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Multi-objective optimization of distributed generation placement and sizing in active distribution networks considering harmonic distortion

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ABSTRACT

This paper presents a multi-objective optimization model for optimal placement and sizing of inverter-based distributed generation (DG) units in active distribution power systems (DPS), considering their impact on harmonic distortion. The model simultaneously minimizes total power losses and total harmonic distortion (THD), ensuring compliance with IEEE 519 standards. To solve this problem, the reptile search algorithm (RUN) is applied and compared with three metaheuristic algorithms: multi-objective particle swarm optimization (MOPSO), multi-objective grey wolf optimizer (MOGWO), and multi-objective whale optimization algorithm (MOWOA). Simulation results on IEEE 33-bus and 69-bus systems show that reptile search algorithm (RUN) reduces power losses by up to 6.1% and THD by 21.7% compared to MOPSO. Moreover, the results confirm a strong correlation between DG output power and harmonic amplitudes, highlighting the importance of power quality aware DG planning.

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1. INTRODUCTION

The integration of distributed generators (DG), especially inverter based technologies such as photovoltaic and wind power, has become an essential component in modern distribution power systems (DPS) [1], [2]. When strategically placed and properly sized, DG units can enhance system efficiency, reduce power losses, improve voltage profiles, and promote energy self-sufficiency [3], [4]. However, the rapid deployment of inverter based DGs also introduces technical challenges chief among them is power quality degradation due to increased harmonic distortion [5], [6].

As more inverter based DGs are connected to the distribution networks, their high frequency switching characteristics can cause significant waveform distortion. This leads to several adverse effects, including equipment overheating, inaccurate measurements, malfunction of protection systems, and reduced equipment lifespan [7], [8]. To maintain acceptable power quality, the IEEE 519 standard mandates that the total harmonic distortion (THD) at each bus must not exceed 5% [9], [10]. Hence, DG planning must account not only for power loss minimization but also for harmonic mitigation, forming a multi-objective and nonlinear optimization problem [11], [12].

Previous studies have proposed various approaches to tackle this challenge, including the use of advanced metaheuristic algorithms for multi-objective optimization [13], [14]. For instance, extensions of well-known algorithms such as artificial bee colony (ABC) [15], [16], grey wolf optimizer (GWO) [17], [18], and whale optimization algorithm (WOA) [19], [20] have shown promising results in solving related problems. However, most of these works either neglect harmonic distortion as a primary consideration or treat it as a secondary constraint, without explicitly modeling the correlation between DG output power and harmonic amplitudes

To address this gap, this study proposes a multi-objective optimization model that explicitly incorporates harmonic distortion into the planning process of inverter based DGs. The model is designed to minimize both active power losses and THD levels, ensuring compliance with IEEE 519 standards [21]. To solve this problem, the reptile search algorithm (RUN), a recent metaheuristic inspired by the predatory behavior of reptiles [22], is adopted and benchmarked against three well-known optimization algorithms: multi-objective particle swarm optimization (MOPSO) [14], multi-objective grey wolf optimizer (MOGWO) [23], and multi-objective whale optimization algorithm (MOWOA) [24].

Simulations are conducted on two standard test systems the IEEE 33-bus and 69-bus DPS. Results show that RUN consistently outperforms the compared methods in terms of optimization quality, convergence speed, robustness, and THD compliance. Moreover, the results reveal a strong correlation between DG output power and harmonic distortion levels at individual buses, emphasizing the importance of power quality aware DG planning in active distribution systems. The key contributions of this paper are as follows:
– A new multi-objective optimization model that incorporates harmonic distortion as a primary objective in DG planning;
– A correlation based harmonic model that links DG output power with voltage distortion levels;
– Application of the RUN to solve the constrained nonlinear optimization problem;
– Comparative simulations on IEEE 33-bus and 69-bus DPS demonstrating the superior performance of RUN over other methods.

2. PROPOSED MATHEMATICAL MODEL

In this section, a multi objective optimization model is developed to determine the optimal placement and sizing of DGs in active DPS, taking into account the propagation of THD. The model consists of two main objective functions: i) minimizing the total technical power losses in the network, and ii) minimizing the THD at the buses where DGs are installed.

2.1. Decision variables

In the proposed model, the decision variables are defined as follows:

a. $x_i \in \{0,1\}$: A binary variable indicating whether a DG unit is installed at bus i (1: installed, 0: not installed).

b. $P_{dg,i}$: The active power output of the DG unit at bus i (kW).

c. $V_h(i)$: The amplitude of the h-order harmonic component at bus i, which is determined based on the DG output power.

Table 1 shows the symbols and notations used in the proposed optimization model

Table 1. Symbols and notations used in the proposed optimization model

Symbol	Description	Unit
x_i	Binary variable indicating dg placement at bus i	–
$P_{DG,i}$	Output power of dg at bus i	KW
V_i	Voltage magnitude at bus i	PU
h	Harmonic order (e.g., 3rd, 5th, 7th)	–
$V_{h,i}$	Amplitude of the h-order harmonic component at bus i	PU
THD_i	Total harmonic distortion at bus i	%
R_{ij}	Resistance of branch connecting bus i and j	OHM
P_{loss}	Total system power loss	KW

2.2. Objective function 1: minimization of power losses

The first objective aims to minimize the total technical power losses in the distribution power systems (DPS) and is formulated as (1):

$$f_1 = \sum_{(i,j)\in L} R_{ij} \cdot \frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \tag{1}$$

where,

L: Set of all branches in the DPS;

P_{ij}, Q_{ij}: Power flows on branch (i, j);
R_{ij}: Resistance of branch (i, j);
V_i: Voltage magnitude at bus i, considering only the fundamental component (50 Hz).

2.3. Objective function 2: minimization of harmonic distortion

The second objective minimizes the THD at buses where DGs are installed. THD at a bus is calculated according to the IEEE 519 standard as (2):

$$THD_i = \sqrt{\sum_{h=3,5,7,\ldots}^{H} \left(\frac{V_h(i)}{V_1(i)}\right)^2} \quad (2)$$

The overall harmonic objective function is expressed as (3):

$$f_2 = \sum_{i \in N_{dg}} THD_i \quad (3)$$

The THD function penalizes high harmonic content at critical nodes, thus promoting DG configurations that reduce distortion at the system level. Where,
- $V_h(i)$: Amplitude of the h^{th}- order harmonic component at bus i;
- $V_1(i)$: Amplitude of the fundamental voltage component at bus i;
- N_{dg}: Set of buses where DGs are installed.

In this study, only dominant harmonic orders (3rd, 5th, and 7th) are considered, as these are typically generated by inverter-based DG units and have the most significant impact on voltage distortion in low voltage distribution systems.

2.4. Technical constraints

The optimization is subject to the following technical constraints:
- Voltage limits:

$$V_{min} \leq V_i \leq V_{max} \quad \forall i \in N \quad (4)$$

Where $V_{\min} = 0.95$ pu, $V_{\max} = 1.05$ pu.
- DG capacity constraint

$$0 \leq P_{dg,i} \leq x_i \cdot P_{dg}^{max} \quad \forall i \in N \ \ (\text{With } P_{DG}^{\max} = 500\,\text{kW}) \quad (5)$$

- Maximum number of DG units

$$\sum_{i \in N} x_i \leq N_{dg}^{max} \ (N_{DG}^{\max} = 3 \text{ (33-bus, } N_{DG}^{\max} = 5 \text{ (69-bus))} \quad (6)$$

- Power quality constraint (harmonic limit)

$$THD_i \leq 5\% \quad \forall i \in bus\ set \quad (7)$$

These constraints ensure that the optimization process respects both technical and regulatory requirements, paving the way for an effective solution approach presented in the following section.

3. RESEARCH METHOD

In this study, the problem of jointly optimizing the placement and sizing of DGs in active DPS is formulated as a multi-objective optimization model. To effectively solve this complex problem, a recent nature inspired metaheuristic, the RUN is employed [22]. RUN is specifically well suited for multi-objective optimization tasks that involve harmonic distortion constraints. Drawing inspiration from the dynamic static predatory behavior of reptiles, RUN maintains a strong balance between global exploration and local exploitation, thereby enhancing its ability to identify high quality solutions. Additionally, the algorithm exhibits rapid convergence and consistent performance across multiple independent runs, making it a robust choice for solving nonlinear and constraint intensive problems such as DG planning with power quality considerations.

3.1. Solution representation and objective function

Each candidate solution in the optimization process consists of:
- DG placement: Represented by a binary vector $x_i \in \{0,1\}$, indicating whether a DG is installed at bus i.
- DG output power: Represented by a continuous vector $P_{dg,i} \in [0, P_{dg}^{max}]$.

The two objective functions are defined as:
- f_1: Total power losses in the network (kW).
- f_2: THD at DG installed buses.

The combined objective function is expressed as (8):

$$F = w_1 \cdot f_1 + w_2 \cdot f_2 + Penalty_{THD} \quad (8)$$

In this study, the weighting coefficients are set to w_1 = 0.6 (power loss) and w_2 = 0.4 (THD) based on preliminary sensitivity analysis. Where $w_1 + w_2 = 1$ are the weighting coefficients, and $Penalty_{THD}$ is a penalty term applied if the THD at any bus violates the IEEE 519 limit.

$$Penalty_{THD} = \begin{cases} 0, & if\, THD_i \leq THD_{max} \quad \forall i \\ \lambda \cdot \sum_i max\,(0, THD_i - THD_{max}), & otherwise \end{cases} \quad (9)$$

To balance the two conflicting objectives, power loss minimization and harmonic distortion reduction, weighting coefficients w_1 and w_2 are introduced in the aggregated fitness function. In this study, w_1= 0.6 and w_2= 0.4 to slightly prioritize the reduction of power losses while still giving sufficient importance to THD minimization. This selection is based on the operational priority of minimizing energy loss in DPS, especially under increasing load conditions, while maintaining acceptable power quality. Sensitivity analysis was conducted and showed that small variations in these weights do not significantly affect the optimal locations but may shift the sizing marginally.

3.2. Proposed algorithm: RUN

The RUN, proposed by Abualigah *et al.* [22], is a novel metaheuristic inspired by the predatory behavior of reptiles such as crocodiles. RUN incorporates two main search phases: Global search to explore the solution space, local search to refine solutions near the current best. The algorithm maintains population diversity and avoids premature convergence, making it highly effective for solving nonlinear constrained problems.

3.3. Solution update mechanism

RUN updates the solution position through two main stages:

Exploration phase: $X_i^{t+1} = X_i^t + r_1 \cdot sin(r_2) \cdot |r_3 \cdot X_{best} - X_i^t|$ (10)

Exploitation phase: $X_i^{t+1} = X_{best} + r_4 \cdot (X_j^t - X_k^t)$ (11)

Where X_i^t: solution of individual i at iteration t; X_{best}: current global best solution; X_j, X_k: randomly selected individuals; r_1, r_2, r_3, r_4: random control parameters.

3.4. