

ENHANCED CUCKOO SEARCH-BASED OPTIMIZATION FOR SINGLE DISTRIBUTED GENERATION PLACEMENT AND SIZING IN RADIAL DISTRIBUTION SYSTEMS

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ORIGINAL STUDY

Enhanced Cuckoo Search-based Optimization for Single Distributed Generation Placement and Sizing in Radial Distribution Systems

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Abstract

This paper presents an Enhanced Cuckoo Search Algorithm (ECSA) to optimally place and size Distributed Generation (DG) in radial distribution systems to minimize real power loss within operating constraints. The proposed ECSA has exponentially decaying adaptive Lévy flights, constraint-aware solution repair with dynamic penalty coefficients, and diversity-directed stochastic replacement to enhance search robustness and convergence speed. It was tested with 30 independent runs on the IEEE 33-bus, IEEE 69-bus, and a practical Nigerian 32-bus distribution network. The simulations show that the ECSA lowers the active power loss of the IEEE 33-bus system from 201.58 kW to 102.75 kW (49.03 %), and the IEEE 69-bus system from 224.60 kW to 81.59 kW (61.67 %), both statistically significant at $p > 0.01$. For the 32-bus network of Imalefalafia, losses were reduced from 95.07 kW to 14.78 kW (84.45 %), and the minimum voltage was increased from 0.9524 p.u. to 0.9821 p.u. For all test systems, the proposed ECSA consistently outperformed fifteen benchmark metaheuristic algorithms in convergence speed, solution quality, and strength, making it useful for DG planning applications.

Keywords: Distributed generation, Enhanced Cuckoo Search Algorithm, Power loss minimization, Voltage profile improvement, Distribution networks, Metaheuristic optimization

1. Introduction

Radial Distribution Systems (RDS) are the last stage in the supply of electric power to end customers and, therefore, an important source of power quality and system reliability. Because of the high resistance-to-reactance (R/X) ratio of distribution feeders and the constant increase in load demand, they tend to exhibit substantial active power losses and poor voltage profiles. [1,2].

Among the technical solutions provided by the researchers [3,4], Distributed Generation (DG) is one of the most effective means to improve the voltage profile and to prevent power loss in radial distribution networks [5,6]. These advantages contribute to increasing interest in DG planning based on optimization for modern distribution networks.

However, careful consideration should be given to the location and magnitude of the DG integration. Unexpectedly, an unplanned deployment can

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result in system problems such as voltage violations, high losses, and protection coordination [7]. The complicated nature of RDS optimization due to highly non-linear power flow equations, as well as multiple operational constraints, has led to extensive study on various other optimization methods [8,9]. Metaheuristic algorithms are gaining popularity for this purpose, as they are known to be able to address non-convex, combinatorial optimization problems without needing any gradient information [10–12].

The existing literature presents a variety of optimal allocations for DG. Alvarado-Reyes et al. [13] used imperialist competitive algorithm to optimize the integration of PV-DG into microgrids, but their reliance on computational resources is generally rare. The Whale Optimization Algorithm (WOA) used by Reddy et al. [14] was effective on larger-scale systems, but also established convergence issues. Knansal et al. [15] used analytical techniques along with Particle Swarm Optimization (PSO) to improve the voltage profile, but the technique exhibited slow convergence and suffered from accuracy issues. Selim et al. [16] combined the Sine Cosine Algorithm (SCA) optimization with analytical methods to optimize the size and location of DG units in RDS, but the technique had a serious convergence challenge. Despite the success of hybrid methods such as Ant Lion Optimizer (ALO) [17] and Grey Wolf Optimizer (GWO) [18], they demand several runs or a high amount of parameter tweaking in order to show good results on average.

Hung and Mithulanathan [19] used an analytical approach based on loss reduction for multi-DG allocation, though the formulation appeared to be limited by the various types of DG. Mahmoud et al. [20] presented the Optimal Power Flow (OPF) technique, which is faster computationally, but not very adaptive to changing conditions on the network. El-Fergany [21] has used the Backtracking Search Optimization Algorithm (BSOA), characterized as robust and simple, but requiring a careful tuning of the control parameters, which is time-consuming, to obtain optimal solutions. Kashyap et al. [22] used the popular Genetic Algorithm (GA), which is robust but converges prematurely and is computationally inefficient.

The trend towards hybrid optimization technologies is indicative of the continuous search for balanced performance. Aman et al. [23] proposed a Hybrid HPSO for multi-constraint scenarios, but they faced a parameter tuning problem also. Bayat and Bagheri [24] introduced a heuristic approach for joint placement of DG and capacitor banks. It is

fast and easy, but has the risk of misshapen global optima in complex networks. Nowdeh et al. [25] proposed a multi-objective hybrid GWO and TLBO algorithm. It was complex to compute, but very powerful and yet at a very high expense. Similarly, machine learning-based optimization has been a promising frontier recently.

Recent studies have made progress in the use of metaheuristic and hybrid optimization techniques in power system applications. Recent studies have utilized metaheuristic algorithms to optimally distribute renewable energy resources, including photovoltaic and wind generators, within distribution networks, effectively reducing power loss and enhancing voltage profiles on IEEE benchmark systems [26]. Hybrid cuckoo-based techniques are also used in engineering optimization. These methods combine cuckoo search with other algorithms to reduce convergence and improve the quality of solutions [27]. Other studies have explored hybrid metaheuristics such as PSO/ABC, PSO/BFO, and CS/BFO to improve power systems' loadability and voltage stability [28]. Pujari et al. [29] utilized GWO-SCA to optimize renewable DG to reduce active power loss and improve voltage profile in RDS. The problem of DG optimization was solved by Ref. [30], using a hybrid Analytical GWO approach to minimize power system interruption and reduce power loss. Rahman et al. [31] investigated optimization of DG placement and sizing in a power system using the Loss Sensitivity Factor-Mutated Ant Lion Optimizer (LSF-MALO) algorithm to minimize power losses, enhance voltage stability, and reduce economic losses. A recent review of hybrid DG placement approaches highlights the growing integration of intelligent search methods to maintain higher reliability in distributed generation planning [32]. Collectively, these developments suggest that hybrid and AI-based approaches are far from promising, but still a challenge in resource-based contexts to implement in practice.

The Cuckoo Search Algorithm (CSA) is a good option here. It is particularly effective in power system optimization problems because it balances exploitation using the Lévy flight mechanisms. But the standard CSA implementations frequently have difficulty with constraint over in complex engineering problems and may require premature convergence or inadequate exploration depth.

Critical research gaps identified from the literature and previous review feedback include:

- Insufficient validation of algorithmic enhancements through rigorous ablation studies.

- Lack of statistical robustness in performance comparisons.
- Inadequate documentation of parameter bounds and constraint handling for reproducibility.
- Limited application to real-world distribution networks with practical validation.

This study specifically addresses these gaps in the design of an Enhanced Cuckoo Search Algorithm (ECSA) with explicit constraint handling mechanisms.

In contrast to the existing CSA, which is based largely on fixed Lévy flight dynamics and random nest replacement, the proposed ECSA provides an enhanced coordinated enhancement system focused directly on convergence behavior. ECSA improves convergence on the search space by means of three tightly coupled mechanisms: exponentially decaying adaptive Lévy flights that promote aggressive global exploration in initial iterations and controlled local use near convergence, constraint-aware solution repair that actively restores feasibility rather than rejecting ineligible candidates, and diversity-based stochastic replacement that prevents premature convergence by regenerating weak-performing solutions when population diversity decreases. Together, these processes enable faster, more stable, and reliable convergence than is usually the case in the CSA.

While some studies have utilized standard or hybridized CSA models for DG placement, the proposed ECSA introduces a novel search model with improved convergence dynamics.

Specifically, the proposed ECSA's novelty is established through the following tightly integrated innovations:

- (i) **Directional Diversity Injection with Targeted Stochastic Replacement:** Unlike classical CSA, where abandoned nests are replaced randomly, the proposed ECSA adds a population-diversity-aware stochastic replacement strategy. Diversity is quantified using a normalized Euclidean measure, and only the best-performing nests are selectively replaced when diversity falls below an adaptive threshold. Also, the substitution is not random but is directed toward promising areas via an injection of diversity through Lévy. This mechanism is not found in existing CSA-based DG placement studies and thus serves to reduce the likelihood of premature convergence.
- (ii) **Constraint-Aware Repair Coupled with Dynamic Penalty Coefficients:** ECSA does not purport to punish infeasible solutions but instead develops a repair-driven feasibility enforcement mechanism by which voltage, DG capacity, penetration limits, and thermal violations are actively corrected using closed form projection rules. These are further complemented by iteration-adaptive penalty coefficients to enable the smooth transition from exploration to strict feasibility enforcement. This double approach provides the opportunity to transform infeasible solutions into desirable solutions rather than them being ignored – a technique not readily employed in existing CSA or hybrid DG optimization methodologies.
- (iii) **Exponentially Decaying Lévy Flight Strategy for Balanced Search:** The Lévy step size is not only adaptive but also follows the exponential decay law so that it can be expanded in the early versions and controlled to exploit near convergence. This time-varying search pressure is also analytically embedded in the flight mechanism and produces a more deterministic exploration/exploitation trajectory than heuristic tuning as seen in earlier works.
- (iv) **Synergistic Integration Validated via Ablation Studies:** This work, in contrast to prior CSA enhancements reporting isolated improvements, rigorously demonstrates, via ablation experiments that adaptive Lévy flights, constraint-aware repair, and diversity-guided replacement create a coordinated performance increase in convergence speed, robustness, and solution quality.

For this reason, the proposed ECSA is not parameterized CSA but a structurally redesigned optimization approach that includes population diversity control, feasibility-preserving repair, and deterministic exploration decay, which is fundamentally different from CSA based and hybrid DG optimization.

