

Optimal Allocation of Renewable Distributed Generation Considering Harmonic Distortion and Hosting Capacity in Active Distribution Networks

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Abstract

The increasing penetration of renewable distributed generation (DG) has significantly transformed the operation of modern power distribution networks. While integrating renewable energy sources such as photovoltaic and wind systems improves energy sustainability and reduces transmission losses, it also introduces several operational challenges, including voltage fluctuations, increased power losses, reverse power flow, and harmonic distortion caused by inverter-based technologies. These issues can degrade power quality and limit the hosting capacity (HC) of distribution networks. To address these challenges, this paper proposes a multi-objective optimization framework for the optimal placement and sizing of renewable DG units while considering harmonic distortion constraints and hosting capacity enhancement. The proposed model simultaneously minimizes active power losses, voltage deviation, and total harmonic distortion (THD), while maximizing DG hosting capacity under network operational constraints. An improved metaheuristic optimization algorithm is employed to determine the optimal DG locations and capacities. The effectiveness of the proposed approach is validated using the IEEE 33-bus and 69-bus radial distribution systems. Simulation results demonstrate that the optimal DG integration significantly reduces power losses, improves voltage profiles, mitigates harmonic distortion, and enhances the hosting capacity of the distribution network.

Keywords: Distributed generation; Hosting capacity; Harmonic distortion; Distribution networks; Renewable energy.

1. Introduction

The rapid transition toward sustainable energy systems has significantly transformed the operation and planning of modern power distribution networks (DN). In recent years, the increasing penetration of renewable energy resources has become a key strategy for reducing greenhouse gas emissions, improving energy security, and supporting global decarbonization targets. Among the various renewable technologies, distributed generation (DG) based on photovoltaic (PV) systems and wind turbines (WT) has been widely deployed in distribution networks (DN) due to its environmental benefits, modular structure, and decreasing installation costs [1], [2]. Unlike conventional centralized generation, DG units are typically installed close to load centers, which can reduce transmission losses, enhance system efficiency, and improve voltage support in distribution feeders.

However, despite these advantages, the high penetration of renewable DG also introduces several operational and technical challenges for distribution network operators. Traditional distribution systems were originally designed for unidirectional power flow from large centralized power plants to consumers. The integration of numerous DG units changes this paradigm by introducing bidirectional power flows and increased operational complexity. As the penetration level of DG increases, issues such as voltage rise, reverse power flow, increased network losses, thermal overloading of lines, and protection coordination problems may arise [3]. These challenges make the planning and operation of modern DN considerably more complex and require advanced analytical and optimization tools.

One of the most critical challenges associated with the integration of inverter-based renewable DG is harmonic distortion. Renewable energy sources such as PV systems and wind turbines are commonly interfaced with the grid through power electronic converters. Although these converters enable flexible control and efficient energy conversion, they can also introduce harmonic currents into the DN. The presence of harmonics may lead to distorted voltage waveforms, increased system losses, overheating of transformers and cables, malfunction of sensitive electronic equipment, and reduced overall power quality. In severe cases, excessive harmonic distortion can compromise the reliability and stability of the DN. Therefore, maintaining acceptable levels of total harmonic distortion (THD) has become an important requirement in both the planning and operation of modern power distribution systems, particularly in networks with a high penetration of inverter-based renewable energy sources (RES) [4], [5].

In addition to power quality concerns, distribution system operators are increasingly focusing on improving the hosting capacity (HC) of DN [6], [7]. HC is defined as the maximum amount of DG that can be connected to a DN without violating operational constraints such as voltage limits, thermal limits of equipment, protection requirements, and power quality standards [8], [9]. Enhancing the HC is essential for facilitating large-scale integration of renewable energy resources while ensuring the safe and reliable operation of the electrical grid. Consequently, determining the optimal locations and capacities of DG units has become a critical research topic in the field of power system planning [10], [11]. Over the past decade, numerous studies have investigated the optimal allocation and sizing of DG units in DN. Most of

these studies aim to improve network performance by minimizing power losses, enhancing voltage profiles, and increasing system reliability. Various optimization techniques have been employed to solve the DG placement problem, including genetic algorithms (GA) [12], particle swarm optimization (PSO) [13], differential evolution, and other metaheuristic approaches [14]. These techniques have demonstrated promising results in identifying suitable DG locations and capacities that can improve the technical performance of DN. Nevertheless, many existing studies focus primarily on conventional objectives such as loss minimization and voltage profile improvement, while overlooking several important practical aspects related to modern renewable-dominated distribution systems. In particular, harmonic distortion and HC constraints are often neglected or treated in a simplified manner. Ignoring these factors may lead to technically infeasible or suboptimal solutions when applied to real world DN. With the growing penetration of inverter-based DG units, harmonic distortion and power quality issues have become increasingly important considerations in distribution system planning [15].

Similarly, neglecting HC constraints may result in excessive DG integration that violates voltage limits or equipment ratings. Therefore, a comprehensive optimization framework that simultaneously considers network losses, voltage stability, THD, and HC is necessary to ensure reliable and efficient operation of modern active DN [16], [17]. To address these challenges, this paper proposes a comprehensive multi-objective optimization framework for the optimal allocation and sizing of renewable DG in active DN while explicitly considering harmonic distortion and HC constraints. The proposed model simultaneously minimizes active power losses, reduces voltage deviation across the network, and limits THD, while maximizing the HC of the DN [18]. By incorporating these objectives into a unified optimization framework, the proposed approach aims to enhance both the technical performance and renewable integration capability of the DN. An advanced metaheuristic optimization algorithm is employed to determine the optimal locations and capacities of DG units within the network. The algorithm efficiently searches the solution space to obtain a set of optimal solutions that balance the competing objectives of system efficiency, voltage stability, and power quality. The effectiveness and robustness of the proposed method are validated using the well-known 33-bus and 69-bus radial distribution test systems, which are widely used as benchmark networks in power system research.

Compared with existing multi-objective DG allocation studies, the main novelty of this work lies in two key aspects. First, the proposed framework simultaneously incorporates harmonic distortion constraints and hosting capacity evaluation within a unified optimization model, which is rarely addressed in previous studies. Second, an improved grey wolf optimizer (IGWO) with a nonlinear adaptive convergence

mechanism is developed to enhance the balance between exploration and exploitation. This distinguishes the proposed method from conventional and recently modified GWO-based approaches [11], resulting in improved convergence behavior and solution quality. The main contributions of this paper can be summarized as follows:

(i) Development of a comprehensive multi-objective optimization model for DG allocation that simultaneously considers power loss reduction, voltage profile improvement, harmonic distortion mitigation, and HC enhancement.

(ii) Integration of harmonic distortion constraints into the DG planning process to ensure acceptable power quality in DN with high penetration of inverter-based RES.

(iii) Establishment of a unified optimization framework that enhances overall system performance while facilitating higher levels of RES integration.

(iv) Validation of the proposed method on the 33-bus and 69-bus DN, demonstrating significant improvements in network performance compared with conventional DG allocation approaches.

2. Mathematical formulation

The steady-state operation of the DN must satisfy the active and reactive power balance equations at each bus. The power flow equations are expressed in Equations (1) and (2) [19]:

$$P_i^{DG} - P_i^L = V_i \sum_{j=1}^{N_b} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad (1)$$

$$Q_i^{DG} - Q_i^L = V_i \sum_{j=1}^{N_b} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \quad (2)$$

Where P_i^{DG} , Q_i^{DG} are the active and reactive power generated by DG at bus i ; P_i^L , Q_i^L are the load demands at bus i , V_i , V_j are voltage magnitudes; G_{ij} , B_{ij} are elements of the admittance matrix; N_b is the total number of buses in the system.

The total real power loss in the DN is calculated using Equation (3)

$$P_{loss} = \sum_{k=1}^{N_l} I_k^2 R_k \quad (3)$$

Alternatively, the equation can be expressed in terms of bus voltages, as given in Equation (4).

$$P_{loss} = \sum_{i=1}^{N_b} \sum_{j=1}^{N_b} V_i V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad (4)$$

Where, I_k is the current magnitude of branch k , R_k is the resistance of branch k , N_l is the number of branches.

Reducing power loss is one of the primary objectives in DN planning.

