to minimize the objective function under operating restrictions by integrating analytical techniques for DG size with a PSO-based strategy for identifying ideal sites. The suggested method showed gains in the bus voltage profile and DGs' ideal power factor. The efficiency of the hybrid approach on 33-bus and 69-bus test systems was demonstrated by comparisons with particle swarm optimization (PSO) and current fast improved analytical (IA) techniques. In radial distribution systems, Bayat and Bagheri [19] suggested a novel heuristic approach for the best placement of DG and capacitor banks. DG units and capacitor banks were sited and sized using this method, which was based on simple formulations and mathematical calculations, in a variety of bus systems, such as 33-bus, 69-bus, and 119-bus networks. The effectiveness and resilience of the suggested heuristic approach were shown by comparative studies with algorithms from more contemporary techniques, demonstrating its superior performance, speed, and suitability for large distribution networks.

An innovative method was employed by Aman *et al.* [20], who concentrated on the best simultaneous placement and sizing of many DGs to optimize system load-ability while respecting system limitations including voltage magnitudes, line limits, and DG penetration level. The work introduces the hybrid particle swarm optimization (HPSO) algorithm, which prioritizes minimizing power losses and optimizing system load-ability when determining the optimal solution. The effectiveness of the proposed method was evaluated with test systems for radial distribution with 16, 33, and 69 buses. Furthermore, the authors compared the proposed approach with the existing Ettehadi method, demonstrating its superiority in terms of reducing power losses, maximizing system load-ability, and improving voltage quality. In an effort to reduce power loss in distribution networks, Mahmoud *et al.* [21] suggested the best installation plan for a number of DG technologies using an efficient analytical (EA) technique. The process maximized the power factors of several types of DGs, expanding its use to include the distribution of an ideal mixture of different DG types with different generation capacities. Additionally, a novel approach called EA-OPF was developed by combining the EA method with the optimal power flow (OPF) algorithm. This approach effectively managed overall system limitations. Through testing on distribution test systems with 33 and 69 buses, the efficacy of these techniques was shown. The computed results were compared to the simulated results from a comprehensive OPF algorithm for both distribution test systems in order to verify the findings. The outcomes demonstrated that the proposed methods outperformed the state-of-the-art techniques in terms of accuracy and computation speed. Ali *et al.* [22] optimized the positioning and size of DG units in RDNs using the ant lion optimizer (ALO). In particular, 33 and 69 standard bus systems used photovoltaic (PV) cells as DG units with the goal of lowering overall active losses and improving the voltage profile of every bus system. This multi-pronged strategy made use of renewable resources, which enhanced RDN performance and led to greener energy generation. Using numerical comparisons with other optimization methods, the study verified the superiority and efficacy of the suggested ALO algorithm.

Selim *et al.* [23] employed a novel strategy that blended analytical and metaheuristic algorithms for the best DG allocation in radial distribution systems (RDS). The approach used the loss sensitivity factor (LSF) to narrow down the search area for DG placements and an analytical method for determining initial DG sizes using mathematical formulations. The optimal DG allocation was then ascertained by use of a metaheuristic sine cosine algorithm (SCA), which employed the LSF and analytical methods instead of random initialization. In the IEEE 33-bus and 69-bus standard RDSs, the suggested hybrid method showed improved convergence and greater performance. The efficacy of the suggested strategy to effectively distribute several DGs within RDS was demonstrated by comparison with other optimization techniques and regular SCA. The grey wolf optimizer (GWO) was used by El-Sayed *et al.* [24] to solve the problems associated with DG unit integration into distribution systems. This novel method sought to enhance voltage profiles and lower active power losses in radial distribution networks by optimizing the location, size, and quantity of DG units. Through a comparison analysis between GWO and the genetic algorithm (GA) optimization approach, the study proved the superior effectiveness of the proposed GWO strategy. The study concentrated on performance evaluations for IEEE 33-bus and 69-bus test radial distribution systems. Nowdeh *et al.* [25] used a novel approach that used renewable energy sources, specifically solar panels (PVs) and wind turbines (WTs), to address loss reduction and enhance the reliability of radial distribution networks. The authors introduced a new optimization technique known as the multi objective hybrid teaching learning-based optimization-grey wolf optimizer (MOHTLBOGWO) that employs a fuzzy decision-making approach. The proposed method was evaluated on the IEEE 33-bus and 69-bus radial distribution networks using both single-objective and multi-objective optimization techniques. The findings showed that multi-objective optimization offers a more accurate approach that considers all objective indices when compared to single-objective approaches. Additionally, the results demonstrate the effectiveness of the suggested approach in lowering losses, improving reliability, raising net savings, and surpassing earlier research, demonstrating its superior performance over conventional optimization strategies like TLBO and GWO.

Hung and Mithulananthan [26] tackled the problem of positioning several DG units for a notable loss reduction in extensive primary distribution networks in a novel way. Using improved analytical (IA) expressions, their method calculates the ideal size of various DG kinds and identifies the best places for allocation. Additionally, the study outlines novel methods for determining the optimal power factor in DG that can provide both reactive and real power, including exhaustive load flow (ELF) and loss sensitivity factor (LSF). The IA approach outperformed solutions derived from the LSF and ELF approaches, proving their efficacy through extensive testing on three different distribution test systems. El-Fergany [27] used a newly developed swarm optimization technique called the backtracking search optimization algorithm (BSOA) to distribute DGs in radial distribution networks. BSOA was used to improve voltage profiles and reduce network actual loss in an effort to increase operational efficiency. It is notable for having just one control parameter and being insensitive to beginning values. Additionally, power factor optimization and decreased network reactive power loss were the goals of the objective function, which included a weighting factor. The initial DG placements were determined using fuzzy expert algorithms that used bus voltages and loss sensitivity factors. This approach addressed the limitations of loss-sensitivity variables and helped determine the ultimate placement of DGs. The study looked at two different kinds of DGs and validated the proposed approach on a variety of radial distribution networks with different sizes and levels of complexity. Kashyap *et al.* [28] optimized the distribution of DG in radial distribution systems using a GA. The primary goals were to minimize active power losses and keep voltage profiles within predetermined bounds. The IEEE 33-bus and 69-bus systems were tested to assess the efficacy of the strategy.

