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Optimization of distributed generation placement in distribution network based on queen honey bee migration algorithm

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Abstract

In this research, an optimal distributed generation (DG) placement method for radial distribution systems based on queen honey bee migration (QHBM) and backward forward sweep (BFS) is presented. The suggested approach makes it possible to evaluate DG placement options in terms of branch currents, voltage profiles, and active power losses in a physically consistent manner. DG units are characterized as photovoltaic-based sources operating at unity power factor using an explicit net load formulation at the bus level, ensuring a clear interplay between DG injection and current-based load flows. Throughout the optimization process, a constraint-aware migration technique is employed to explicitly impose voltage limitations with the goal of minimizing overall active power losses while maintaining bus voltage magnitudes within allowable bounds. The proposed method was tested on an IEEE 69-bus radial distribution system to evaluate its performance. The results show that the placement of three DG units with a total installed capacity of approximately 2600 kW at buses 61, 64, and 17 produces a significant improvement in network operation. Under this arrangement, active power losses drop markedly from 224.4419 kW in the base condition to 72.7840 kW, corresponding to a reduction of 67.6 %. At the same time, the lowest bus voltage rises from 0.9104 p.u. to 0.9931 p.u., while voltage levels across the network consistently remain within the allowable range of 0.95–1.05 p.u. The study's findings suggest that QHBM-BFS can be used as a trustworthy and useful method for figuring out where DG should be placed in radial distribution systems.

Keywords: distributed generation; distributed generation placement; power loss minimization; QHBM; radial distribution network; voltage profile.

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I. Introduction

Indonesia's electricity demand is predicted to increase steadily through 2050 at an average annual growth rate of roughly 5.9 % [1]. Rapid technological advancement, urbanization, population growth, and continuous industrial expansion are all strongly associated with this tendency. Distribution networks must increase in both coverage and operational complexity as power consumption rises, especially in urban and semi-urban areas. However, this expansion poses serious technical problems, particularly at buses that are farther away from primary substations, such as decreasing voltage profiles and rising power losses [2].

Distribution networks are intrinsically more vulnerable to power losses than transmission systems because of their radial design, uneven load distribution, and comparatively high resistance-to-reactance (R/X) ratios. Numerous studies have shown that distribution losses can make up 10 % to 13 % of the total electrical energy generated [3]. Longer feeder lengths, increased load, and unfavorable power flow conditions are the main causes of these losses. These losses frequently lead to inadequate voltage regulation, which can deteriorate power quality and decrease system reliability. Therefore, lowering power losses while enhancing voltage performance has emerged as a crucial goal for the creation and operation of contemporary distribution systems.

To address these problems, numerous technical solutions have been proposed, including feeder reconfiguration, load balancing, capacitor placement, and the integration of distributed generation (DG). DG integration has emerged as one of the most promising methods among these since it may provide power locally and reduce reliance on centralized generation. The direct integration of small-scale power sources, typically located close to load centers, into the distribution network is referred to as DG [4]. DG systems often use renewable energy sources such as photovoltaic, wind, and microturbine technologies [4][5]. The increasing use of distributed generation is being driven by a number of advantages, such as high energy efficiency, modular design, deployment flexibility, fewer transmission requirements, and environmental benefits [6].

When used correctly, DG can effectively reduce a number of distribution system issues, such as excessive power losses, voltage drops, feeder congestion, and load imbalance [7]. However, the benefits of DG integration are heavily influenced by its location and capacity. Unfavorable operating conditions, including increased losses, voltage violations, reverse power flow, and decreased system reliability, can arise from improper DG installation [8][9][10] when compared to the pre-DG scenario [11]. Because of this, DG placement is a challenging project that requires careful design that takes network topology, load distribution, and operational constraints into account.

To bridge the gap with the aforementioned state of the art, this work uses the queen honey bee migration (QHBM) algorithm, which was first presented in [12]. QHBM integrates adaptive mechanisms including sector probability selection and resistance-based movement and is modeled after the migration behavior of queen honeybee colonies when choosing new hive sites. Prior research [12][13] has demonstrated that, when compared to a number of traditional metaheuristic techniques, QHBM can achieve effective convergence while improving the balance between exploration and exploitation, especially in complex search fields. In the meantime, a power flow study is necessary for precise answers to DG location issues. The Back and Forward Sweep (BFS) method, which is renowned for its numerical stability and computational efficiency under high R/X circumstances [3] in radial distribution networks, is used in this study to analyze power flow. This paper suggests a methodical and physically consistent approach for DG placement that attempts to minimize overall active power losses while preserving acceptable voltage profiles at all buses by combining QHBM with BFS-based power flow analysis.

The IEEE 69-bus radial distribution system [14], which is frequently used as a benchmark because of its lengthy feeders, uneven load distribution, and high sensitivity to DG placement, is used to verify the efficacy of the suggested method. Comparative analyses with GA-based optimization and non-optimized DG placement are conducted to demonstrate the robustness and effectiveness of the proposed QHBM-based framework, particularly under multi-DG placement scenarios.

In parallel, numerous metaheuristic approaches have been applied to the DG placement problem. State-of-the-art studies explore hybrid and evolutionary schemes such as generative algorithm (GA)-based optimization and Differential Evolution, which have demonstrated significant power loss reductions while improving voltage performance [14]. Bio-inspired variants have also been used in similar cases [15][16][17]. Additional nature-inspired strategies, including firefly-based loss minimization and a load-flow-guided DG allocation framework, further demonstrate that integrating realistic power flow modeling with heuristic search can significantly improve DG planning outcomes [18][19]. Beyond DG placement itself, optimization methodologies related to distributed energy systems have also benefited from advances in metaheuristics, as evidenced by the successful application of the QHBM algorithm in the photovoltaic maximum power point tracking problem [20].

The optimal placement and sizing of DG units in radial distribution systems have been extensively investigated in the literature, particularly using metaheuristic optimization techniques. One of the early and widely cited studies was conducted by Prakash and Lakshminarayana that applied the PSO algorithm to determine optimal DG locations in the IEEE 33-bus and 69-bus distribution systems. Their results demonstrated that appropriate DG installation can significantly reduce power losses, with reported optimal DG capacities of 2954 kW for the 33-bus system and 2753 kW for the 69-bus system. The difference in DG capacity requirements was attributed to variations in load demand and network topology, emphasizing the need for system-specific optimization strategies [21].

II. Materials and Methods

A. System description

DG placement tests are conducted on the IEEE 69-bus radial distribution system as depicted in Figure 1. The total active and reactive power demands of the system are 3800 kW and 2690 kVAr, respectively [22]. This test system has been widely adopted as a benchmark for evaluating DG placement strategies due to its radial topology, long feeder structure, and high sensitivity to DG location, capacity and loading variations [23][24], and voltage drops [25][26]. The system operates at a nominal voltage level of 12.6 kV with a base apparent power of 10 MVA, representing a typical medium-voltage distribution network. It consists of one slack bus serving as the reference bus and 68 load buses interconnected through radial feeders, reflecting common characteristics of practical distribution systems. These loads are unevenly distributed along the feeders, resulting in non-uniform current flow and noticeable voltage drops, particularly at buses located far from the slack bus. The distribution lines exhibit varying resistance and reactance values, which contribute to cumulative voltage degradation and increased power losses along long feeder sections.

Due to its radial configuration, long feeder lengths, and non-uniform load distribution, the IEEE 69-bus system is highly sensitive to the placement and sizing of distributed generation units. Improper DG installation may lead to suboptimal loss reduction or voltage violations, whereas optimal placement can significantly enhance system performance by reducing active power losses and improving voltage regulation. These characteristics make the IEEE 69-bus radial distribution network a challenging and realistic test system for assessing DG placement optimization methods [14][21], and it has therefore been extensively used in the literature [23][24][27] for studies focusing on power loss minimization [10][19] and voltage profile improvement [2][7].

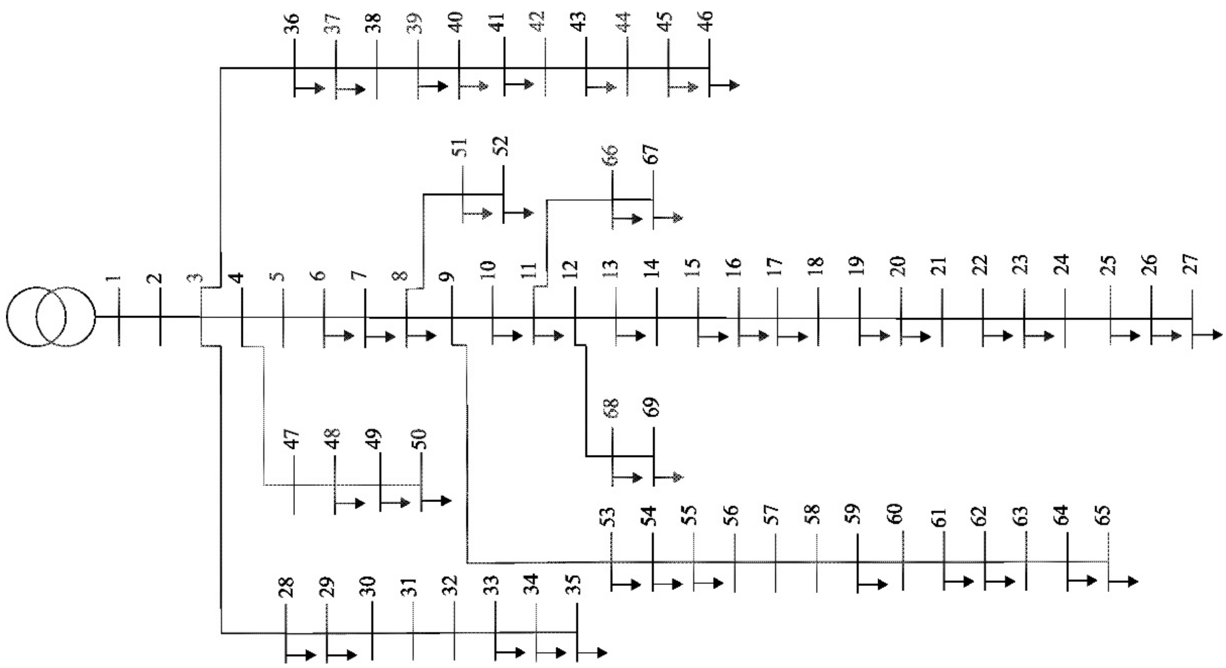

Figure 1. IEEE 69-bus of radial distribution network.