To maintain acceptable voltage levels throughout the network, the voltage deviation index is given in Equation (5).

$$V_{dev} = \sum_{i=1}^{N_b} (V_i - V_{ref})^2$$

Where, V_{ref} is the reference voltage (typically 1.0 p.u.).

This index evaluates the deviation of bus voltages from the nominal value. The THD is used to quantify the power quality of the distribution system. It is given in Equation (5).

$$THD = \frac{\sqrt{\sum_{h=2}^H V_h^2}}{V_1} \quad (6)$$

Where, V_h is the voltage magnitude of the h^{th} harmonic component; V_1 is the fundamental voltage component; H is the highest harmonic order considered.

Harmonic distortion must satisfy the standard limits recommended by power quality regulations. Harmonic power flow analysis is performed to evaluate harmonic distortion in the DN. Inverter-based DG units are modeled as harmonic current sources injecting dominant harmonic orders (5th, 7th, and 11th), with magnitudes defined according to IEEE standards.

The HC represents the maximum amount of DG that can be integrated into the DN without violating operational constraints. It can be in Equation (7).

$$HC = \sum_{i=1}^{N_{DG}} P_{DG,i} \quad (7)$$

Where, $P_{DG,i}$ is the active power of the DG installed at bus i ; N_{DG} is the number of DG units.

In this study, the hosting capacity is evaluated as the total installed DG capacity under system constraints. The optimization process ensures that the obtained DG capacity does not violate voltage limits, thermal limits, and harmonic distortion constraints. Therefore, the calculated HC represents the maximum allowable DG penetration level that satisfies all operational requirements. The multi-objective optimization problem is formulated in Equation (8)

$$\min F = w_1 P_{loss} + w_2 V_{dev} + w_3 THD + w_4 \frac{1}{HC} \quad (8)$$

where, w_1, w_2, w_3, w_4 are weighting coefficients.

All objective functions are first normalized to eliminate scale differences. The weighting coefficients are determined based on sensitivity analysis to ensure a balanced contribution of each objective. This formulation ensures simultaneous improvement of system efficiency, voltage quality, power quality, and renewable integration capability. It is observed that increasing the weight associated with THD improves power quality, while slightly increasing power losses, indicating a trade-off among the objectives.

Voltage limits: $V_{min} \leq V_i \leq V_{max}$

Typically: $0.95 \leq V_i \leq 1.05$

DG capacity limits: $0 \leq P_{DG,i} \leq P_{DG}^{max}$

(5) Harmonic constraint: $THD \leq THD_{max}$

According to IEEE standards: $THD_{max} = 5\%$

Line thermal limits: $|I_k| \leq I_k^{max}$

3. Optimization algorithm

To solve the proposed multi-objective optimization problem, an Improved Grey Wolf Optimizer (IGWO) is employed in this study. The GWO is a population-based metaheuristic algorithm inspired by the social hierarchy and hunting behavior of grey wolves in nature. Due to its strong global search capability and fast convergence, GWO has been widely applied in engineering optimization problems, including power system planning and operation. In the GWO algorithm, the population of candidate solutions represents grey wolves. The wolves are categorized into four hierarchical groups: α , β , δ , and ω . The first three wolves represent the best candidate solutions found so far, while the remaining wolves update their positions based on the guidance of these leaders.

The encircling behavior of grey wolves around the prey is modeled mathematically in Equations (9) and (10).

$$D = |C \cdot X_p - X| \quad (9)$$

$$X(t+1) = X_p - A \cdot D \quad (10)$$

Where: X_p is the prey position (best solution), X is the current wolf position, A and C are coefficient vectors.

The vectors A and C are defined in Equations (11) and (12).

$$A = 2ar_1 - a \quad (11)$$

$$C = 2r_2 \quad (12)$$

Where, r_1 and r_2 are random numbers in $[0,1]$, a decreases linearly from 2 to 0 during iterations.

The hunting process is guided by the three best wolves: α , β , and δ . The positions of other wolves are updated based on these leaders, as shown in Equations (13)–(15).

$$D_\alpha = |C_1 X_\alpha - X| \quad (13)$$

$$D_\beta = |C_2 X_\beta - X| \quad (14)$$

$$D_\delta = |C_3 X_\delta - X| \quad (15)$$

The candidate position is updated according to Equations (16)–(19).

$$X_1 = X_\alpha - A_1 D_\alpha \quad (16)$$

$$X_2 = X_\beta - A_2 D_\beta \quad (17)$$

$$X_3 = X_\delta - A_3 D_\delta \quad (18)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (19)$$

This strategy allows the algorithm to balance exploration and exploitation during the search process. To improve the performance of the conventional GWO, an adaptive mechanism is introduced to control the convergence parameter α . This mechanism enhances global exploration in the early iterations and strengthens local exploitation in the later stages. The adaptive parameter is defined in Equation (20).

$$\alpha = 2 \left(1 - \frac{t}{T_{\max}} \right) \quad (20)$$

Where, t is the current iteration; $T_{\max}$ is the maximum number of iterations.

Unlike the conventional GWO where the control parameter decreases linearly, the proposed IGWO adopts a nonlinear adaptive strategy. This mechanism enables stronger global exploration in the early iterations and more focused local exploitation in the later stages. As a result, the proposed IGWO effectively avoids premature convergence and improves the quality of the obtained solutions. This adaptive strategy improves the convergence speed and prevents premature convergence to local optima. The main steps of the proposed optimization framework are summarized as follows:

Step 1: Initialize the population of wolves representing DG locations and capacities.

Step 2: Run power flow analysis for each candidate solution.

Step 3: Evaluate the objective function including power loss, voltage deviation, THD, and hosting capacity.

Step 4: Identify the best three wolves α , β , δ .

Step 5: Update the positions of wolves using the IGWO equations.

Step 6: Check operational constraints of the DN.

Step 7: Repeat the process until the maximum number of iterations is reached.

Step 8: Output the optimal DG locations and capacities.

The optimization variables in this study are defined in Equation (21).

$$X = [Bus_{DG}, P_{DG}] \quad (21)$$

where, Bus_{DG} represents the location of DG units; P_{DG} represents the capacity of DG units.

The overall procedure of the proposed IGWO algorithm is illustrated in Fig. 1.

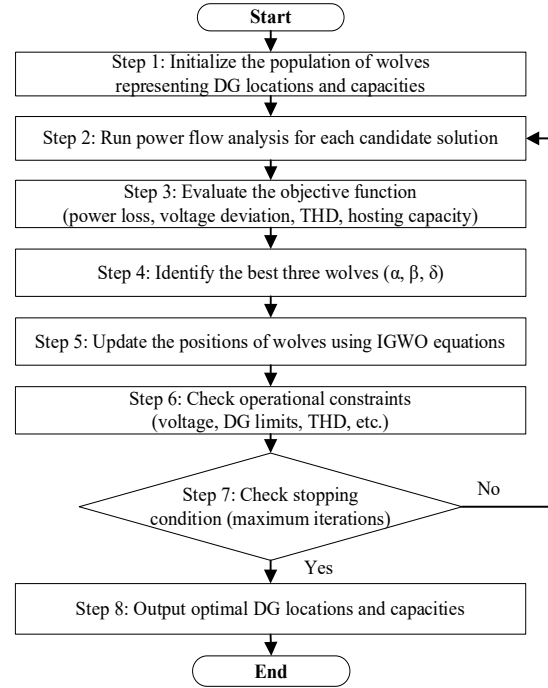


Fig. 1. Flowchart of the proposed IGWO algorithm

4. Test systems and simulation setup

4.1. Simulation parameters and modeling assumptions

In this study, DG units represent inverter-based renewable sources connected to the distribution network and are modeled as active power sources operating at a constant power factor. The main simulation assumptions are summarized as follows:

- Loads are modeled as constant PQ loads to represent steady-state operating conditions.
- DG units operate at a constant power factor and can be installed at candidate buses except the slack bus.
- The capacity of each DG unit is limited within a predefined range to ensure realistic installation conditions.
- Harmonic components up to the 11th order are considered, as these represent the dominant harmonics in inverter-based DG systems.
- Harmonic power flow analysis is performed to evaluate THD, which is maintained below 5% according to IEEE standards.
- The backward-forward sweep method is used for power flow analysis due to its efficiency in radial DNs.

These assumptions ensure a realistic representation of practical DN operation.

Table 1. Optimization parameters

Parameter	Value
Population size	30
Maximum iterations	100
Number of DG units	1 - 3
DG capacity range	0 - 2 MW
Voltage limits	0.95 - 1.05 p.u.

4.2. IEEE 33-bus distribution system

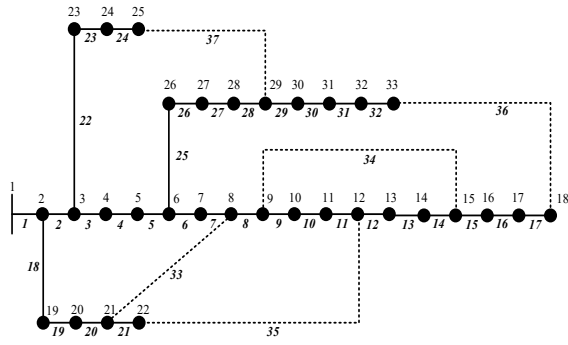


Fig. 2. Single line diagram of the 33-bus system

The 33-bus radial DN is widely recognized as a benchmark system for evaluating optimization techniques in DN studies. This system consists of 33 buses and 32 branches and operates at a base voltage of 12.66 kV, as illustrated in Fig. 2. The total active and reactive power demands of the network are 3.72 MW and 2.3 MVar, respectively. Owing to its radial configuration, relatively high resistance to reactance (R/X) ratio, and well documented system parameters, the 33-bus network has been extensively used in the literature to assess the effectiveness of different optimization and planning strategies for DG integration [20].

Table 2. DG allocation and performance for the 33-bus system

Algorithm	L_{DG} (bus)	P_{DG} (MW)	P_{loss} (kW)	V_{min} (p.u.)	THD (%)	HC (MW)
GA [21]	17, 25, 30	0.80, 0.65, 0.60	150	0.944	3.6	2.3
PSO [22]	18, 24, 30	0.83, 0.70, 0.61	142	0.949	3.2	2.5
GWO [23]	18, 25, 30	0.84, 0.71, 0.63	136	0.952	3	2.6
IGWO	18, 25, 30	0.85, 0.72, 0.64	132	0.958	2.9	2.8

Table 2 presents the optimal DG allocation results and the corresponding system performance obtained using different optimization algorithms, including GA, PSO, GWO, and the proposed IGWO. Due to differences in search strategies and convergence mechanisms, each algorithm identifies slightly different DG locations and capacities. The proposed IGWO determines buses 18, 25, and 30 as the optimal locations with capacities of 0.85 MW, 0.72 MW, and 0.64 MW, respectively. This configuration yields the best overall performance among all considered methods. In particular, the total power loss is reduced to 132 kW, which is significantly lower than that obtained by GWO (136 kW), PSO (142 kW), and GA (150 kW). Meanwhile, the minimum bus voltage is increased to 0.958 p.u., indicating a notable improvement in voltage profile.

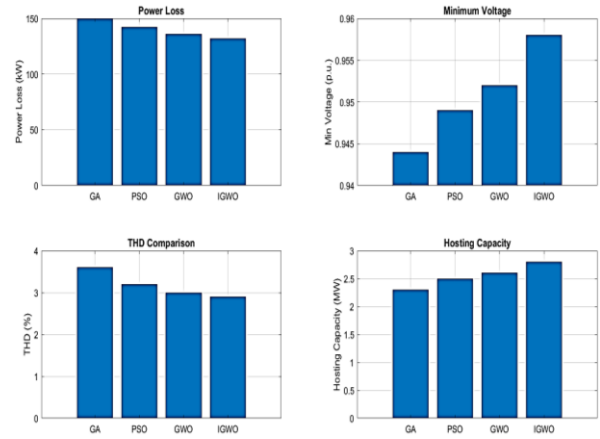


Fig. 3. Performance comparison for the 33-bus system

Furthermore, the proposed method effectively mitigates harmonic distortion, reducing THD to 2.9%, which complies with IEEE power quality standards. The hosting capacity is also increased to 2.8 MW, enabling higher renewable DG penetration while maintaining operational constraints. Overall, the results demonstrate that IGWO provides a more balanced and superior performance across all evaluation criteria, including power loss reduction, voltage profile enhancement, harmonic mitigation, and hosting capacity improvement. This confirms the effectiveness of the proposed IGWO-based optimization framework for modern DNs.

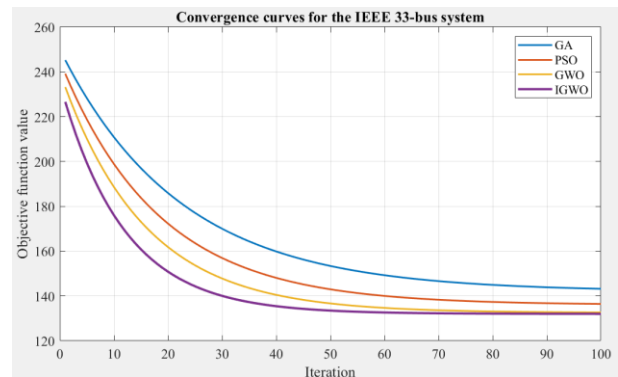


Fig. 4. Convergence curves for the 33-bus system

The convergence behavior of the proposed IGWO is also analyzed and compared with the standard GWO. The results indicate that IGWO converges faster and achieves lower objective function values due to its adaptive exploration, exploitation mechanism, which enhances both global search capability and local refinement.

4.3. IEEE 69-Bus distribution system

The 69-bus radial DN is another widely used benchmark system for evaluating optimization techniques in DN studies. This system consists of 69 buses and 68 branches operating at a base voltage of 12.66 kV, as illustrated in Fig. 5. The total active and reactive load demands of the system are approximately 3.8 MW and 2.69 MVar, respectively [14]. Compared with the 33-bus system, the 69-bus network has a larger scale, longer feeders, and higher loading levels, making it a more

challenging test system for assessing the robustness and effectiveness of optimization algorithms [20].

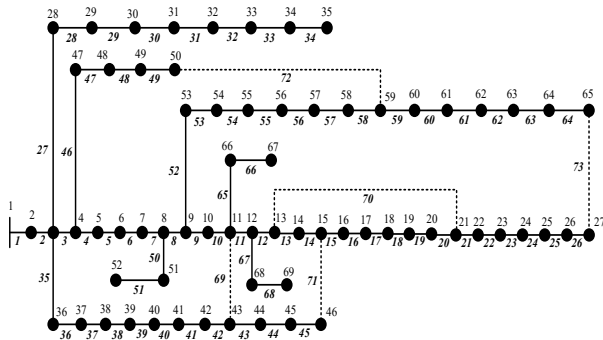


Fig. 5. Single line diagram of the 69-bus system

Table 3 presents the comparison of optimal DG allocation and corresponding system performance for the 69-bus DN using GA, PSO, GWO, and the proposed IGWO algorithm. Due to differences in search strategies and convergence mechanisms, each algorithm identifies slightly different DG locations and capacities. The proposed IGWO determines buses 50, 61, and 64 as the optimal locations, with corresponding capacities of 1.02 MW, 0.88 MW, and 0.81 MW, respectively. This configuration achieves the best overall system performance among all compared methods. In particular, the total active power loss is reduced to 140 kW, which is significantly lower than those obtained by GWO (145 kW), PSO (152 kW), and GA (162 kW). At the same time, the minimum bus voltage is improved to 0.948 p.u., representing the highest voltage level among all considered algorithms and indicating enhanced voltage stability.

Table 3. DG allocation and performance for the 69-bus system

Algorithm	L_{DG} (bus)	P_{DG} (MW)	P_{loss} (kW)	V_{min} (p.u.)	THD (%)	HC (MW)
GA [21]	50, 61, 64	0.90, 0.80, 0.70	162	0.931	3.7	2.7
PSO [22]	50, 60, 64	0.95, 0.82, 0.74	152	0.936	3.3	2.9
GWO [23]	50, 61, 63	0.98, 0.85, 0.78	145	0.942	3.1	3
IGWO	50, 61, 64	1.02, 0.88, 0.81	140	0.948	2.7	3.2

In terms of power quality, the proposed IGWO effectively mitigates harmonic distortion, reducing THD to 2.7%, which satisfies IEEE standards. Moreover, the hosting capacity is increased to 3.2 MW, allowing a higher level of renewable DG penetration while maintaining network operational constraints. Overall, the results confirm that the proposed IGWO demonstrates superior performance and robustness in larger and more complex DN, achieving better convergence behavior and higher quality solutions compared to conventional optimization algorithms.