Most of the reviewed works in this study only addressed distribution network issues such as voltage stability, voltage control, power flow control, power quality improvement, transient and dynamic control, reactive power control, losses reduction, and current control using different Meta-Heuristic optimization techniques. Congestion, line losses, voltage fluctuation, and system running expenses in RDNs persisted despite these methods' inability to considerably lower power losses or enhance the voltage profile. Because of these limitations, this work uses cuckoo search algorithm (CSA) as an optimization technique to determine the ideal location and dimensions of DG on the IEEE 33-bus and IEEE 69-bus test systems, which are industry standards. In the same way, on the useful Nigerian Imalefalafia 32-bus RDN.

The application of CSA to the ideal size and positioning of DGs is still poorly understood, despite the fact that it has proven to be robust in solving optimization challenges. The ability of CSA to handle DG allocation in radial distribution networks is used in this work. A realistic Nigerian radial distribution system and two common IEEE test systems were used as test cases. CSA and other published optimization techniques were compared using IEEE 33-bus and IEEE 69-bus systems. The use of CSA to address DG allocation problems in radial distribution networks is what makes this study novel.

This paper has made the following contributions:

- Development of CSA for DG placement and sizing: introduction of a comprehensive CSA tailored specifically for the optimal placement and sizing of DG within radial distribution networks.
- Application across varied network models: implementation and testing of the CSA approach across diverse radial distribution network models, including IEEE 33-bus, IEEE 69-bus, and practical distribution networks like the Nigerian Imalefalafia 32-bus system.
- Enhanced network performance metrics: enhancement of voltage profiles in the radial distribution networks and reduction of actual and reactive power losses lead to an improvement in network performance measures.
- Comparison against existing optimization techniques: comparative analysis conducted to contrast the effectiveness and superiority of the CSA approach against established optimization methods prevalent in current literature.
- Demonstrated superiority in allocation: evidence showcasing the CSA's superior ability in efficiently allocating DG within radial distribution systems, as substantiated by its enhanced performance in reducing power losses and optimizing voltage profiles.

– Advancements in optimal solutions: demonstrated capability of the CSA approach to consistently identify and offer more optimal solutions for DG placement and sizing, particularly highlighted by its proficiency in handling both active and reactive power loss considerations.

Collectively, these contributions enhance the body of knowledge in power system optimization approaches by advancing the comprehension and implementation of the CSA for optimal DG location and sizing inside radial distribution networks. The framework for the best DG location and sizing in radial distribution networks is described in depth in the following sections of the article. The approach to problem formulation is presented in section 2, with a focus on the use of the CSA optimization technique. The results and discussion from several network models, evaluating real and reactive power losses and voltage profile enhancements, are presented in section 3. The effectiveness of CSA and its wider ramifications are highlighted in section 4, which also offers recommendations for future study directions for the best way to allocate DG in radial distribution networks.

2. METHODOLOGY

This section's goal is to determine the distribution power losses and DG sizing in order to improve the voltage profile.

2.1. Objective function

The goal of the objective function presented in this research is to reduce actual power losses while tackling the distribution network challenge of DG installation and sizing. This objective function is computed as (1)

$$F = P_L = \sum_{i=1}^{N_{br}} R_i \, |I_i|^2 \tag{1}$$

where, R_i and I_i are real current and resistance of the i^{th} branch, respectively. N_{br} is the quantity of branches.

a. Constraints

Inequality and equality constraints are itemized. The bus voltage limits are inscribed as:

b. Restricted voltage amplitudes at the bus

$$V_{min} \le V_i \le V_{max} \tag{2}$$

where V_{min} and V_{max} are the bus voltage amplitudes' lowest and maximum values, respectively.

c. Power limits of DG

$$P_{DGi}^{min} \le P_{DGi} \le P_{DGi}^{max} \tag{3}$$

where P_i is the DG components injected active power at the i^{th} bus.

d. Power balance constraints

$$\sum_{i=1}^{N_{sc}} P_{DGi} = \sum_{i=1}^{N_{sc}} P_{Di} + P_L \tag{4}$$

where N_{sc} is the sum of all the sections, P_L is the system's actual power loss, P_{DGi} is where the bus at i, generates the actual power i, P_{Di} is the bus's i, electricity demand.

2.2. Cuckoo search algorithm

Cuckoos are fascinating birds of prey, attractive in part because of their aggressive methods of reproduction as well as their melodic vocalizations. Some species, such as the Guira and Ani cuckoos, use communal nests where they lay their eggs. In order to increase the likelihood that their own eggs will hatch, they occasionally move the eggs of other species. Numerous species of cuckoo engage in obligatory brood parasitism, whereby they lay their eggs in the nests of other host birds, frequently belonging to distinct species [29]. Three main manifestations of this phenomenon can be distinguished: nest takeover, cooperative breeding, and intraspecific brood parasitism. Sometimes host birds confront invasive cuckoos head-on; they may destroy the foreign eggs or leave their nest to build a new one elsewhere if they find eggs that are not their own. The New World brood-parasitic Tapera is one of the cuckoo species that have evolved to the point where female parasitic cuckoos are skilled at mimicking the color and pattern of the eggs of specific host species. Their reproductive success is eventually increased by this specialization, which lowers the possibility that their eggs will be rejected. Furthermore, several species deposit their eggs at remarkably odd times. Cuckoo parasites frequently choose nest sites where the host bird has just produced eggs. In general, cuckoo eggs hatch a little bit before those of their hosts. When a cuckoo chick hatches, its initial inclination is to kick its host bird's eggs out of the nest so it may get more of the food it provides. Research has also shown that cuckoo chicks may imitate their host chicks' sounds in order to increase their chances of finding food. Three streamlined guidelines are used to provide a concise explanation of the new Cuckoo Search method: There are a certain number of host nests, and a host bird has a probability of identifying a cuckoo's egg that falls between 0 and 1. (2) Future generations inherit nests that produce eggs of the highest caliber. (3) One egg is laid by each cuckoo at a time, and it is deposited in a nest at random. In this case, the host bird has two options: either throw away the egg or leave the nest and build a new one. To simplify, this last assumption roughly says that a percentage pa of the total number of nests are replaced by new nests, each with a fresh set of random solutions. When dealing with a maximizing problem, the value of the objective function may be directly correlated with the fitness of a solution. Fitness functions that mimic genetic algorithms can be created. In this simplistic illustration, each egg in a nest represents a solution, and a cuckoo's egg represents a potential new solution. The idea is to swap out subpar solutions (cuckoos) for possibly better ones in the nests. The focus is on a simpler model where each nest contains just one egg, although this approach can be expanded to scenarios where each nest contains many eggs, indicating a collection of solutions. In accordance with these guidelines, Table 1 presents the basic stages of the CSA technique together with the supplied pseudocode [30].

Table 1. Pseudo code of the CSA via Lévy flights

```
start
  Function of interest f(x), where x=(x1…...xd) T
  create the initial population of
  n host nests xi (i=1, 2.......n)
while Assuming t < MaxGeneration, or (stop condition)
  Receive a random cuckoo via Lévy flights
  Analyze its suitability and quality Fi
  Select at random one of the n nests (let's say, j);
  if (Fi > Fj),
            replace j with the new answer;
end
  A portion (pa) of the worst nests
            are abandoned and replaced with new ones;
  Hold onto the best solutions
            or nests containing high-quality solutions;
  Prioritize the solutions and choose the best one at the moment,
 end while
  Postprocess the data and visualize the outcome.
end
```

When coming up with new solutions, denoted as $x^{(t+1)}$for a cuckoo i, a Lévy flight is executed.

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus \text{Levy}(\lambda) \tag{5}$$

In this context, α, where α > 0, represents the step size, a parameter linked to the problem's scales of interest. Typically, α=1 suffices for most cases. In essence, the given equation describes a stochastic equation for a random walk. Random walks frequently operate as Markov chains, where the transition probability (the second term) and the current location (the first component of the equation) are the sole factors influencing the future position. The symbol ⊕ signifies element-wise multiplication, a concept akin to those employed in PSO. However, because of its significantly greater step length over time, the random walk employing Lévy flight works better in this situation for searching the search space. Lévy flight introduces a random walk where the step length is derived from a Lévy distribution.

$$\text{Levy} \sim u = t^{-\lambda}, \quad (1 < \lambda \leq 3) \tag{6}$$

Algorithm 1. Proposed methodology
Step 1: Initialize the population:
- Generate an initial population of cuckoos representing potential solutions.
- Assign random positions and sizes for the DG unit within the feasible range.

Step 2: Evaluate fitness:
- Determine the overall power loss in the distribution network to assess each cuckoo solution's fitness.
- As the objective function, use the total power loss to gauge fitness.

Step 3: Sort the population:
- In ascending order, arrange the cuckoo solutions according to their fitness levels.
- The cuckoos with lower power loss (better fitness) should be positioned towards the beginning of the sorted list.

Step 4: Generate new solutions:
- Create new solutions (cuckoos) by executing Levy flights or random walks in the solution space.
- The limitations on the DG unit's position and size should be upheld by the Levy flights or random walk.

Step 6: Evaluate new solutions and update the population:
- Determine the overall power loss to assess the suitability of the new options.
- Replace the least-fit cuckoos in the population with new solutions that have better fitness.
- Retain the sorted order of the population.

Step 7: Perform nest destruction and egg laying:
- Randomly select a few cuckoos (nests) from the population.
- Replace their solutions (eggs) with new random solutions within the feasible range.

Step 8: Evaluate new solutions and update the population:
- Evaluate the fitness of the new solutions resulting from nest destruction and egg laying.
- Replace the least-fit cuckoos in the population with new solutions.
- Retain the sorted order of the population.

Step 9: Verify the condition of termination:
- Check to see if the termination condition—such as the maximum number of iterations reached or the desired accuracy of the solution attained—has been satisfied.
- If the termination condition is satisfied, move on to Step 9. If not, return to Step 4.

Step 10: Output the optimal solution:
- Select the cuckoo with the highest fitness (lowest power loss) as the best choice.
- Using the best option, determine the DG unit's position and dimensions.

The algorithm of the proposed method is illustrated in the flowchart as shown in Figure 1.

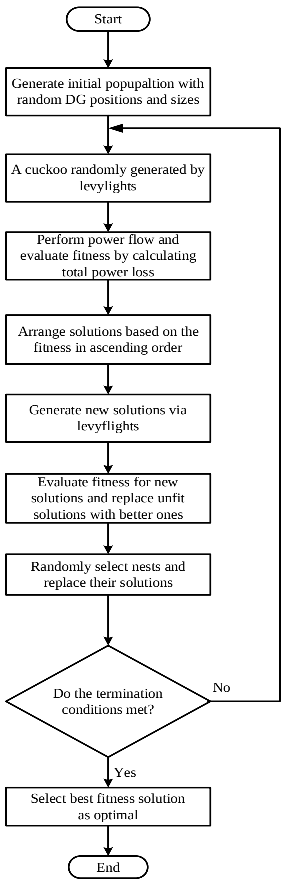

Figure 1. Flowchart of the proposed CSA optimization method

3. RESULTS AND DISCUSSION

The methodology proposed for optimal placement and sizing of DG underwent implementation in MATLAB and was subjected to extensive testing across multiple systems. This section highlights and deliberates upon the test outcomes from three distinct distribution systems. DG was assigned a power factor of one (1). The optimization process employed a CSA program designed specifically for simulating the optimal placement and sizing of DG within radial distribution systems. Table 2 provides detailed parameters of the applied CSA technique used to solve the problems in this research.