Even though adaptive step-size control, constraint handling, and diversity preservation mechanisms have all been used in earlier studies of evolutionary optimization, most enhanced CSA variants treat these strategies as separate or optional improvements. By contrast, the proposed ECSA has a combined enhancement architecture that computes adaptive Lévy flight scaling, feasibility restoration, and diversity-guided nest replacement over multiple iterations of the

optimization cycle. This integrated operational strategy simultaneously ensures feasibility enforcement, exploration-exploitation balance, and preservation of population diversity, and it fundamentally differs from the CSA-based placement and sizing methods previously described.

This research's major contributions are summarized as follows:

1. A structurally improved cuckoo search method that incorporates adaptive Lévy flights, exponential decay, constraint-aware solution repair, and diversity-based stochastic replacement in a single optimization strategy for the placement and positioning of DGs in radial distribution systems.
2. A full performance validation, encompassing ablation studies, the statistical analysis of 30 independent runs, and the use of 15 state-of-the-art metaheuristic algorithms on the IEEE 33-bus and IEEE 69-bus distribution networks.

The rest of this paper is organized as follows: the optimization problem and constraints are formulated in Section 2. Section 3 outlines the proposed ECSA methodology. The experimental results, including ablation studies and statistical benchmarks, are presented in Section 4. Section 5 contains concluding remarks and directions for future research.

2. Problem formulation

Restoration of power and voltage stability are both important, but in this particular case study, minimization of power loss was the focus, as it has a direct bearing on voltage profiles. Minimizing losses contributes to voltage stability across buses and helps operate the network efficiently under different loading conditions.

A deterministic loading model is adopted in this study to isolate the intrinsic optimization behavior of the proposed ECSA and to enable direct and fair comparison with existing DG placement methodologies.

The optimal placement and size of a single DG unit is explored in this study as a planning problem in radial distribution systems. Though modern distribution networks may contain more than one DG unit, single-DG formulation provides both isolation of algorithmic behaviour, avoids combinatorial explosion of the search space, and equal benchmarking against the vast majority of the existing literature reporting single-DG studies. The

proposed Enhanced Cuckoo Search Algorithm is formulation independent and easily extendable to many DG units by building the decision-vector dimension, which clearly has been identified as one of the priorities for future research.

2.1. Objective function

The main objective is to reduce the total active power losses in the radial distribution system through optimal placement and sizing of DG. The objective function is defined as:

$$\min f = P_{\text{loss}}^{\text{total}} = \sum_{k=1}^{N_{\text{br}}} R_k |I_k|^2 \quad (1)$$

where:

$P_{\text{loss}}^{\text{total}}$ = system total active power loss

N_{br} = total number of branches

R_k = branch k resistance

I_k = branch k current magnitude

The branch current is expressed as the bus voltages and network admittance matrix.

$$I_k = \sum_{m=1}^{N_{\text{bus}}} Y_{km} V_m \quad (1a)$$

where:

Y_{km} = elements of the bus admittance matrix

V_m = voltage at bus m

In other words, power loss can be computed by using power flow variables.

$$P_{\text{loss}}^{\text{total}} = \sum_{k=1}^{N_{\text{br}}} \frac{P_k^2 + Q_k^2}{|V_k|^2} R_k \quad (1b)$$

where:

P_k = active power flow in branch k

Q_k = reactive power flow in branch k

V_k = voltage at sending end of branch k

2.2. System operational constraints

2.2.1. Power flow constraints

The power balance equations for each bus i are given by:

$$P_{Gi} - P_{Di} = V_i \sum_{j=1}^{N_{\text{bus}}} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad (2)$$

$$Q_{Gi} - Q_{Di} = V_i \sum_{j=1}^{N_{\text{bus}}} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \quad (3)$$

where:

P_{Gi}, Q_{Gi} = active and reactive power generation at bus i

P_{Di}, Q_{Di} = active and reactive power demand at bus i

G_{ij}, B_{ij} = real and imaginary parts of bus admittance matrix element Y_{ij}

$\theta_{ij} = \theta_i - \theta_j$ = voltage angle difference between buses i and j

2.2.2. Voltage security constraints

Bus voltages must remain within statutory limits to ensure power quality and equipment safety:

$$V_{\min} \leq V_i \leq V_{\max} \quad \forall i \in \{1, 2, \dots, N_{\text{bus}}\} \quad (4)$$

with:

$$V_{\min} = 0.95 \text{ p.u.}$$

$$V_{\max} = 1.05 \text{ p.u.}$$

2.2.3. DG capacity constraints

The size of DG units is constrained by technical and practical considerations:

$$P_{DG}^{\min} \leq P_{DG,i} \leq P_{DG}^{\max} \quad \forall i \in \{1, 2, \dots, N_{\text{bus}}\} \quad (5)$$

with:

$$P_{DG}^{\min} = 0 \text{ MW}$$

$$P_{DG}^{\max} = 3.0 \text{ MW}$$

Additionally, the total DG penetration is limited to maintain system stability:

$$\sum_{i=1}^{N_{\text{bus}}} P_{DG,i} \leq \lambda \cdot \sum_{i=1}^{N_{\text{bus}}} P_{D,i} \quad (6)$$

where $\lambda = 0.6$ represents the maximum allowed DG penetration level (60 % of total load).

2.2.4. Thermal constraints

Line current limits ensure equipment thermal ratings are not exceeded:

$$|I_k| \leq I_k^{\max} \quad \forall k \in \{1, 2, \dots, N_{\text{br}}\} \quad (7)$$

where I_k^{\max} is the thermal rating of branch k .

2.2.5. Power balance constraints

The overall system power balance must be maintained:

$$\sum_{i=1}^{N_{\text{bus}}} P_{Gi} = \sum_{i=1}^{N_{\text{bus}}} P_{Di} + P_{\text{loss}}^{\text{total}} \quad (8)$$

$$\sum_{i=1}^{N_{\text{bus}}} Q_{Gi} = \sum_{i=1}^{N_{\text{bus}}} Q_{Di} + Q_{\text{loss}}^{\text{total}} \quad (9)$$

where $Q_{\text{loss}}^{\text{total}}$ represents total reactive power losses.

2.2.6. Radiality constraints

For radial distribution systems, the network topology must remain radial after DG integration. This can be expressed using graph theory concepts:

$$N_{\text{br}} = N_{\text{bus}} - N_{\text{sub}} \quad (10)$$

where N_{sub} is the number of substations (typically 1).

2.3. Solution space definition

The solution vector for the optimization problem is defined as:

$$\mathbf{x} = [L_{DG}, P_{DG}] \quad (11)$$

where:

$L_{DG} \in \{1, 2, \dots, N_{\text{bus}}\}$ represents DG location (bus number)

$P_{DG} \in [P_{DG}^{\min}, P_{DG}^{\max}]$ represents DG size

For multi-DG extensions, the solution vector can be generalized to $\mathbf{X} = [b_1, P_1, b_2, P_2, \dots, b_k, P_k]$, where k represents the number of DG units.

The feasible solution space \mathcal{F} is defined as:

$$\mathcal{F} = \{\mathbf{x} \in \mathbb{R}^2 \mid \text{all constraints (2)-(10) are satisfied}\} \quad (12)$$

2.4. Power flow analysis formulation

The backward-forward sweep power flow used for fitness evaluation:

Forward Sweep:

$$V_j^{k+1} = V_i^k - Z_{ij} \cdot I_{ij}^k \quad (13)$$

Backward Sweep:

$$I_{ij}^k = \left(\frac{S_j}{V_j^k} \right)^* + \sum_{m \in \mathcal{C}_j} I_{jm}^k \quad (14)$$

where $Z_{ij} = R_{ij} + jX_{ij}$ is line impedance, S_j is complex power at bus j , and \mathcal{C}_j is set of children buses.

3. Enhanced Cuckoo Search Algorithm

3.1. Standard Cuckoo Search Algorithm

The standard CSA mimics the brood parasitic behavior of cuckoo species [33–38], operating on three fundamental principles:

1. Each cuckoo lays one egg in a randomly selected nest.
2. Nests with high-quality eggs are retained for subsequent generations.

3. The number of available host nests is fixed, with a probability p_a of alien egg discovery

3.2. Proposed enhancements

3.2.1. Adaptive Lévy flights with mathematical formulation

The step size in Lévy flights is made adaptive using exponential decay:

$$\alpha(t) = \alpha_0 \cdot \exp\left(-\gamma \cdot \frac{t}{T_{\max}}\right) \quad (15)$$

where,

$\alpha_0 = 0.1$ is the initial step size,

$\gamma = 5$ is the decay rate,

t is current iteration, and

$T_{\max} = 200$.

The Lévy flight step generation follows:

$$\text{step} = \frac{u}{|v|^{\frac{1}{\beta}}} \quad (16)$$

where,

$u \sim N(0, \sigma_u^2)$,

$v \sim N(0, \sigma_v^2)$, and $\beta = 1.5$ for the Lévy distribution.

The standard deviations are computed as:

$$\sigma_u = \left(\frac{\Gamma(1 + \beta) \cdot \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \cdot \beta \cdot 2^{\frac{\beta-1}{2}}}\right)^{\frac{1}{\beta}}, \sigma_v = 1 \quad (17)$$

The new solution generation becomes:

$$x_i^{t+1} = x_i^t + \alpha(t) \cdot \text{step} \cdot (x_i^t - x_{\text{best}}^t) \quad (18)$$

3.2.2. Constraint-aware solution repair with penalty formulation

A multi-term dynamic penalty function that applies to all operational constraints were implemented, for total control of constraint violation.

where:

$\phi_V = 1000$: Voltage constraint penalty coefficient

$\phi_{DG} = 1000$: DG capacity constraint penalty coefficient

$\phi_{\text{pen}} = 1500$: DG penetration limit penalty coefficient

$\phi_I = 1200$: Thermal constraint penalty coefficient

$\phi_{\text{pwr}} = 2000$: Power balance constraint penalty coefficient

$\lambda = 0.6$: Maximum DG penetration level (60 % of total load)

The augmented objective function becomes:

$$F(x) = P_{\text{loss}}^{\text{total}}(x) + P(x) \quad (20)$$

Constraint Repair Mechanism

For severe violations, direct repair mechanisms (Equations (21)–(24)) ensure the solution can be satisfied by direct repair, while adaptive penalty coefficients (Equation (25)) create sufficient constraint pressure in the optimization process.

Voltage Violation Repair:

$$V_j^{\text{repaired}} = \min(V_{\max}, \max(V_{\min}, V_j)) \quad (21)$$

DG Capacity Repair:

$$P_{DG}^{\text{repaired}} = \min(P_{DG}^{\max}, \max(P_{DG}^{\min}, P_{DG})) \quad (22)$$

Penetration Limit Repair:

$$P_{DG}^{\text{adjusted}} = \min\left(P_{DG}, \lambda \cdot \sum_{i=1}^{N_{\text{bus}}} P_{D,i}\right) \quad (23)$$

Thermal Limit Repair:

If $|I_k| > I_k^{\max}$, the solution is rejected and regenerated using:

$$x_{\text{new}} = x_{\text{best}} + \mathcal{N}(0, \sigma^2) \cdot (1 - D(t)) \quad (24)$$

Adaptive Penalty Coefficients

As iterations progress, the penalty coefficients change:

$$\phi(t) = \phi_0 \cdot \left(1 + \frac{t}{T_{\max}}\right) \quad (25)$$

As the algorithm approaches the ultimate solution, this guarantees more stringent constraint enforcement.

$$\begin{aligned} P(x) = & \phi_V \cdot \sum_{j=1}^{N_{\text{bus}}} [\max(0, V_j - V_{\max})^2 + \max(0, V_{\min} - V_j)^2] + \phi_{DG} \cdot [\max(0, P_{DG} - P_{DG}^{\max})^2 \\ & + \max(0, P_{DG}^{\min} - P_{DG})^2] + \phi_{\text{pen}} \cdot \max\left(0, \sum_{i=1}^{N_{\text{bus}}} P_{DG,i} - \lambda \cdot \sum_{i=1}^{N_{\text{bus}}} P_{D,i}\right) + \phi_I \cdot \sum_{k=1}^{N_{\text{br}}} \max(0, |I_k| - I_k^{\max})^2 \\ & + \phi_{\text{pwr}} \cdot \left[\left(\sum_{i=1}^{N_{\text{bus}}} P_{Gi} - \sum_{i=1}^{N_{\text{bus}}} P_{Di} - P_{\text{loss}}^{\text{total}} \right)^2 + \left(\sum_{i=1}^{N_{\text{bus}}} Q_{Gi} - \sum_{i=1}^{N_{\text{bus}}} Q_{Di} - Q_{\text{loss}}^{\text{total}} \right)^2 \right] \end{aligned} \quad (19)$$

3.2.3. Targeted stochastic replacement with diversity measure

The diversity of population is measured using:

$$D(t) = \frac{1}{n \cdot L} \sum_{i=1}^n \sqrt{\sum_{j=1}^d (x_{ij}^t - \bar{x}_j)^2} \quad (26)$$

where $n = 40$ is population size, $d = 2$ (location and size), L is the diagonal length of search space, and \bar{x}_j is the mean of j -th dimension.

The replacement threshold is adaptive:

$$p_a(t) = 0.25 \cdot \left(1 - \frac{D(t)}{D_{\max}}\right) \quad (27)$$

The directional diversity injection follows:

$$x_i^{t+1} = x_i^t + \beta \cdot (x_{\text{best}}^t - x_i^t) + \mathcal{L}(\lambda) \cdot (1 - D(t)) \quad (28)$$

where $\beta = 0.5$ controls directional bias and $\mathcal{L}(\lambda)$ is Lévy random number.

3.2.4. Formal definition of the proposed ECSA framework

The proposed ECSA is formally defined as a triple-enhancement of the standard CSA, in which the search dynamics are controlled by:

$$\text{ECSA} = \{ \mathcal{L}_{\text{adp}}, \mathcal{R}_{\text{con}}, \mathcal{D}_{\text{rep}} \} \quad (29)$$

where

\mathcal{L}_{adp} = adaptive Lévy flight with exponential decay (Eqs. (15)–(18)), \mathcal{R}_{con} = constraint-aware repair mechanism with dynamic penalty enforcement (Eqs. (19)–(25)), and \mathcal{D}_{rep} = diversity-guided stochastic replacement strategy (Eqs. (26)–(28)).

At each iteration t , the candidate solution update is defined as:

$$X_i^{t+1} = \mathcal{D}_{\text{rep}}(\mathcal{R}_{\text{con}}(X_i^t + \alpha(t) \cdot \text{Levy}(\lambda))) \quad (30)$$

which ensures that each new solution is infused with exploration–exploitation control, feasibility restoration, and diversity preservation. This converged formulation provides a difference in the proposed ECSA from other CSA variants that employ these mechanisms independently or heuristically.

3.3. Convergence criteria

The algorithm terminates when either:

$$t \geq T_{\max} \text{ or } \frac{|F_{\text{best}}^t - F_{\text{best}}^{t-10}|}{F_{\text{best}}^{t-10}} \leq \epsilon \quad (31)$$

where $\epsilon = 10^{-5}$ is the convergence tolerance.

3.4. Algorithm implementation

Step 1: Initialization Phase

- Initialize population of $n = 40$ host nests with random feasible solutions within bounds:

$$x_i^0 = [L_{DG,i}, P_{DG,i}] \quad (32)$$

where $L_{DG,i} \in \{1, 2, \dots, N_{\text{bus}}\}$, $P_{DG,i} \in [P_{DG}^{\min}, P_{DG}^{\max}]$

- Set algorithm parameters: $T_{\max} = 200$, $\alpha_0 = 0.1$, $\gamma = 5$, $\beta = 0.5$, $p_a = 0.25$, $\epsilon = 10^{-5}$
- Initialize penalty coefficients: $\phi_V = 1000$, $\phi_{DG} = 1000$, $\phi_{\text{pen}} = 1500$, $\phi_I = 1200$, $\phi_{\text{pwr}} = 2000$

Step 2: Fitness Evaluation

For each solution x_i :

- Perform backward-forward sweep power flow analysis using Equations (13) and (14)
- Calculate base power loss using Equation (1)
- Compute constraint violations penalty using comprehensive Equation (19)
- Evaluate augmented fitness using Equation (20):

Step 3: Population Sorting

- Order all solutions according to fitness values from small to large: $F(x_1) \leq F(x_2) \leq \dots \leq F(x_n)$
- Identify current best solution x_{best}^t

Step 4: Main Optimization Loop

While $t < T_{\max}$ and $\frac{|F_{\text{best}}^t - F_{\text{best}}^{t-10}|}{F_{\text{best}}^{t-10}} > \epsilon$:

Adaptive Lévy Flight Generation

For each solution x_i^t :

- Compute adaptive step size using Equation (15)
- Generate Lévy flight step using Mantegna's algorithm Equation (16)
- Create new candidate solution using Equation (18)

Comprehensive Constraint Handling

For each new candidate solution:

- Apply direct repair mechanisms for severe violations (Eq. (21)–(24))
- Evaluate constraint violations using comprehensive penalty function Equation (19)
- Update adaptive penalty coefficients using Equation (25)
- Compute augmented fitness Equation (20)

Greedy Selection

- Consider the new candidate x_i^{t+1} to be compared with existing x_i^t

- Get the solution with best fitness value

Diversity-based Targeted Replacement

- Calculate population diversity using Equation (26)
- Calculate the probability of adaptive replacement using Equation (27)
- Identify worst $p_a(t) \times n$ solutions
- Use directional diversity injection (Equation (28)) to replace these.

Population Update and Sorting

- Evaluate fitness of newly replaced solutions
- Merge population and sort by ascending fitness
- Update global best solution
- Increment iteration counter: $t = t + 1$

Step 5: Termination and Output

- Return optimal DG configuration $x^* = [L_{DG}^*, P_{DG}^*]$
- The output performance metrics are reduction in power loss, voltage profile and convergence statistics.

Step 6: Solution Validation

Verify that the final solution satisfies all operational constraints (Equations (2)–(10)).

The following pseudocode provides an overview of the entire work flow of the proposed ECSA for clarity and reproducibility.

3.5. Pseudocode of the proposed ECSA

```

Start
Initialize N host nests  $X_i = [bus_i, DGsize_i]$  within bounds
Initialize penalty coefficients  $\alpha_v, \alpha_{dg}, \alpha_{pen}, \alpha_{th}, \alpha_{pb}$ 
Evaluate fitness of all nests using backward/forward sweep
power flow
Identify global best solution  $X_{best}$ 
for  $iter = 1$  to  $MaxIter$ 
  Compute adaptive step size  $\alpha(iter)$  using Eq. (15)
  for each nest  $X_i$ 
    Generate Lévy flight step  $L_i$  using Eq. (16)
    Create new solution  $X_{new} = X_i + \alpha(iter) \times L_i$  (Eq. 18)
    Apply constraint-aware repair (Eqs. 21–24)
    Compute augmented fitness  $F(X_{new})$  using Eq. (20)
    if  $F(X_{new}) < F(X_i)$ 
       $X_i = X_{new}$ 
    end if
  end for
  Compute population diversity Using Eq. (26)
  Compute adaptive replacement probability  $P_{repl}$  using Eq. (27)
  Replace worst nests using directional diversity injection (Eq. 28)
  Update adaptive penalty coefficients using Eq. (25)
  Update  $X_{best}$ 
end for
return  $X_{best}$ 
End

```

3.6. Computational complexity analysis

For a population size of $n = 40$, the time complexity in one iteration is $O(n \cdot N_{bus}^2)$ due to power flow solutions. The space complexity for storing the population is $O(n \cdot d)$. For fair comparison, all benchmark algorithms (GA, PSO, GWO, DE, ABC, CSA and hybrid versions) were designed with parameters recommended in the initial paper or well-known ranges in the current literature. Where multiple parameter settings were available, preliminary pilot runs were conducted to select values that yielded stable convergence behaviour on the test systems. Additionally, all algorithms were run at the same population sizes, stop filters, and maximal iteration limits to avoid implementational bias and to ensure that the observed performance enhancements of the proposed ECSA arise from the algorithm rather than by the preferential tuning of parameters.

4. Results and discussion

This section emphasizes interpretation of the numerical findings. The results are discussed in terms of behavior on the system level, convergence characteristics, improved voltage stability and robustness of the proposed ECSA so as to give clarity about the reasons for the product's superior performance beyond that of numerical comparison.

4.1. Experimental setup

All simulations were carried out using MATLAB R2021a on a PC with an Intel Core i7 processor and 16 GB of RAM for easy reproducibility. Table 1 lists the parameter settings to ensure transparency for follow-up studies. All the optimizations were repeated 30 times using different seeds in order to ensure their statistical significance. The power flow analysis of the radial distribution network was solved utilizing the backward-forward sweep technique. To ensure statistical accuracy, each optimization algorithm was run 30 times randomly using different seeds.

4.2. Statistical evaluation protocol

To ensure the stochasticity of metaheuristic algorithms, all optimization experiments were conducted 30 times on different random seeds. For each test system and optimization method, power loss values were averaged and optimized for the average, mean, and standard deviation over 30 independent runs. This statistical reporting (mean,

standard deviation) ensures that these performance differences are not random initializations but consistent algorithmic behavior. These values of power loss were reported as the best, mean, and standard deviation, respectively, for each method. The results of this statistical analysis ensures that the results provided are representative of the entire performance of the algorithm rather than being isolated from the rest.

In addition to the solution quality, the estimated average execution time of the proposed ECSA was also derived to measure computational efficiency. The average execution times of the ECSA were 1.42 s and 1.88 s on the IEEE 33-bus and IEEE 69-bus test systems, when implemented in MATLAB R2021a on an Intel Core i7 processor with 16 GB RAM. For fairness of reporting, execution times of other algorithms are not included, as they were adopted from published studies executed under different computational environments.

4.3. Performance on IEEE 33-bus system

The IEEE 33-bus system is a standard benchmark for distribution system research, with 32 branches with a total capacity of 3.715 MW and 2.295 MVar. In Fig. 1, the system configuration is illustrated with losses of 201.58 kW (active) and 102.751 kVar (reactive).

The optimization results achieved by the proposed ECSA methodology are presented in Table 2. The algorithm decided bus 6 was the best site with DG capacity of 2.4576 MW, which resulted in a 49.03 % reduction of active power losses. The convergence behavior in Fig. 2 is a successful accelerated journey toward an optimal solution with stable convergence features. All performance values for the IEEE33-bus system are based on the average of 30 independent simulation runs.

Significant improvements in the voltage profile were notable. As illustrated in Fig. 3, the minimum voltage at bus 18 was drastically increased from 0.91341 to 0.95051 p.u. This was after DG integration. Also, the results presented evidence of a

significant positive impact of optimal placement of DG on both network buses.

Fig. 3 shows the voltage profile across the IEEE 33-bus RDS. Bus 18 was pre-installed with DG at 0.91341 p.u., but was significantly higher, at 0.95051 p.u., after installation. Also, the voltages were significantly increased over all network buses. Figs. 4 and 5 compare both real and reactive power losses in the lines with and without DG installation, demonstrating that aggregate active power loss after DG installation is significantly lower.

The effectiveness of this approach has also been further tested by the distribution of power losses across network branches. Fig. 4 compares the power losses before and after DG installation, showing significant reductions across the system. Comparable improvements in reactive power losses are also shown in Fig. 5, where the suggested approach achieves balanced optimization in both the active and reactive power domains.

4.4. Validation on IEEE 69-bus system

The larger IEEE 69-bus system is represented in Fig. 6 and is the largest, with active and reactive loads of 3800 kW and 2700 kVar, respectively, and with 68 branches connected. This complex network was a perfect test for assessing the feasibility of the proposed methodology. The IEEE 69-bus system without DG installation has an active power loss of 224.604 kW, which is consistently used as the reference for all of the comparative approaches.

The optimization results are reported in Table 3, showing that bus 50 was chosen by ECSA as the optimal location for DG with an optimal capacity of 1.8520 MW. The DG installation dramatically reduced the active power by an astounding 63.67 %. Fig. 7 shows a robust performance even with a more complex system. The optimized results for the IEEE 69-bus system are based on mean results from 30 independent simulation runs.

Voltage profile analysis in Fig. 8 demonstrates significant network improvements. The minimum voltage at bus 54 was increased from 0.9102 p.u. to 0.9817 p.u., which indicates a significant increase in voltage stability. For both real and reactive power, a complete analysis of the losses showed consistent performance across the network, but considerable loss reduction was observed in the majority of branches.

Figs. 9 and 10 provide further insight of how successful the ECSA is in improving the performance of the radial distribution system. The active and reactive power losses on the network lines continuously and uniformly reduce with optimally

Table 1. ECSA parameter settings.

Parameter	Value	Description
n	40	Population capacity
T_{max}	200	Maximum Number of iterations
p_a	0.25	Discovery rate
α_0	0.1	Initial step size
γ	5	Decay rate
β	0.5	Directional bias

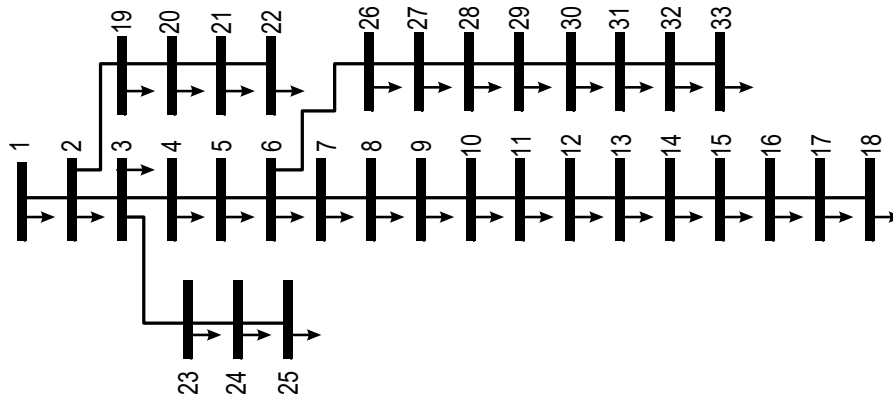


Fig. 1. IEEE 33-bus network.

Table 2. Optimal simulation outcomes for IEEE 33-bus system.

Parameter	Magnitude
DG Bus	6
DG Capacity (MW)	2.4576
Reduced Network Power Loss (kW)	102.75

placed DG. This systematic reduction is not just a consequence of DG injection, but a direct effect of the better search dynamics of ECSA and its intelligent ability of matching the available DG capacity with the loading conditions locally to the system.

The proposed ECSA has a balanced exploration–exploitation strategy, a feasibility-preserving repair mechanism and a diversity-guided replacement scheme that is likely to yield a better performance on the IEEE 69-bus system. This integration of these features allows for avoidance of

local optima and solution viability, allowing faster convergence and better loss minimization than conventional CSA or other metaheuristics.

4.5. Real-world application: imalefalafia 32-bus network

The proposed technique, ECSA, was applied to the 32-bus network of the Ibadan Electricity Distribution Company (IBEDC) in Nigeria. Fig. 11 [39] depicts the one-line diagram of this practical network, having 32 buses and 31 branches with 3.17 MW of active power and 1.04 MVar of reactive power connected.

The results of optimization are shown in Table 4, where bus 18 was identified as the optimal location with an optimal size of 2.7180 MW. The base case analysis showed losses of 95.068 kW

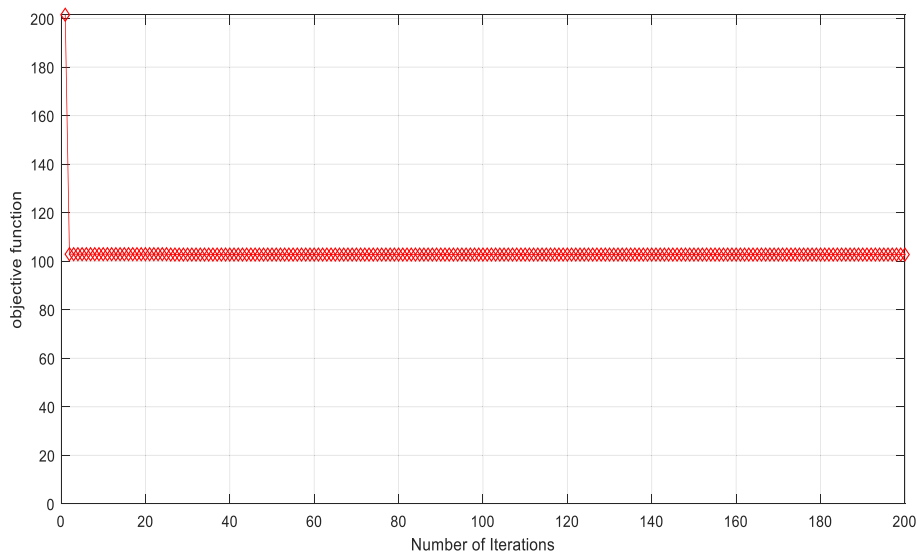


Fig. 2. Convergence curve.

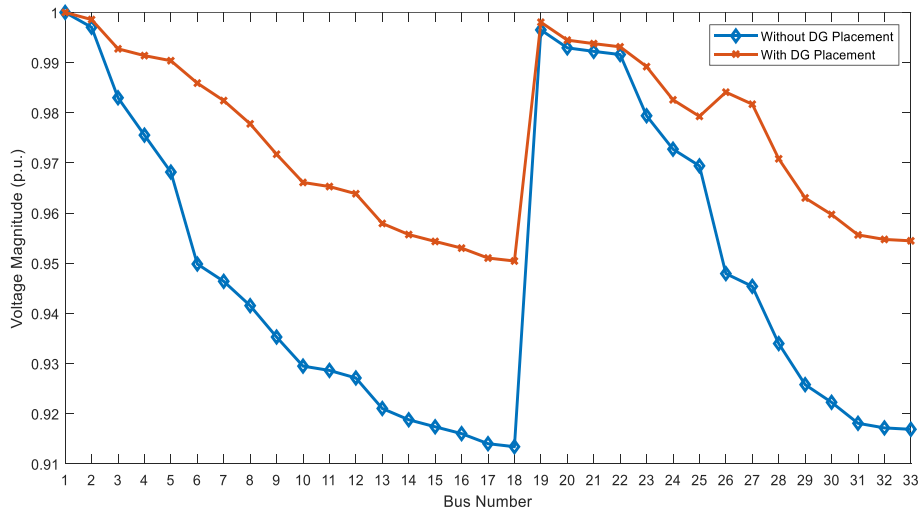


Fig. 3. Voltage profile before and after DG integration.

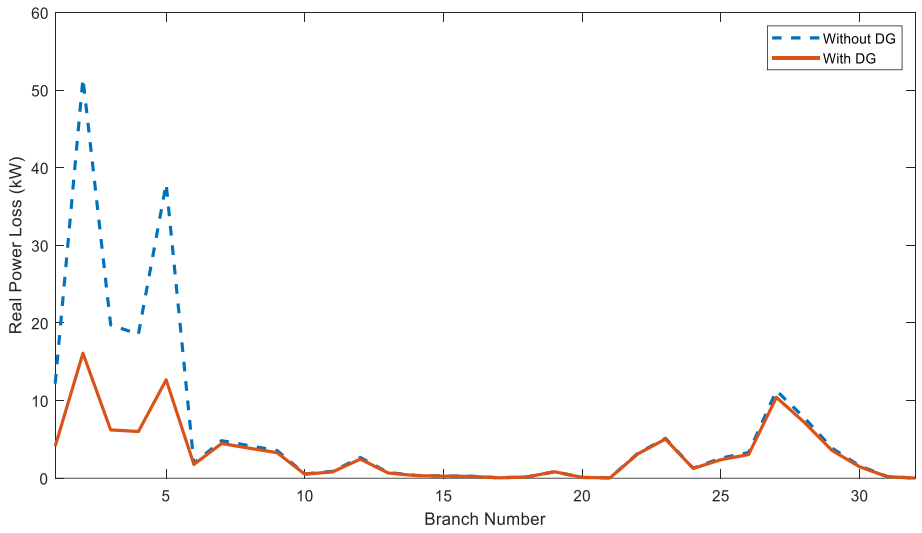


Fig. 4. Real power losses across branches of the IEEE 33-bus network.

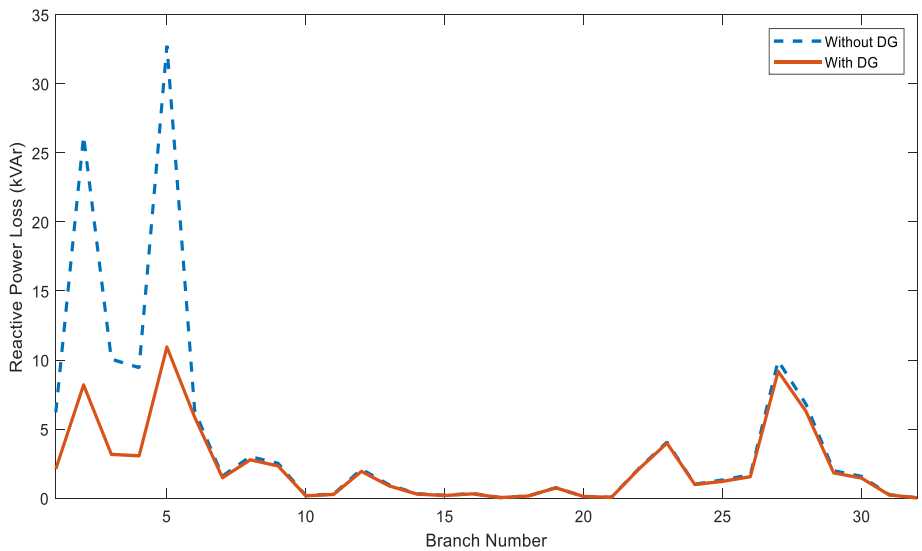


Fig. 5. Reactive power losses across branches of the IEEE 33-bus network.

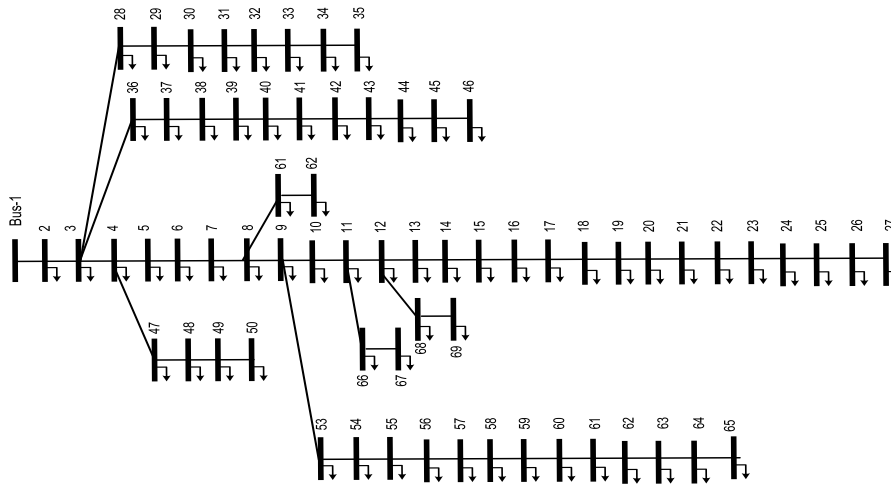


Fig. 6. IEEE 69-bus system.

Table 3. Optimal simulation outcomes for IEEE 69-bus system.

Parameter	Magnitude
DG Bus	50
DG Capacity (MW)	1.8520
Reduced Network Power Loss (kW)	81.5930

(active) and 163.673 kVAr (reactive). After optimization, the network's total active power loss was significantly diminished to 14.778 kW, corresponding to an 84.45 % reduction. Fig. 12 shows the performance of the algorithm on this practical distribution network.

Fig. 13 shows a significant improvement in the voltage profile with the minimum voltage increasing from 0.9524 p.u. to 0.9821 p.u. Figs. 14 and 15, which show real and reactive power loss distributions across branches, respectively, show the consistency of the methodology with large-scale network-wide reductions.

4.6. Ablation study: quantitative analysis of algorithmic enhancements

A systematic ablation test was run on the IEEE 33 bus test system to examine the performance contribution of the proposed improvements. By contrasting the full ECSA with a number of degraded variants, including Standard CSA, CSA with only Adaptive Lévy Flights, CSA with only Constraint-Aware Repair, and CSA with only Targeted Stochastic Replacement, this study has separated the effects of each modification. To keep the statistics robust, each variant was run a minimum of 30 times.

It is evident from the convergence characteristics displayed in Fig. 16 and Table 5 that every

component is involved. The Standard CSA has the slowest convergence of all the CSAs; it takes about 31 iterations to stabilize at a mean power loss of 112.34 kW. The enormous exploration-exploitation imbalance of the baseline performance increases the search time and makes it susceptible to getting trapped in local optima.

Individual upgrades lead to specific and quantifiable enhancements such as:

- Exploration time is greatly reduced by the adapted Lévy Flights. It is the one that converges faster in the first iterations, stabilizing after 12 iterations, which is 40 % faster than CSA usually does. The larger adaptive measures guarantee a more efficient global search through the direct increment of the mean quality of the solutions, resulting in a better mean solution quality of 107.21 kW. But the perpetual oscillation until convergence indicates that there is a slight loss of fine-tuning capability at the last performance step.
- Constraint-aware repair is the most important factor in the availability and stability of solutions. Though the convergence rate is 17 iterations and the mean loss is 110.25 kW, its smoothest convergence curve has less oscillation, and its smoothest curve has a higher frequency. This illustrates its ability to continually drive populations to the feasible location in order to decrease computational waste on incorrect approaches. The low standard deviation across runs confirms that it is a factor in optimizing algorithms.
- Targeted Stochastic Replacement can be used to maintain population diversity. This option

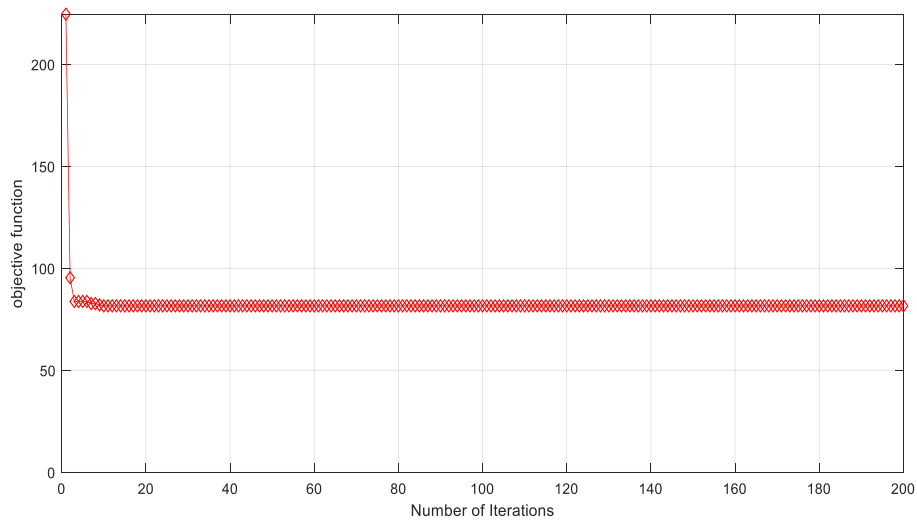


Fig. 7. Convergence curve.