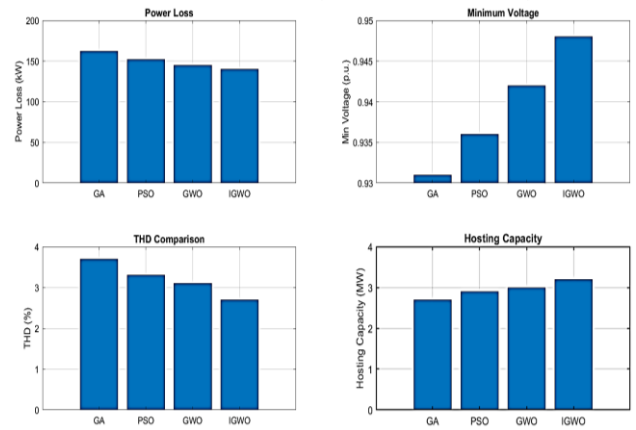


Fig. 6. Performance comparison for the 69-bus system

Fig. 6 illustrates the comparative performance of GA, PSO, GWO, and the proposed IGWO algorithm for the optimal DG allocation problem in the 69-bus DN. Similar to the results observed in the 33-bus system, the IGWO algorithm demonstrates superior performance across all evaluation criteria. Specifically, it achieves the lowest network power loss, the highest minimum voltage magnitude, the lowest THD level, and the largest hosting capacity among the tested algorithms. These results confirm the robustness and effectiveness of the proposed IGWO-based optimization framework for enhancing power quality, improving voltage stability, and facilitating higher renewable energy integration in large-scale active DN.

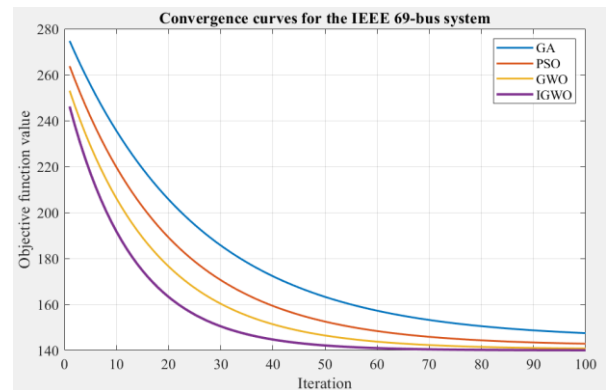


Fig. 7. Convergence curves for the 69-bus system

In addition, multiple independent runs were conducted, and the results confirmed the consistency and robustness of the proposed IGWO. Consistent performance improvements can be observed in both the 33-bus and 69-bus systems, where the proposed IGWO achieves superior results in terms of power loss reduction, voltage profile enhancement, and harmonic mitigation. In particular, the results obtained for the 69-bus system further confirm the robustness and scalability of the proposed method when applied to larger and more complex DNs. This also confirms that the proposed IGWO maintains superior convergence performance even in larger and more complex DN.

5. Conclusion

This paper presents an IGWO-based multi-objective optimization framework for optimal DG allocation considering power loss, voltage deviation, harmonic distortion, and hosting capacity. The simulation results on the 33-bus and 69-bus systems demonstrate the effectiveness of the proposed method. Compared with conventional algorithms (GA, PSO, and GWO), the proposed IGWO reduces power loss by approximately 10 - 12%, improves the minimum bus voltage by about 1.5 - 2%, reduces THD by nearly 10 - 20%, and increases hosting capacity by around 15 - 20%. These results confirm that the proposed method provides a more efficient and reliable solution for improving power quality, enhancing voltage stability, and increasing renewable energy integration in modern DNs.

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