Table 2. CSA parameters for simulation

CSA parameters	Values
Number of host nests (*n*)	30
Maximum number of iterations	200
Probability index (*Pa*)	0.25

3.1. Radial distribution system with IEEE 33-bus

The radial structure of the first system, shown in Figure 2, consists of 32 branches and 33 buses, with a combined capacity of 2.295 MVAr and 3.715 MW. Reactive power losses total 102.751 kVAr, but the system's total real power loss, as determined by the backward/forward load flow technique, is 201.58 kW. Table 3 displays the results pertaining to the best positioning and dimensions of DG, together with the convergence pattern depicted in Figure 3. Figure 4 shows the voltage profile along the radial distribution network of IEEE 33-bus. Prior to DG installation, bus 18 showed a low voltage level of 0.9134 p.u., which significantly increased to 0.9505 p.u. after installation. Furthermore, significant improvements in voltage levels were noted for every network bus. The comparison of real and reactive power losses across branches before and after DG installation is shown in Figures 5 and 6, respectively. The results show a notable decrease in overall real power loss after DG installation.

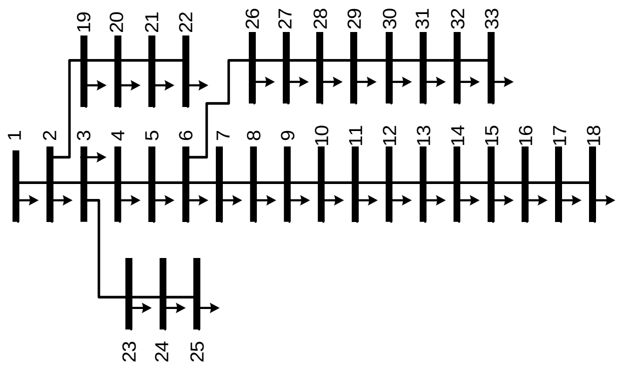

Figure 2. IEEE 33-bus network

Table 3. Optimization Results for IEEE 33-bus network

Optimization parameters	Values
Optimal DG Location	6
Optimal DG Size	2.4576
Objective Function Value (Minimized Total Power Loss in kW)	102.75

3.2. Radial distribution system with IEEE 69-bus

A total load of 3.80 MW and 2.70 MVAr is supported by the 69-bus radial distribution system, which has seven lateral lines and is shown in Figure 7. The optimization results are shown in Table 4, which reveals the optimal location and size of the DG. Figure 8 illustrates the convergence properties of the CSA method and shows its evolution. Figure 9 illustrates the network's voltage profile before and after DG integration in a thorough performance investigation. The network's voltage profile significantly improved after installation, with the minimum voltage at bus 54 rising from 0.9102 p.u. to 0.9817 p.u. Additionally, Figure 10 derived the thorough analysis that shows a significant decrease in actual power losses across the network. In the same way, Figure 11 compares the reactive power losses across network branches. The positive effects of optimally distributed DG through the suggested CSA optimization technique are demonstrated in both figures, particularly the decrease in actual and reactive power losses throughout the network. This demonstrates how well the suggested CSA algorithm works to optimize DG location and sizing, greatly improving network performance as a whole.

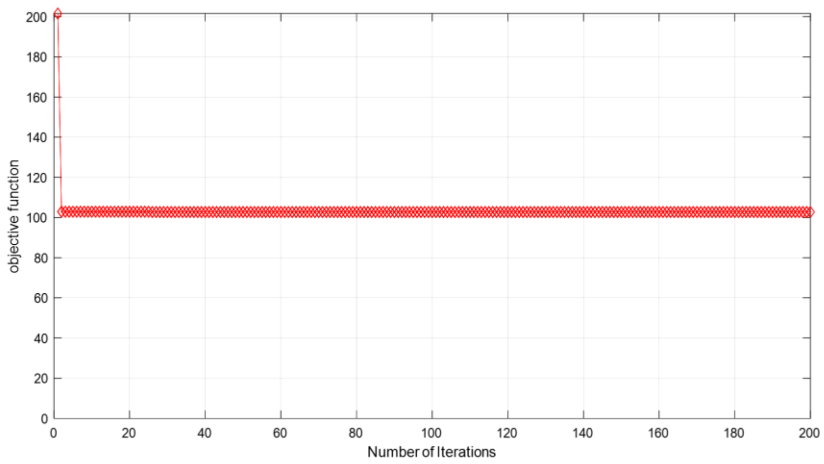

Figure 3. Objective function convergence curve

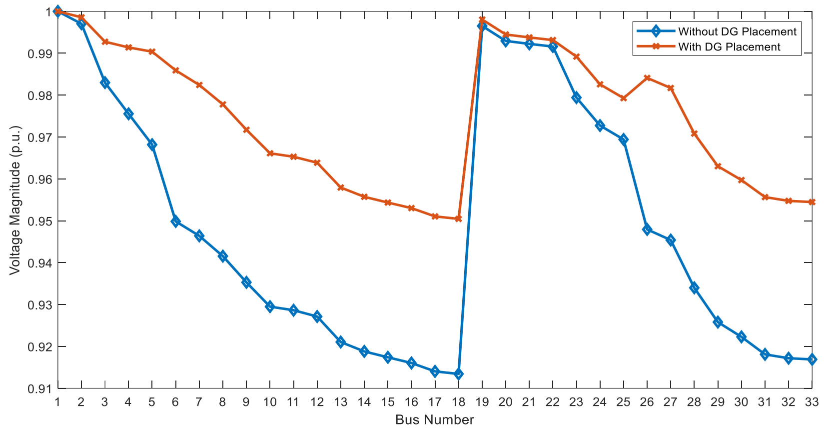

Figure 4. Voltage profile comparison for pre- and post DG installation

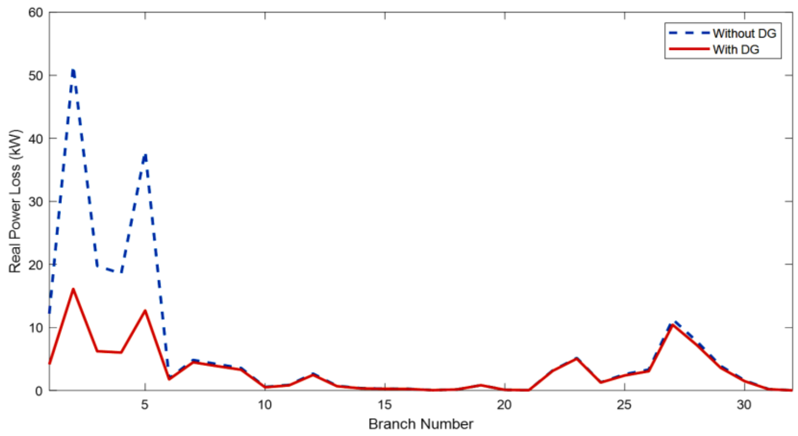

Figure 5. IEEE 33-bus branch real power losses

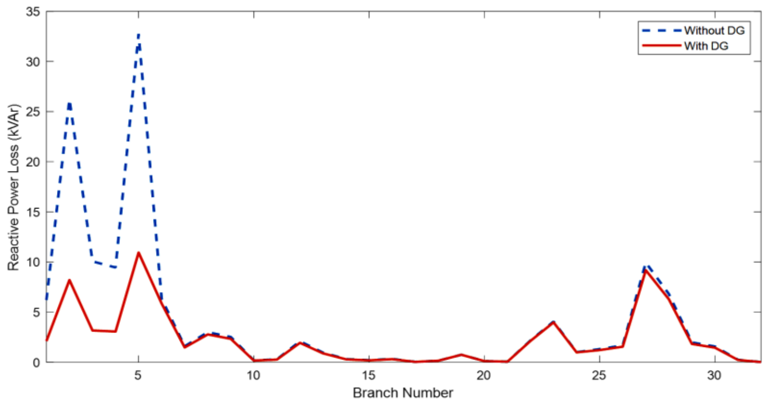

Figure 6. IEEE 33-bus branch reactive power losses

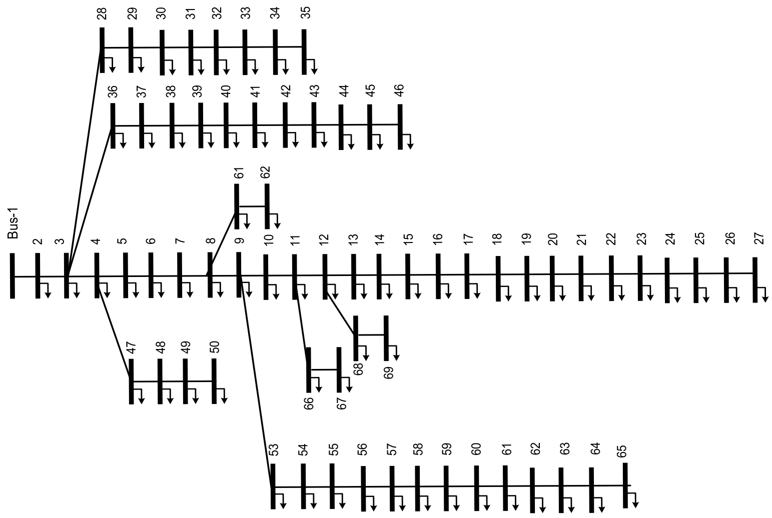

Figure 7. IEEE 69-bus network

Table 4. Results of optimization for the IEEE 69-bus network

Optimization parameters	Values
Optimal DG location	50
Optimal DG Size	1.852
Objective Function Value (Minimized Total Power Loss in kW)	81.593

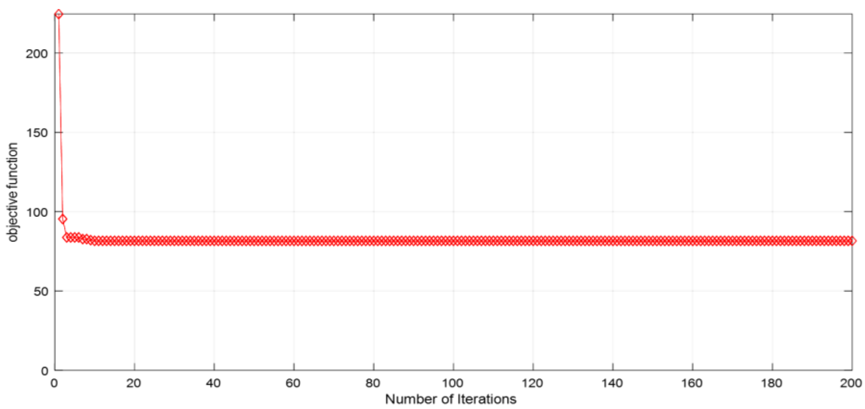

Figure 8. Objective function curve

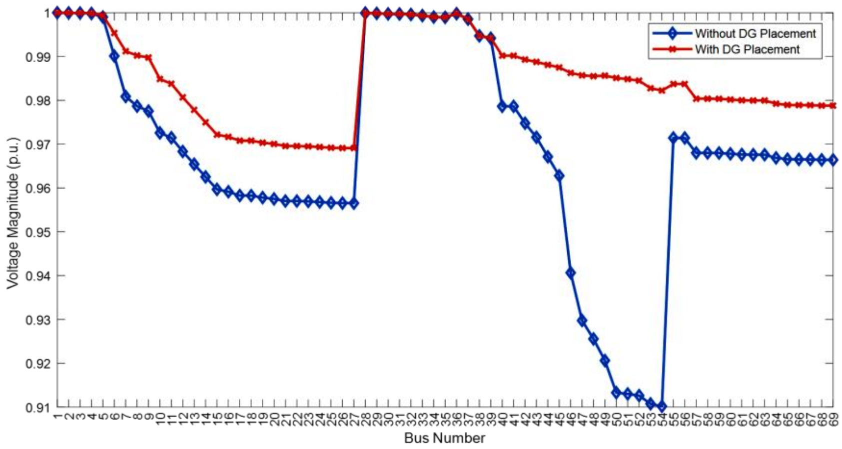

Figure 9. Voltage profile comparison for pre- and post DG installation

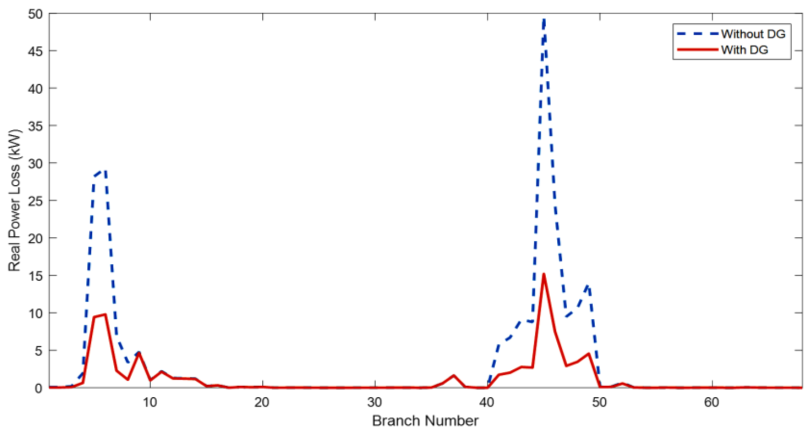

Figure 10. IEEE 69-bus branch real power losses

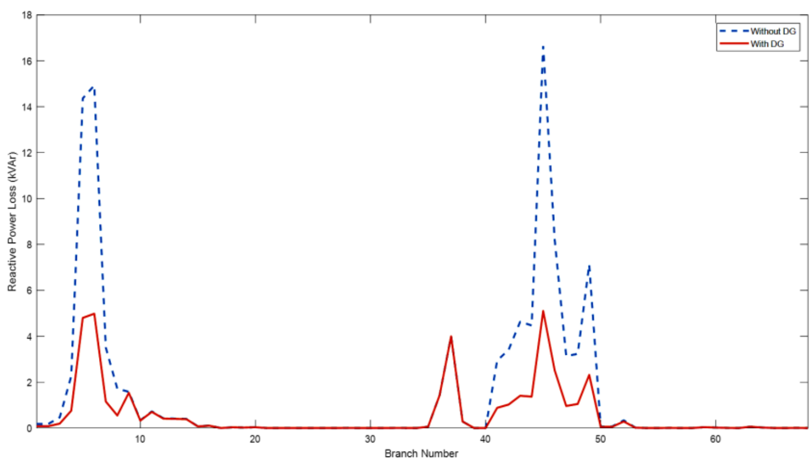

Figure 11. IEEE 69-bus branch reactive power losses

3.2.1. Imalefalafia 32-bus radial distribution system

Figure 12 shows the Imalefalafia, a functional 32-bus radial distribution network operated by the Ibadan Electricity Distribution Company (IBEDC) in Ibadan, Nigeria. The line and bus data for this network were obtained from [31], [32]. It has 31 branches and 32 buses. Its reactive and actual loads are 1.04 MVAr and 3.17 MW, respectively. Using backward/forward load flow techniques, power flow analysis revealed that the network's total active and reactive power losses were 95.068 kW and 163.673 kVAr, respectively. Table 5 presents the optimization results obtained using the suggested CSA optimization method, together with the convergence curve displayed in Figure 13. Furthermore, the network's voltage profile before and after DG installation is shown in Figure 14. This demonstrates how the suggested CSA optimization technique can effectively allocate DG units inside radial distribution networks in order to improve performance. An obvious improvement in the voltage profile in Figure 14 indicates a significant improvement in the network's overall performance following DG installation. Following DG installation, the minimum voltage magnitude increased from 0.9524 p.u. before to 0.9821 p.u. Likewise, all network buses experienced an overall rise in voltage magnitudes. Figure 15 shows significant decreases in real power losses across network branches after DG installation when compared to pre-installation. Reactive power losses are compared across network branches in Figure 16, which shows notable drops after DG installation. The effectiveness of the suggested CSA in strategically allocating DG units within workable radial distribution systems was demonstrated by the overall decrease in real and reactive power losses to 14.778 kW and 25.442 kVAr, respectively, as a result of these reductions across network branches.

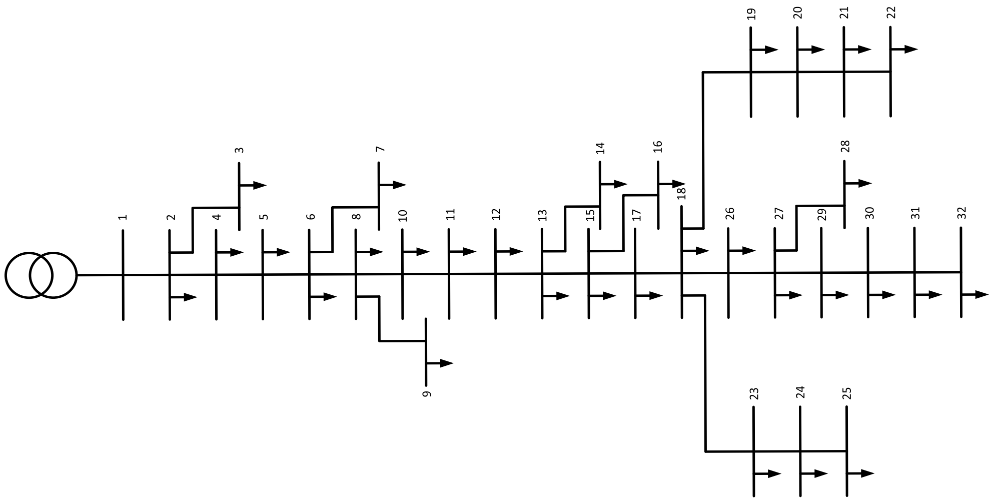

Figure 12. Imalefalafia 32-bus network

Table 5. Optimization results for IEEE 32-bus network

Optimization parameters	Values
Optimal DG Location	18
Optimal DG Size	2.718
Objective Function Value (Minimized Total Power Loss in kW)	14.778

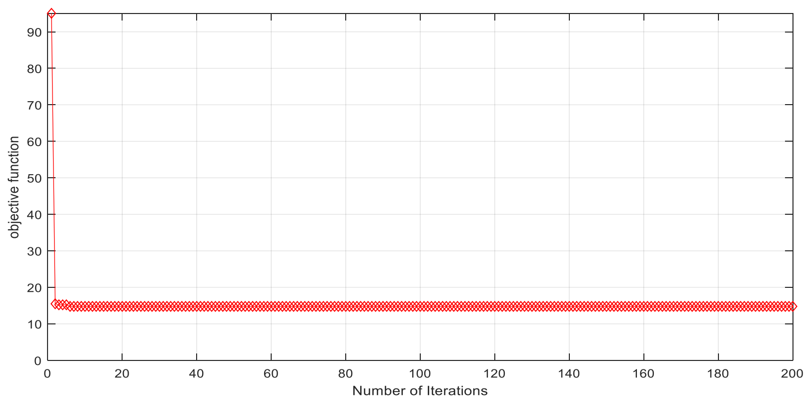

Figure 13. Objective function curve

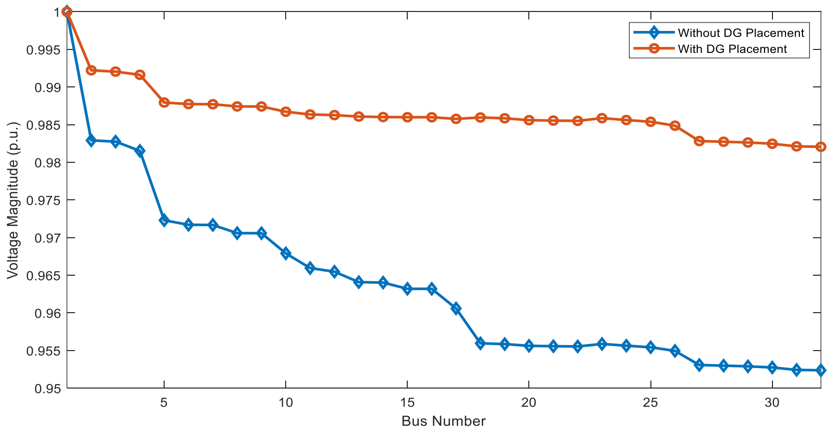

Figure 14. Voltage profile comparison for pre- and post DG installation

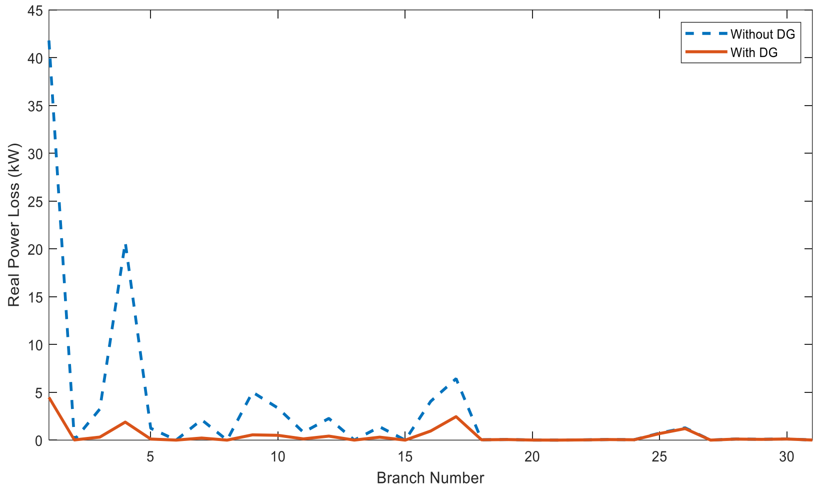

Figure 15. Imalefalafia 32-bus branch real power losses

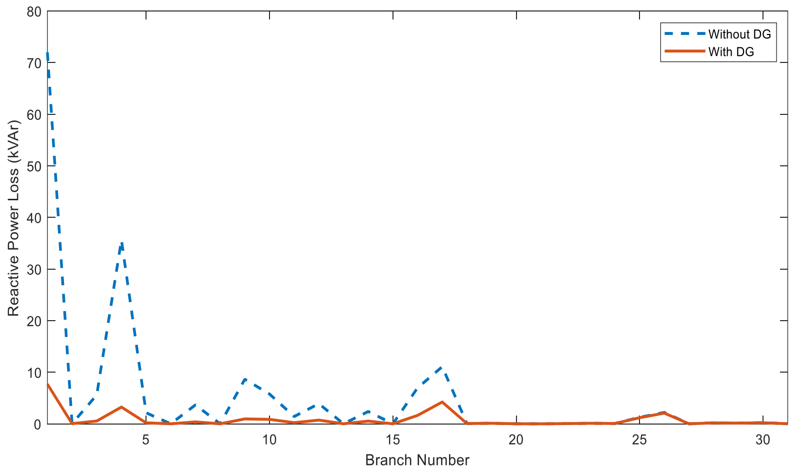

Figure 16. Imalefalafia 32-bus branch reactive power losses

3.2.2. Comparison of the suggested CSA optimization technique with existing literature

The efficiency of the suggested CSA algorithm was confirmed by a thorough comparison with other optimization techniques reported in the literature. Two scenarios were used for the comparison: first, the IEEE