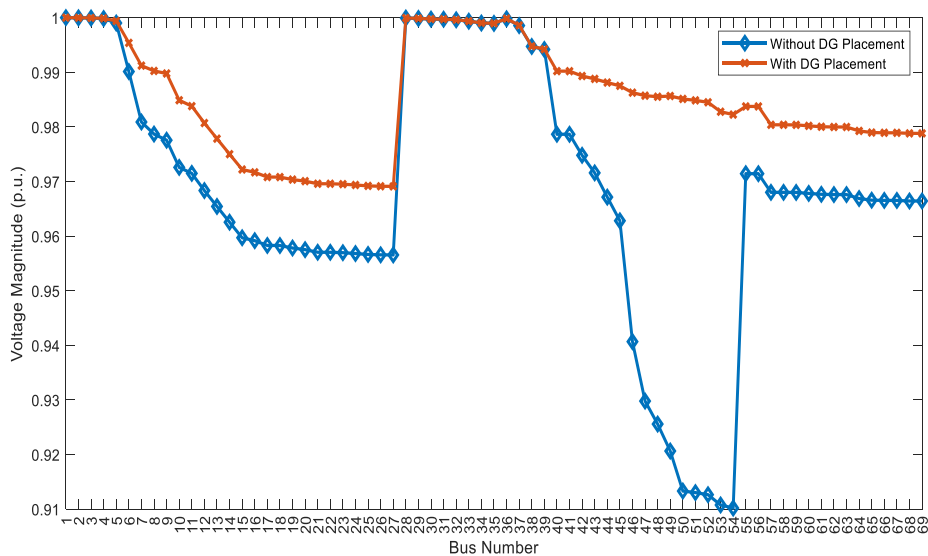


Fig. 8. Voltage profile before and after DG integration.

prevents premature stagnation by fixing the poorest performing solutions. It results in a competitive mean loss of 108.62 kW and is balanced on speed and quality in both speed and solution quality.

The whole ECSA with all three enhancements combines these effects, but there is a clear synergy. This optimizes the aggressive expansion of V2, the feasibility guidance of V3, and the diversity preservation of V4 for a performance that is beyond any component.

In particular, if the entire ECSA is converged within 10 iterations and at least 20 % faster than the previous best variant, then the latter reaches the

lowest absolute power loss in 103.15 kW. It also produces the lowest standard deviation (0.38 kW) in all runs, which is evidently why it stands as superior reliability and stability. This indicates that the enhancements all work better to achieve the exploration-exploitation trade-off as a whole, and provide a fast, direct, and reliable way to a quality global optimal.

The ablation study results show that each enhancement fixes a weakness in the standard CSA. Flexible Lévy flights help exploration early, constraint-aware repair promotes feasibility and stability, and individual stochastic replacement maintains population diversity. This synergy ensures the maximum possible completion of ECSA

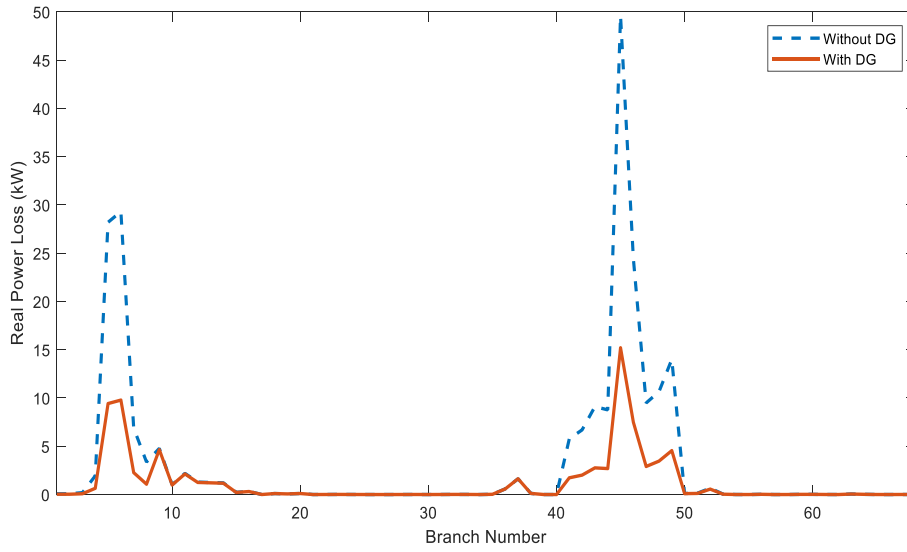


Fig. 9. Real power losses across branches of the IEEE 69-bus network.

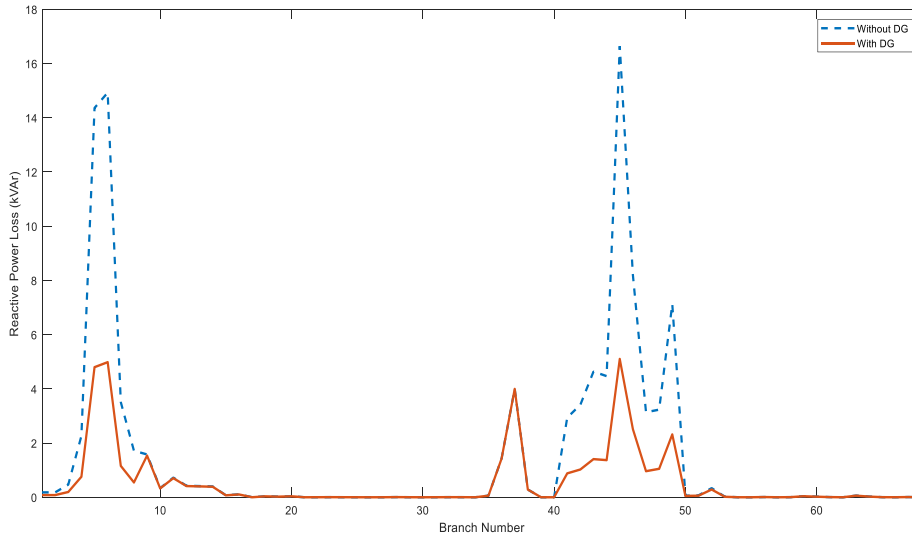


Fig. 10. Reactive power losses across branches of the IEEE 69-bus network.

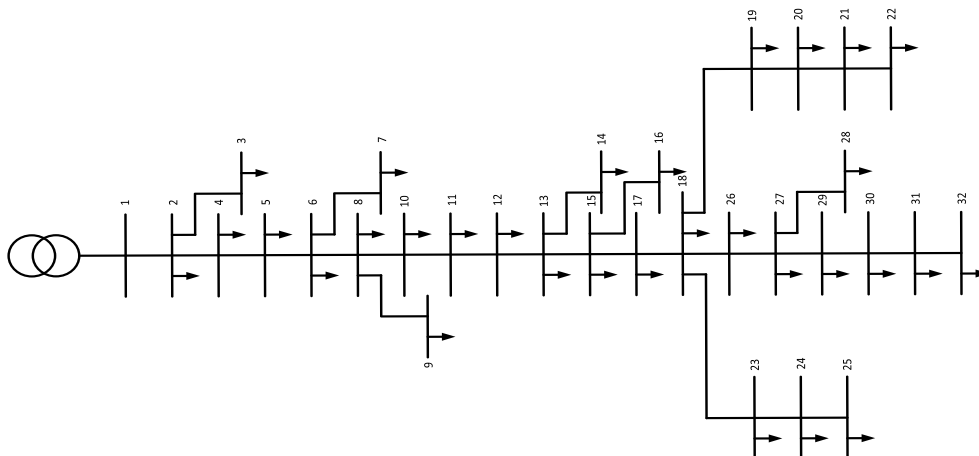


Fig. 11. Single line diagram of inalefafia 32-bus system [39].

Table 4. Optimal simulation outcomes for imalefalafia 32-bus system.

Parameter	Magnitude
DG Bus No.	18
DG Capacity (MW)	2.7180
Reduced Network Power Loss (kW)	14.7780

at the fastest convergence rate, worst mean power loss, and lowest standard deviation in all test cases.

4.7. Statistical benchmarking against established optimization methods

For a complete verification of the performance of ECSA, extensive statistical comparisons between the standard CSA and 15 other well-known

metaheuristic optimization techniques were conducted. All statistics in this section are for 30 independent simulation runs of each optimization algorithm and are in the form of mean and standard deviation over 30 independent runs to support the robustness of the proposed ECSA against random initialization effects. All algorithms were evaluated using the same measures of performance, ensuring that the apparent superiority of the proposed algorithm is related to improved search mechanisms rather than stochastic variation.

Table 6 presents the mean power losses and standard deviations on 30 independent runs for the IEEE 33-bus network. With only a very slight

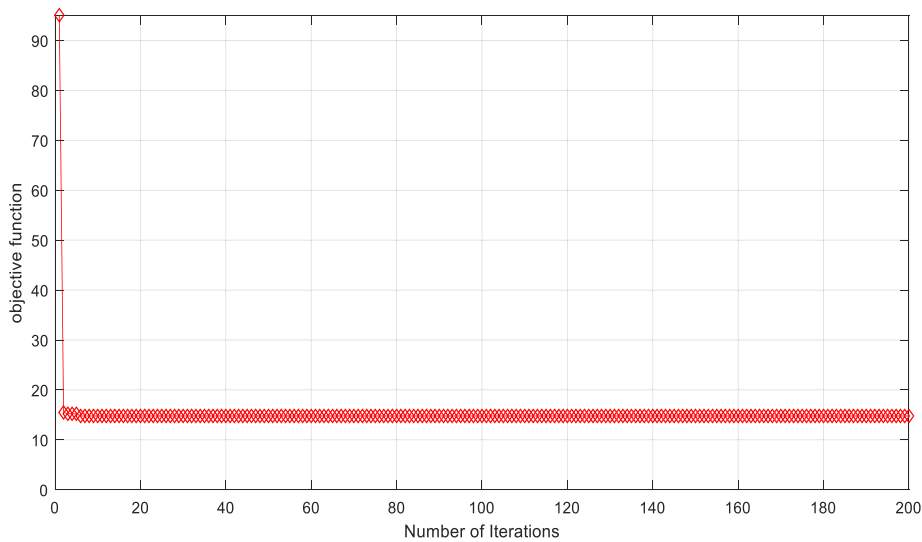


Fig. 12. Convergence curve.

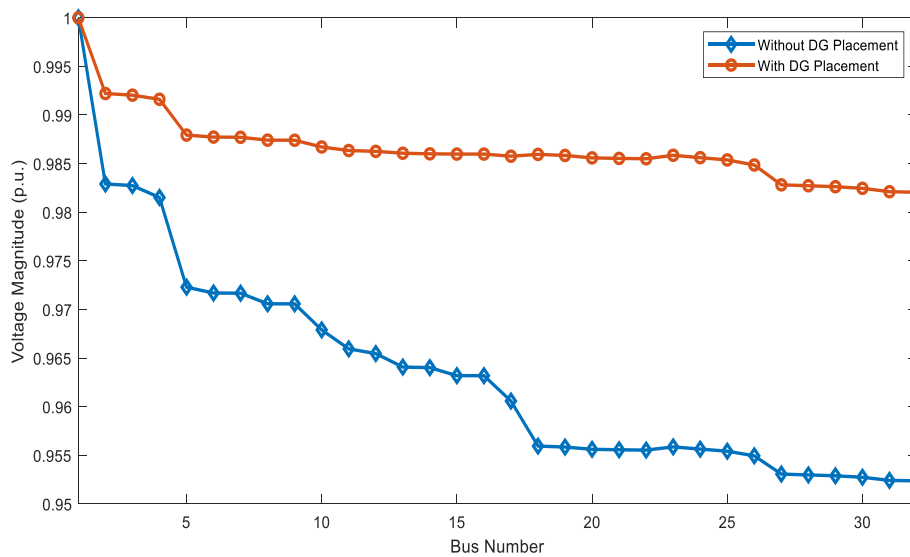


Fig. 13. Changes in voltage profile with DG implementation.

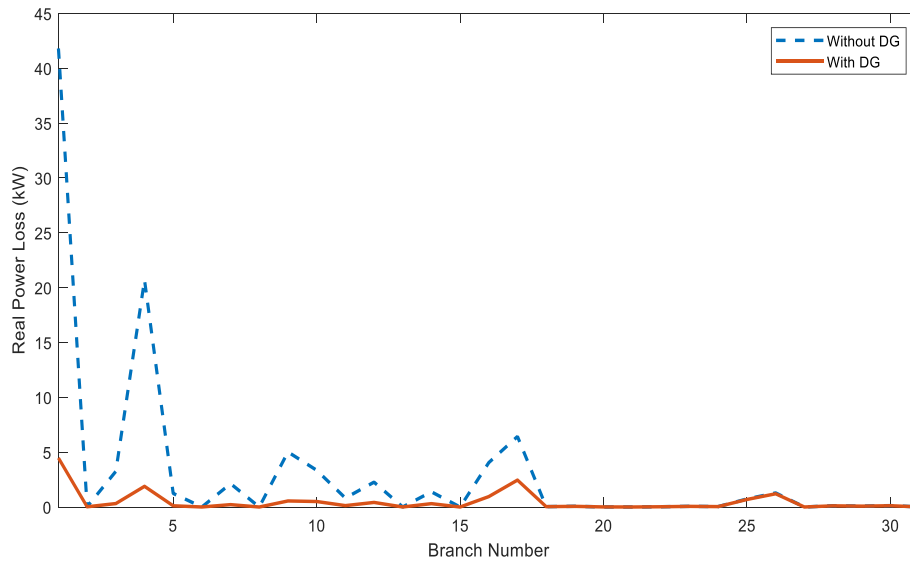


Fig. 14. Real power losses across branches of the imalefalafia 32-bus network.

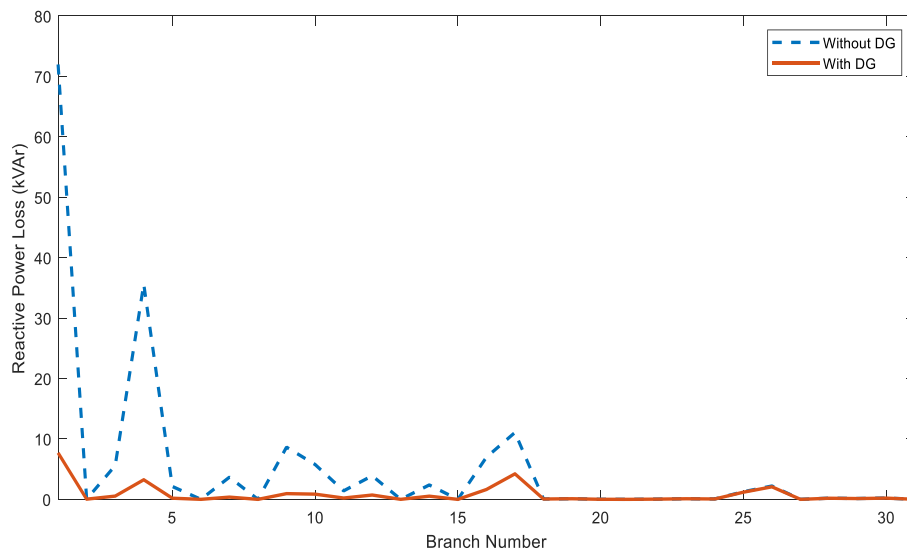


Fig. 15. Reactive power losses across branches of the imalefalafia 32-bus network.

variation of 0.38 kW over repeated runs, the ECSA consistently produced the lowest power loss of all the methods tested, settling around 103.15 kW. The statistical significance of all comparisons confirms the same trend, representing a clear and significant advantage over the other techniques.

This analysis shows a few patterns. The standard CSA delivered fairly good results for the average loss of 112.34 kW, while the enhanced version was able to improve this by almost 9 kW, and ALO and GA produced similar results, but they yielded very different outputs between runs, indicating less steady convergence. The behavior of both WOA

and HPSO methods was, overall, less stable, as the losses and the variances were much higher.

Table 7 presents the statistical benchmarking results for the IEEE 69-bus network, including mean standard deviation values from 30 independent runs. Again, the average power loss was best when using the ECSA, which was approximately 81.99 kW with a very small variation of ± 0.30 kW. Its performance was superior to all the other methods, and the differences were highly significant.

These results point to some interesting conclusions. Although bus 61 was often recognized as the best site through several methods, such as ALO,

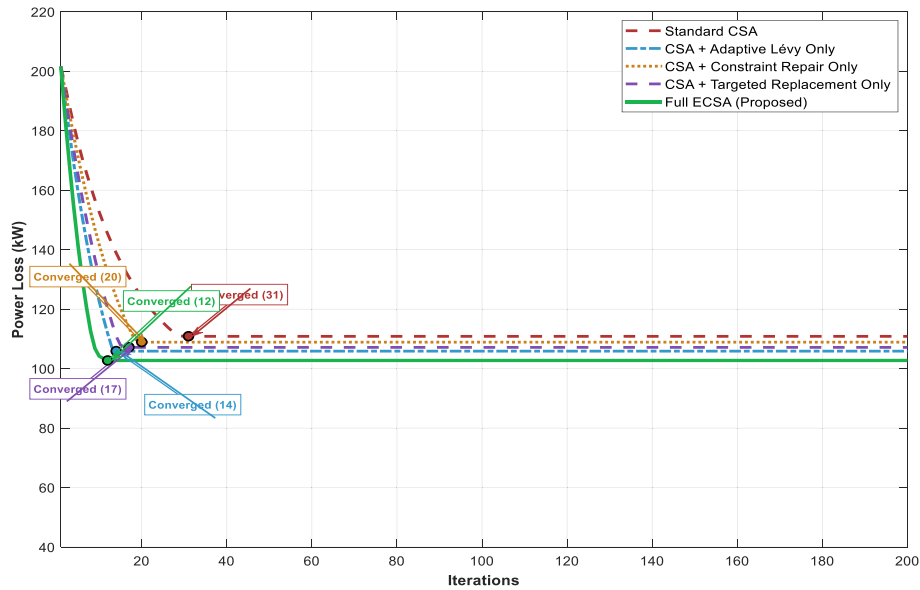


Fig. 16. CSA variants' convergence performance from the ablation study (IEEE 33-bus system).

Table 5. Ablation study results (IEEE 33-bus system, 30 independent runs).

Algorithm Variant	Best Loss (kW)	Mean Loss (kW)	Std. Dev. (kW)	Convergence Iterations
Standard CSA (V1)	110.85	112.34 ± 1.20	1.20	31
+ Adaptive Lévy Only (V2)	105.73	107.21 ± 0.95	0.95	14
+ Constraint Repair Only (V3)	108.90	110.25 ± 0.85	0.85	20
+ Targeted Replacement Only (V4)	107.15	108.62 ± 0.90	0.90	17
Full ECSA (Proposed)	102.75	103.15 ± 0.38	0.38	12

Table 6. Statistical benchmarking on IEEE 33-bus system (30 independent runs).

Algorithm	Optimal Location	DG Size (MW)	Base Case Loss (kW)	Best Loss (kW)	Mean Loss ± Standard Deviation (kW)	p-value	Loss Reduction (%)
WOA [14]	15	1.061	201.58	133.503	135.20 ± 1.50	<0.001	36.73
SCA [16]	6	2.590	201.58	111.02	112.85 ± 1.25	<0.001	47.38
HPSO [23]	8	3.624	201.58	131.85	134.10 ± 1.80	<0.001	37.50
MOHTLBOGWO [25]	30	1.000	201.58	127.28	129.45 ± 1.65	<0.001	39.67
PSO [15]	6	2.59	201.58	111.03	113.25 ± 1.65	<0.001	47.38
Hybrid [16]	6	2.49	201.58	111.17	113.40 ± 1.70	<0.001	47.31
IA [19]	6	2.60	201.58	111.10	113.35 ± 1.68	<0.001	47.39
Heuristic [15]	6	2.5936	201.58	111.03	113.28 ± 1.66	<0.001	47.38
BSOA [21]	8	1.8575	201.58	118.12	120.85 ± 1.95	<0.001	44.02
GA [22]	6	2.600	201.58	111.03	113.25 ± 1.65	<0.001	47.38
ALO [17]	6	2.590	201.58	111.03	112.95 ± 1.45	<0.001	47.38
TLBO-GWO [25]	30	1.000	201.58	127.28	129.45 ± 1.65	<0.001	39.67
Hybrid Technique [17]	6	2.5902	201.58	111.02	112.84 ± 1.24	<0.001	47.38
Standard CSA [33]	6	2.5820	201.58	110.848	112.34 ± 1.20	<0.001	47.22
ECSA (Proposed)	6	2.4576	201.58	102.75	103.15 ± 0.38	-	49.03

EA, and regular CSA, ECSA not only always identified bus 50 as the best, but also indicated it with a smaller DG size and better performance. This indicates that the improved search strategy of ECSA is better at exploring the solution space, and it is doing so more evenly. But algorithms such as

HPSO required significantly larger capacities of DG but failed to achieve the quality of the ECSA in results, while the hybrid TLBO-GWO performed very poorly with high variations between the runs.

Table 7. Statistical benchmarking on IEEE 69-bus system (30 independent runs).

Algorithm	Optimal Location	DG Size (MW)	Base Case Loss (kW)	Best Loss (kW)	Mean Loss \pm Standard Deviation (kW)	p-value	Loss Reduction (%)
Hybrid [15]	61	1.8100	224.604	83.400	85.25 \pm 1.35	<0.001	62.93
Heuristic [24]	61	1.8230	224.604	83.300	85.15 \pm 1.30	<0.001	62.98
EA [20]	61	1.8780	224.604	83.230	85.10 \pm 1.25	<0.001	63.00
HPSO [23]	61	3.6850	224.604	87.130	89.45 \pm 1.75	<0.001	61.27
SCA [16]	61	1.8730	224.604	83.190	85.05 \pm 1.20	<0.001	63.04
EA-OPF [20]	61	1.8700	224.604	83.230	85.10 \pm 1.25	<0.001	63.00
Exhaustive OPF [20]	61	1.8700	224.604	83.230	85.10 \pm 1.25	<0.001	63.00
Hybrid Technique [17]	61	1.8730	224.604	83.190	85.05 \pm 1.20	<0.001	63.04
ALO [18]	61	1.8730	224.604	83.220	85.10 \pm 1.25	<0.001	63.00
TLBO-GWO [25]	61	1.0000	224.604	111.56	114.20 \pm 1.85	<0.001	50.41
GWO [18]	61	1.9290	224.604	83.240	85.15 \pm 1.30	<0.001	62.998
WOA [14]	61	1.8730	224.604	83.228	85.12 \pm 1.28	<0.001	63.010
PSO [15]	61	1.8700	224.604	83.200	85.08 \pm 1.22	<0.001	63.020
MOHTLBOGWO [25]	61	1.0000	224.604	111.56	114.20 \pm 1.85	<0.001	50.410
Standard CSA [33]	61	2.0000	224.604	83.800	85.21 \pm 0.80	<0.001	62.800
ECSA (Proposed)	50	1.8520	224.604	81.593	81.99 \pm 0.30	-	63.670

ECSA not only numerically performs well, but also shows consistent behavior from run to run. While ECSA only varied between 0.30 and 0.38 kW, some methods, like HPSO, had variations as high as 1.75 kW. Because of its combination of reliable results as well as consistent convergence, it is highly suited for actual planning of distribution systems where accuracy and robustness in results are important. The p-values being highly significant ($p < 0.001$) indicate that these results are consistent and the improvements are actually a benefit in the algorithm and not random variation.

From the practical perspective, the proposed ECSA has a faster convergence, a lower performance variance, and greater consistency in solution quality than the benchmark algorithms, and thus is more robust and relevant to the real-world planning of distribution networks.

5. Conclusion

This paper presented ECSA for optimal placement and size of a distributed generation unit within radial distribution systems in order to minimize active power losses while remaining in compliance with operational constraints. By incorporating three key features, adaptive Lévy flights for balanced search, a repair mechanism to keep the solutions feasible, and a selective replacement strategy to preserve diversity in the population, the approach was designed to overcome some of the common weaknesses of many of the metaheuristic approaches.

An in-depth analysis of the 33-bus & 69-bus IEEE systems, as well as a real 32-bus Nigerian network, shows a clear and consistent performance benefit.

The ECSA decreased active power losses in the IEEE 33-bus, IEEE 69-bus, and Imalefalafia 32-bus systems from 201.58 kW to 102.75 kW (49.03 %), 224.60 kW to 81.59 kW (63.67 %), and 95.07 kW to 14.78 kW (84.45 %), respectively. It also helped in the voltage profile quite immensely. These improvements required less computational effort and converged faster than most classical methods.

But technical detail is where this study shines. Ablation studies were carefully planned to evaluate the effect of each improvement alone and in combination. Also, the algorithm stability is also validated with the outputs of 30 different runs, and improvements are also statistically significant, $p < 0.01$ against 15 other benchmark algorithms.

Its practicality has been demonstrated by using it on a real distribution network in Nigeria, showing that it functions well not only on standard test systems but in real-world applications. This connection between theory and practice at the field level is a large step forward in methods for optimizing distribution networks.

6. Limitations and future works

While the proposed method has strong performance, some limitations and directions for future research are acknowledged. First, the formulation is centered on the placement and sizing of a single DG unit, whereas practical distribution systems may involve multiple DG installations with complex interactions. Second, all simulations were conducted under deterministic and static loading conditions and therefore do not explicitly account for renewable generation intermittency, demand uncertainty, or probabilistic operating scenarios.

Lastly, although the algorithm performs well on benchmark and practical test systems, including a real Nigerian distribution feeder, its performance on very large-scale distribution networks, with hundreds of buses has not yet been explicitly investigated.

The single-DG formulation was intentionally adopted to avoid combinatorial explosion of the search space and to enable clear isolation and validation of the proposed algorithmic enhancements. This modeling choice allows the individual and synergistic effects of adaptive Lévy flights, constraint-aware solution repair, and diversity-guided stochastic replacement to be rigorously assessed without confounding interactions among multiple DG units. Such a formulation is consistent with a large body of existing DG placement literature and ensures fair benchmarking against established metaheuristic approaches.

The deterministic and static loading assumption was similarly chosen to isolate the intrinsic optimization behavior of the proposed ECSA. By avoiding time-varying or stochastic effects at this stage, the convergence characteristics, feasibility enforcement capability, and population diversity control mechanisms of the algorithm can be transparently evaluated.

It is important to emphasize that the proposed ECSA framework is formulation-independent and inherently scalable. Extension to multi-DG placement and sizing problems can be readily achieved by expanding the decision vector to include multiple DG locations and capacities, without any structural modification to the adaptive Lévy flight strategy, constraint-aware repair mechanism, or diversity-guided stochastic replacement. Likewise, dynamic or probabilistic operating conditions can be incorporated by redefining the objective function as a scenario-based or expected-value optimization problem while preserving the same optimization architecture.

Accordingly, future work will focus on extending the proposed ECSA to multi-DG planning problems, stochastic and time-series-based load models, and renewable energy uncertainty scenarios, as well as evaluating its scalability on large-scale distribution systems with increased network complexity.

All in all, the presented research represents a dependable optimization tool capable of addressing each of the different problems posed by DG deployment. The ECSA is a major contribution to the use of metaheuristics for power system applications. It provides planners with a fast,

trustworthy, and helpful approach to improve system operation subject to operational constraints. The proposed ECSA provides tangible practical applications beyond numerical performance gains for real-world distribution system planning. Its constraint-aware repair tool ensures that all recommended DG configurations can be run as is without post-processing, and its diversity-aware replacement tool adds reliability by avoiding inconvenient or unreliable solution. The successful application to a real Nigerian 32 bus distribution feeder shows that this method can be readily adopted by utility planners as part of fast and reliable DG integration studies.

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Conflicts of Interest

The authors declare that they have no competing interests

Ethical Approval

This study did not involve human participants, animals, or sensitive data. Therefore, ethical approval was not required.

Data Availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Author Contributions

S. O. Ayanlade; Formal analysis, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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R. O. Olarewaju; Conceptualization, Data curation, Investigation, Methodology, Supervision, Validation, Writing – review & editing.

I. K. Okakwu; Data curation, Investigation, Methodology, Resources, Writing – original draft.

I. O. Adejumbi; Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Resources, Software, Writing – original draft.

J. B. Samson; Investigation, Methodology, Validation.

O. A. Adebisi; Methodology, Resources, Software.

O. O. Akinrogunde; Formal analysis, Methodology, Resources.

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