B. DG placement problem

The DG placement problem is formulated for the IEEE 69-bus radial distribution system described, with the objective of minimizing the total active power loss while maintaining acceptable voltage profiles at all buses. DG units are permitted to be installed only at load buses, excluding the slack bus, and are modelled as photovoltaic-based sources operating at unity power factor.

The optimization aims to determine the optimal DG installation decision, which includes the bus location and the installed DG capacity. Accordingly, the decision vector is defined as equation (1):

$$x = \{b_i, P_{DG,i}\},\ i = \{1,2, \ldots, N_{DG}\} \quad (1)$$

where $b_i \in \{2,3, \ldots .69\}$ denotes the location of the i^{th} DG unit and $P_{DG,i}$ represents its installed active power capacity. N_{DG} is the number of DG units considered in the optimization scenarios.

The DG placement problem is mathematically formulated as the following constrained optimization problem equation (2):

$$min P_{loss}(x) \quad (2)$$

Subject to:

$$V_{min} \leq |V_n(x)| \leq V_{max}, \quad \forall n$$

$$0 \leq P_{DG,i} \leq P_{DG,i}^{max}, \quad \forall i$$

$$b_i \in \{2,3, \ldots .69\}$$

where P_{loss} and $|V_n|$ denote the total active power loss in the test system and voltage magnitude at bus n, respectively. The voltage limit are set to V_{min} is 0.95 pu and V_{max} is 1.05 pu.

The power flow equality constraints of the network are implicitly satisfied through the BFS load flow analysis. For each candidate solution x, BFS is executed to compute branch currents, bus voltages, and total active power loss. Only solutions that satisfy all voltage constraints are considered feasible. The optimization process is considered successful when a feasible solution yielding reduced active power loss and improved voltage profile is obtained.

C. The proposed QHBM-BFS

The proposed DG placement approach integrates the QHBM with BFS power flow analysis to form a unified optimization framework, hereafter referred to as the QHBM–BFS method. In this framework, QHBM functions as the global search engine to identify optimal DG placement decisions, while BFS serves as the embedded load flow solver to evaluate the electrical performance of each candidate solution. In QHBM, the optimization process is guided by two main agents, namely the queen and scout bees. The queen represents the current best candidate solution, defined by the decision vector x, which encodes the bus locations and capacities of DG units. Scout bees are deployed around the queen within a predefined search radius to explore neighboring solutions, see [28]. Each scout solution is evaluated using BFS power flow analysis, and its fitness is defined as the total active power loss as in equation (2).

After updating the queen's position, the new candidate solution is projected onto the feasible decision space by enforcing DG capacity limits and allowable bus indices. BFS power flow analysis is then executed to evaluate the updated solution. If the new solution satisfies all voltage constraints and yields a lower total active power loss than the current best solution, it replaces the previous queen position. This iterative process continues until the stopping criterion, defined by the maximum number of iterations, is satisfied.

Motivated by its proven robustness in handling complex search spaces [20], QHBM is extended in this study to address the DG placement problem in radial distribution networks. By embedding BFS directly within the QHBM optimization loop, the proposed QHBM–BFS framework ensures physically consistent evaluation of DG placement solutions throughout the search process. This tight coupling allows accurate assessment of branch currents, voltage profiles, and active power losses at each iteration, making the proposed approach particularly suitable for radial distribution systems.

D. Pseudocode

This subsection presents the pseudocode of the proposed QHBM–BFS algorithm for optimal distributed generation placement in radial distribution systems. The pseudocode consolidates the optimization and power flow evaluation into a single integrated procedure, where the QHBM governs the global search for DG locations and capacities, while the BFS is embedded as the load flow solver to evaluate power losses and voltage profiles for each candidate solution. By explicitly incorporating net-load modelling, voltage constraints, and resistance-based migration within one unified algorithmic flow, the pseudocode provides a clear and reproducible description of the proposed method and serves as a direct implementation guide for the mathematical formulations presented in the preceding subsections.

Algorithm 1. Integrated QHBM–BFS for DG Placement

Input:

Radial network data R_{ij}, X_{ij}; bus loads P_{L_n}, Q_{L_n}; slack bus voltage V_1;

DG parameters: number of DG units N_{DG}, maximum DG capacity $P_{DG,i}^{max}$, unity power factor;

Voltage limits V_{min}, V_{max};

QHBM parameters: number of scouts n_s, search radius r_s, resistance scale g_s, maximum iterations K_{max};

BFS parameters: tolerance ε, maximum BFS iterations K_{BFS}.

Output:

Optimal DG decision $\mathbf{x}^* = \{b_i^*, P_{DG,i}^*\}$,

minimum power loss P_{loss}^*,

voltage profile $\mathbf{V}^*$.

1: **Initialize** queen position $\mathbf{x}^0 = \{b_i^{(0)}, P_{DG,i}^{(0)}\}$,
 Where ($b_i^{(0)} \in \{2,\ldots,69\}$, and $0 \le P_{DG,i}^{(0)} \le P_{DG,i}^{max}$).

2: **Evaluate $\mathbf{x}^{(0)}$ using** BFS:
 Set net loads, run backward–forward sweep, compute $P_{\text{loss}}^{(0)}$, $\mathbf{V}^{(0)}$, and feasibility flag $F^{(0)}$

3: **Set** $\mathbf{x}^* \leftarrow \mathbf{x}^{(0)}, P_{\text{loss}}^* \leftarrow P_{\text{loss}}^{(0)}, \mathbf{V}^* \leftarrow \mathbf{V}^{(0)}$ if $F^{(0)} =$ **true**.

4: **for** iteration $k = 0$ to $k_{\max} - 1$ **do**

5: **Deploy scouts** around $\mathbf{x}^{(k)}$ within radius r_s to generate candidate solutions $\mathbf{x}_{s,i}^{(k)}, i = 1, \ldots, n_s$.

6: **for each scout $\mathbf{x}_{s,i}^{(k)}$ do**

7: **Net-load update:**
 $P_n^{\text{net}} = P_{L_n}, Q_n^{\text{net}} = Q_{L_n}$;
 for each DG at bus b_i:
 $P_{b_i}^{\text{net}} = P_{L_{b_i}} - P_{\text{DG},i}, Q_{b_i}^{\text{net}} = Q_{L_{b_i}}$;

8: **BFS power flow:**
 Initialize voltages;
 repeat
 Compute load currents $I_n^{(k)} = \left(\frac{P_n^{\text{net}} + jQ_n^{\text{net}}}{V_n^{(k-1)}}\right)^*$
 Backward sweep: $I_{ij}^{(k)} = \sum_{n \in \mathrm{D}(j)} I_n^{(k)}$
 Forward sweep: $V_j^{(k)} = V_i^{(k)} - Z_{ij} I_{ij}^{(k)}$
 until voltage mismatch $\le \varepsilon$.

9: **Compute fitness:**
 $P_{\text{loss},i}^{(k)} = \sum_{(i,j) \in \mathrm{L}} R_{ij} \left|I_{ij}\right|^2$

10: **Check feasibility:**
 If $V_{\min} \le |V_n| \le V_{\max}$ for all n, set $F_i^{(k)} =$ true; else $F_i^{(k)} =$ false.

11: Assign scout i to sector j and store evaluation $e_{r(ij)}$.

12: **end for**

13: **Compute sector information:**
 $C_j = \frac{1}{n_s} \sum_{i=1}^{n_s} e_{r(i,j)}, \qquad j = 1, \ldots, 8$

14: **Compute sector probabilities:** $P_j = \frac{C_j}{\sum_{j=1}^{8} C_j}$

15: **Select migration direction $\boldsymbol{\theta}^{k+1}$** from sector $j^* = \arg\max p_j$.

16: **Update resistance and step length:**
 $g_m^{(k+1)} = g_s^{(k)} \cdot rand(0,1), \qquad r_m^{(k+1)} = 1 - g_m^{(k+1)}$

17: **Update queen position:**
 $\boldsymbol{x}^{(k+1)} = \boldsymbol{x}^{(k)} + r_m^{(k+1)} \cdot \boldsymbol{\theta}^{(k+1)}$

18: **Project $\boldsymbol{x}^{(k+1)}$** onto feasible bounds
 $(b_i \in \{\mathbf{2}, \ldots, \mathbf{69}\}, \mathbf{0} \le P_{DG,i} \le P_{DG,i}^{max})$

19: **Evaluate updated queen using BFS as in Steps 7-10**

20: **if** solution is feasible **and** $P_{loss}^{(k+1)} < P_{loss}^*$ **then**
 $\mathbf{x}^* \leftarrow \mathbf{x}^{(k+1)}$
 $x^* \leftarrow P_{loss}^{(k+1)}$
 $\mathbf{V}^* \leftarrow \mathbf{V}^{(k+1)}$

21: **end for**

22: **return** $\mathbf{x}^*, P_{loss}^*, \mathbf{V}^*$

E. Simulation setup

1) Simulation parameter

All simulations are performed using the MATLAB® platform based on the proposed QHBM–BFS framework applied to the IEEE 69-bus radial distribution system. The QHBM-BFS parameter settings are summarized in Table 1. In addition, the test system parameter and base values are also depicted in Table 1. Those parameters are consistently applied across all simulation scenarios to ensure fair comparison and reproducibility of the results. In addition, the test system parameters are aforementioned.

Table 1.
QHBM-BFS parameters.

Parameter	Symbol	Value
Number of DG units,	N_{DG}	Single or multiple (scenarios dependent)
Number of scout bees (population)	n_s	8
Scanning/search radius	r_s	2
Resistance parameter	g_m	0.95
Maximum QHBM iterations	i_{max}	500
BFS convergence tolerance	ε	10
Voltage limits	V_n	0.95 – 1.05 p.u.
Base power	S_{base}	100 MVA
Base voltage	V_{base}	12.66 kV

2) Scenarios

To comprehensively evaluate the effectiveness and robustness of the proposed QHBM–BFS framework, several simulation scenarios are designed based on different DG deployment conditions. These scenarios are constructed to reflect practical operating cases in radial distribution networks and to assess the impact of DG placement strategies on system power loss and voltage profile behavior. All scenarios are analyzed using the same BFS power flow model, system parameters, and operational constraints to ensure methodological consistency.

- **Scenario 1** (base case – without DG). IEEE 69-bus radial distribution system is evaluated without any distributed generation installed. This case represents the original operating condition of the network and serves as the reference benchmark. It establishes baseline characteristics of active power loss and bus voltage profiles against which the performance of all DG-based scenarios is assessed.
- **Scenario 2** (single-DG placement); a single DG unit is optimally placed using the proposed QHBM–BFS framework. The objective of this scenario is to evaluate the capability of the algorithm to identify electrically sensitive bus locations for DG installation and to examine the corresponding impact on network operating characteristics relative to the base case.
- **Scenario 3** (multiple-DG placement); investigates the performance of the proposed approach under higher DG penetration levels. Two and three DG units are sequentially deployed using the QHBM–BFS framework. After each DG placement, the network load profile is updated through a net-load formulation, and the subsequent DG placement is optimized based on the modified system condition. This scenario is designed to assess the scalability of the proposed method and its ability to handle interactions among multiple DG units in a radial distribution network.

3) Metrics

The performance of the proposed QHBM–BFS framework is evaluated using metrics obtained directly from the BFS power flow results. The main performance indicator is the total active power loss, which represents the sum of resistive losses across all distribution lines, P_{loss} and serves as the primary optimization objective.

The bus voltage profile, V_n is examined to evaluate voltage regulation along the radial network, while the minimum bus voltage is used to indicate the worst-case voltage condition. Voltage feasibility is ensured by requiring all bus voltages to remain within the permissible range (as in Table 1), and only feasible solutions are considered in the analysis. In addition, the convergence behavior of the optimization process is assessed by observing the evolution of active power loss over the optimization iterations, providing insight into the stability and effectiveness of the proposed method.

4) Validation

For comparison purposes, a GA is implemented under the same system conditions and constraints as the proposed QHBM–BFS framework. The GA employs a population size of eight individuals, which is set equal to the scout population used in QHBM to ensure comparable search diversity. Tournament selection is applied to choose parent solutions, followed by single-point crossover with a probability of 0.8. Random mutation is used with a mutation probability of 0.1 to maintain population diversity. The GA optimization process is executed for a maximum of 500 generations, and each candidate solution is evaluated using the same BFS power flow routine and DG constraints as those used in the proposed method. This configuration ensures a fair and consistent comparison between GA-based and QHBM-based DG placement approaches.

III. Results and Discussions

A. Baseline case

The baseline operating condition corresponds to the IEEE 69-bus radial distribution system without any DG installed. The results of the BFS power flow analysis for this case are summarized in Table 2, while the corresponding voltage profile is illustrated in Figure 2.

As shown in Figure 2, the voltage profile exhibits a continuous decline along the radial feeder, with the minimum voltage reaching 0.9104 per unit., which occurs at buses located far from the slack bus. This behaviour is typical of radial distribution networks with long feeder lengths and non-uniform load distribution, where cumulative voltage drops increase toward downstream buses. Similar voltage degradation patterns have been widely reported in previous studies on the IEEE 69-bus system and comparable radial networks [1][2][3].

Table 2.
Results of power flow analysis before installation of DG.

IEEE 69-bus radial distribution network	
Total ploss	224.4419 kW
Voltage profile min	0.9104 p.u
Voltage profile max	1.0000 p.u