33-bus radial distribution network was used as a benchmark test system, and then the normal IEEE 69-bus radial distribution network was used. The purpose of this comparison study was to show how well the suggested CSA approach works with various radial distribution systems. In Table 6, the suggested CSA approach is contrasted with several metaheuristic techniques used to optimize DG on the IEEE 33-bus radial distribution network. Most methods, except WOA, HPSO, MOHTLBOGWO, BSOA, and TLBO-GWO, identified bus 6 as the optimal DG location. However, there were differences in the optimized DG capacities on this bus, except for SCA, ALO, and PSO, which allocated 2.59 MW as the optimal size, and IA and GA, which allocated 2.60 MW as the optimal DG size. Notably, the proposed CSA technique allocated a DG size of 2.4576 MW (as indicated in Table 6). Additionally, Table 6 illustrates that the proposed CSA method achieved a greater percentage loss reduction of 49.03, demonstrating its superiority over other optimization techniques reported in the existing literature. Moreover, after optimization using the proposed CSA optimization method, the minimum voltage profile also showed improvement compared to other optimization algorithms, as presented in Table 6. Thus, the proposed CSA optimization method proved effective in sizing and locating DG within radial distribution networks, outperforming other optimization methods in this context.

The suggested CSA methods' greater performance over alternative optimization techniques on a larger-scale test system is confirmed by Table 7, which compares them with other approaches on the industry-standard IEEE 69-bus radial distribution network. Several techniques listed in Table 7 were included in the comparison. The best site to put DG was found to be bus 61 by all optimization techniques with the exception of the suggested CSA method. On the other hand, bus 50 was identified as the ideal DG position by the suggested CSA approach. With the exception of the TLBO-GWO approach, it is significant that the suggested method assigned a smaller DG size of 1.852 in comparison to other methods. Comparing the suggested CSA method to other optimization techniques, it significantly outperformed them in terms of reduction percentage, achieving 63.67%. Additionally, as Table 7 illustrates, the suggested CSA method successfully increased the minimum voltage magnitude at bus 27 in comparison to alternative optimization techniques. Comparing the performance of the radial distribution network to other optimization techniques listed in Table 7, the suggested CSA optimization method for DG location and size optimization thus greatly improved the network's performance.

Table 6. Comparison on standard IEEE 33-bus network

Method	Optimal Location	DG Size (MW)	Base Case Power Loss	Power Loss after DG	Percentage Reduction	Minimum Voltage Magnitude
WOA [7]	15	1.061	210.9974	133.503	36.73	0.9327
HPSO [16]	8	3.624	210.99	131.85	37.5	
SCA [19]	6	2.590	210.9862	111.02	47.38	0.9424 (18)
MOHTLBOGWO [21]	30	1.000	210.98	127.28	39.67	0.9285
PSO [14]	6	2.59	211	111.03	47.38	
Hybrid [14]	6	2.49	211	111.17	47.31	
IA [22]	6	2.60	211	111.10	47.39	
Heuristic [15]	6	2.5936	211	111.03	47.38	
BSOA [25]	8	1.8575	210.9862	118.12	44.02	0.9441
GA [26]	6	2.600	210.9862	111.03	47.38	0.9425
ALO [18]	6	2.590	210.9862	111.03	47.38	0.9424 (18)
TLBO–GWO [21]	30	1.000	210.9862	127.28	39.67	0.9285
Hybrid Technique [19]	6	2.5902	210.9862	111.02	47.38	0.9424 (18)
Proposed CSA	6	2.4576	201.58	102.75	49.03	0.9504 (18)

Table 7. Comparison on standard IEEE 69-bus network

Method	Optimal Location	DG Size (MW)	Base Case Power Loss	Power Loss after DG	Percentage Reduction	Minimum Voltage Magnitude (Bus)
WOA [7]	61	1.873	225.023	83.2279	63.01	0.9683
PSO [14]	61	1.870	225	83.2	63.02	N/A
Hybrid [14]	61	1.810	225	83.4	62.93	N/A
Heuristic [15]	61	1.823	225	83.3	62.98	N/A
HPSO [16]	61	3.685	224.95	87.13	61.27	N/A
EA [17]	61	1.878	225	83.23	63.00	N/A
EA-OPF [17]	61	1.870	225	83.23	63.00	N/A
Exhaustive OPF [17]	61	1.870	225	83.23	63.00	N/A
SCA [19]	61	1.873	224.96	83.19	63.04	0.9683 (27)
Hybrid Technique [19]	61	1.873	224.96	83.19	63.04	0.9683 (27)
ALO [18]	61	1.873	224.96	83.22	63.00	0.968287 (27)
TLBO–GWO [21]	61	1.000	224.96	111.56	50.41	0.9478
GWO [20]	61	1.929	224.96	83.24	62.998	0.9687 (27)
MOHTLBOGWO [21]	61	1.000	224.97	111.56	50.41	0.9478
Proposed CSA	50	1.852	224.604	81.593	63.67	0.9691 (27)

4. CONCLUSION

This paper tackles the DG location and capacity allocation problem by introducing the CSA optimization approach. The goal of this technique is to improve DG allocation for lowering actual and reactive power losses while improving voltage profiles inside IEEE 33-bus, IEEE 69-bus, and the real-world Nigerian Imalefalafia 32-bus radial distribution systems. The suggested CSA method and alternative optimization techniques are compared using the IEEE 33- and 69-bus standardized systems. The results show that the suggested CSA optimization approach is consistently better than other approaches for efficiently allocating DG in radial distribution networks. The suggested approach produces the best voltage profile and the lowest levels of reactive and active power losses.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

All data are available in the manuscript.

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