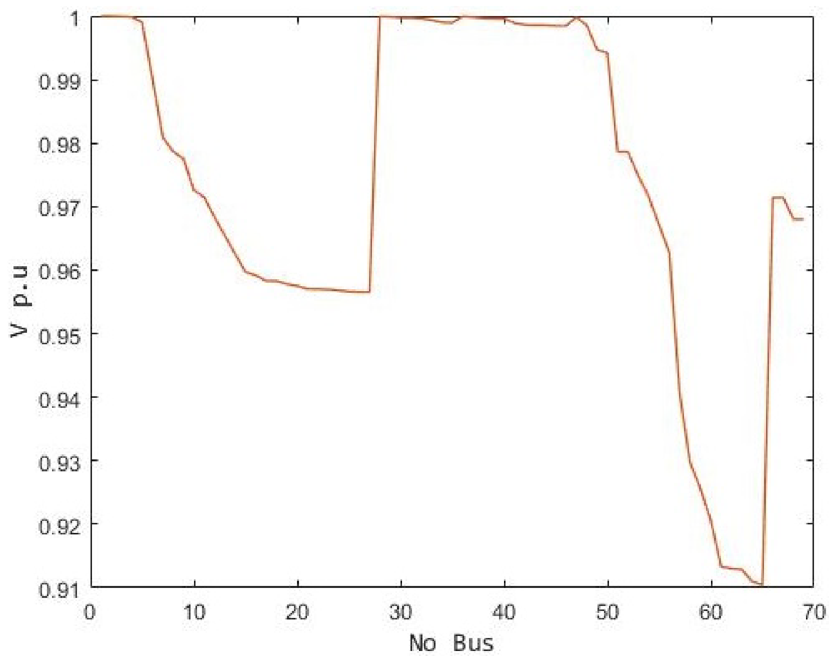

Figure 2. Voltage profile before installing DG.

In addition, the total active power loss recorded in Table 2 is approximately 224.4419 kW, indicating relatively inefficient power delivery under base-case conditions. This magnitude of loss is consistent with benchmark results reported in the literature for the IEEE 69-bus system using BFS-based power flow analysis [4][5]. These baseline results confirm that the test system represents a challenging and realistic benchmark for DG placement studies. Therefore, the baseline case provides a meaningful reference for evaluating the effectiveness of different DG placement strategies.

B. Manual DG placement

To highlight the importance of optimization, a manual DG placement scenario is evaluated, where DG units are installed at buses 27, 65, and 46 without using any optimization algorithm. The corresponding results are presented in Table 3, while the voltage profile comparison is illustrated in Figure 3.

For the single-DG case, manual placement achieves only an 8.5 % reduction in total power loss compared to the baseline case. This modest improvement indicates that arbitrarily selected DG locations are generally unable to target electrically sensitive buses

Table 3.
Comparison of QHBM-GA-Random DG Installation results.

Item	Method	Before DG	1 DG	2 DG	3 DG
DG location (bus)	QHBM	–	61	61, 64	61, 64, 17
	GA	–	61	61, 62	61, 63, 15
	Random	–	27	27, 65	27, 65, 46
Installed capacity (kW)	QHBM	–	878	878, 627	534,1425,715
	GA	–	–	–	1425
	Random	–	–	–	715
Total ploss (kW)	QHBM	224.4419	119.4070	86.6239	72.7840
	GA	224.4419	119.4070	87.6038	73.7789
	Random	224.4419	205.4780	133.6760	99.5554
Voltage profile min (p.u.)	QHBM	0.9104	0.9502	0.9669	0.9931
	GA	0.9104	0.9502	0.9669	0.9912
	Random	0.9104	0.9163	0.9525	0.9723
Voltage profile max (p.u.)	QHBM	1.0000	1.0000	1.0000	1.0008
	GA	1.0000	1.0000	1.0000	1.0000
	Random	1.0000	1.0071	1.0013	1.0045

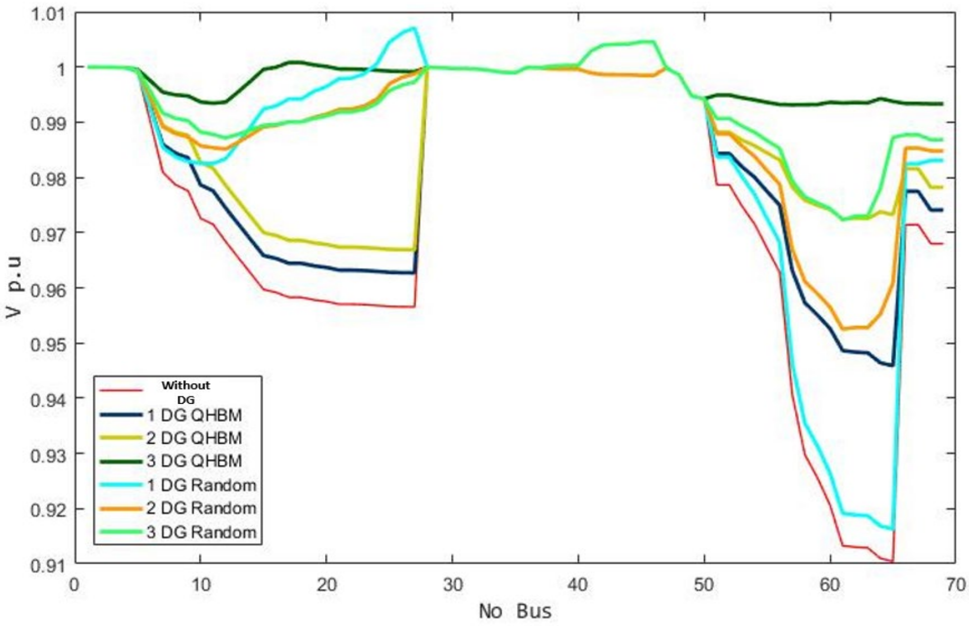

Figure 3. Comparison of voltage profile values after installation of DG QHBM-random.

that significantly influence branch currents and voltage drops. Similar observations have been reported in earlier DG placement studies, where non-optimized installations yield limited technical benefits [6][7].

When two and three DG units are installed manually, the total power loss reductions increase to approximately 50.4 % and 59.7 %, respectively. Although these reductions are higher than those obtained with a single DG, they remain inferior to the results achieved using optimization-based approaches, (Table 3). Furthermore, Figure 3 indicates that manual placement may introduce localized overvoltage conditions, particularly at buses close to DG locations, a phenomenon also reported in previous studies on non-optimized DG deployment [8]. Overall, the results demonstrate that manual DG placement cannot consistently guarantee optimal loss reduction or voltage profile improvement, underscoring the necessity of systematic optimization methods.

C. QHBM–BFS DG placement

In this study, the queen honey bee migration (QHBM) algorithm is employed to determine the optimal placement of distributed generation on the IEEE 69-bus distribution network. The optimization results obtained using QHBM are presented in Table 3, while the corresponding voltage profiles after DG installation are illustrated in Figure 4.

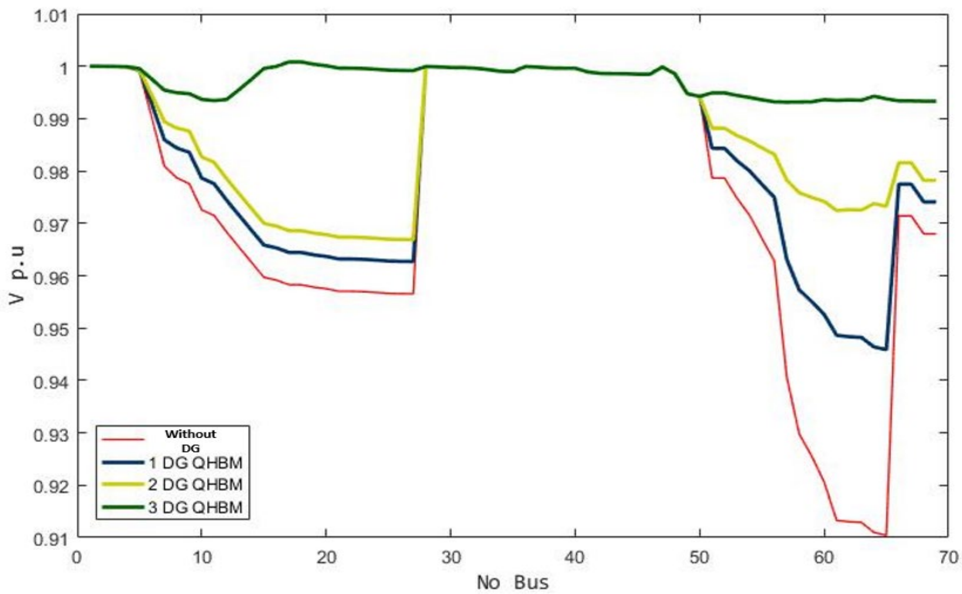

Figure 4. Graph of voltage profile after DG installation with QHBM.

D. Single-DG placement

When a single DG unit with a capacity of 878 kW is installed at bus 61, the total active power loss is reduced from 224.4419 kW to 119.4070 kW, corresponding to a loss reduction of approximately 46.8 %. At the same time, the minimum bus voltage improves from 0.9104 p.u. to 0.9502 p.u., observed at bus 65. This improvement is clearly visible in Figure 4, where the voltage profile becomes noticeably flatter compared to the baseline case.

The effectiveness of this placement can be explained by the location of bus 61, which lies in an electrically sensitive downstream region of the network. DG injection at this bus significantly reduces the current flowing through upstream branches, thereby lowering resistive losses and mitigating voltage drops. Similar findings regarding the importance of downstream DG placement have been reported in GA- and PSO-based DG placement studies [9][10].

E. Two-DG placement

For the placement of two DG units at buses 61 and 64, with a combined installed capacity of approximately 1500 kW, the total active power loss is further reduced to 86.6239 kW, achieving a loss reduction of about 61.5 % relative to the baseline. The minimum voltage profile increases to 0.9669 p.u., indicating enhanced voltage stability throughout the network. The most critical voltage is observed at bus 27, reflecting the redistribution of power flows after the installation of the second DG.

This result demonstrates the ability of QHBM–BFS to coordinate multiple DG placements by sequentially updating the net-load profile, ensuring that each additional DG contributes effectively to system performance without causing adverse interactions.

F. Three-DG placement

When three DG units are optimally placed at buses 61, 64, and 17, with a total installed capacity of approximately 2600 kW, the total active power loss decreases to 72.7840 kW, corresponding to a maximum loss reduction of 67.6 %. The voltage profile exhibits the best performance among all scenarios, with a minimum voltage of 0.9931 p.u., again observed at bus 65. These results indicate near-ideal voltage regulation across the network.

Overall, the results in Table 3 and Figure 4 confirm that the proposed QHBM–BFS framework effectively identifies electrically sensitive bus locations where DG installation yields maximum technical benefits, consistent with findings reported in other bio-inspired DG placement studies [11][12].

G. Performance comparison with GA

To further assess the effectiveness of the proposed method, the optimization results obtained using QHBM are compared with those achieved using a GA. The comparative results are summarized in Table 3, and the voltage profile comparison is illustrated in Figure 5.

For the single-DG case, both QHBM and GA identify the same optimal bus location (bus 61) and achieve identical values of total power loss and voltage profile. This result indicates that, for relatively simple optimization scenarios, both algorithms are capable of

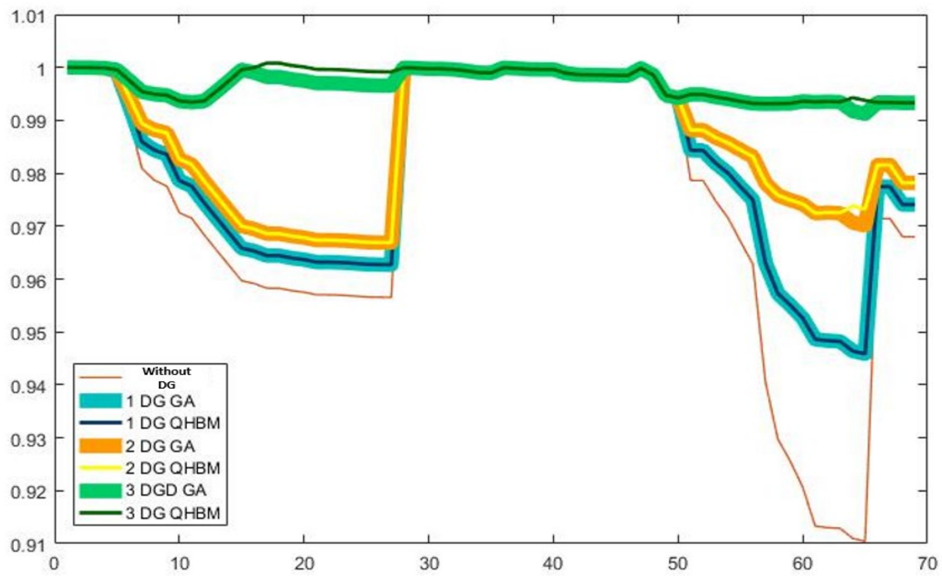

Figure 5. Comparison of voltage profile values after installation of DG QHBM – GA.

locating the global optimum, as also reported in earlier GA-based DG placement studies [9].

However, for the placement of two and three DG units, QHBM consistently outperforms GA. As shown in Table 3, QHBM achieves lower total power loss values (86.6239 kW and 72.7840 kW) compared to GA (87.6038 kW and 73.7789 kW). Similarly, the minimum voltage obtained using QHBM is slightly higher than that achieved using GA. Comparable convergence degradation of GA in multi-DG placement problems has been noted in previous studies due to premature convergence and loss of population diversity [13][14].

The superior performance of QHBM can be attributed to its queen scout migration mechanism, which combines focused exploitation around promising regions with stochastic exploration. In contrast, GA relies on population-wide genetic operators that may disrupt high-quality solutions, particularly in discrete, multi-DG placement problems.

H. Discussions and limitations

Based on the results presented in Tables 2–5 and Figures 2–5, it can be concluded that the proposed QHBM–BFS framework provides the most effective DG placement strategy for the IEEE 69-bus distribution system. The method achieves the highest reduction in active power loss and the most significant improvement in voltage profile while maintaining operational constraints.

Nevertheless, several limitations should be acknowledged. First, the computational burden of QHBM–BFS is higher than that of simplified sensitivity-based methods, as BFS power flow is executed at each optimization iteration. Second, the performance of QHBM is influenced by parameter selection, such as scout population size and scanning radius, which may require tuning for larger or more complex networks. These limitations suggest that future work could focus on adaptive parameter tuning and computational acceleration strategies.

IV. Conclusion

This paper has proposed a QHBM–BFS-based framework for optimal DG placement in radial distribution systems. The results on the IEEE 69-bus network show that QHBM and GA provide comparable performance for single-DG placement, indicating that conventional optimization methods remain effective for simple scenarios. However, as the number of DG units increases, the advantages of the proposed approach become more pronounced. For multi-DG placement, the proposed QHBM–BFS framework achieves approximately 1.1–1.2 better performance than GA and manual placement in terms of power loss reduction and voltage profile improvement. This improvement is mainly attributed to the queen–scout migration mechanism, which enables more effective exploration and coordination among multiple DG units. Overall, the proposed method offers a robust and practical solution for DG placement, particularly under higher DG penetration levels in radial distribution networks.

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Declarations

Author contribution

A.D. Fachriyyah and **Aripriharta** contributed equally as the main contributors of this paper. All authors read and approved the final paper.

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Competing interest

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

The use of AI or AI-assisted technologies

During the preparation of this work the author(s) used Chat GPT in order to Proofread. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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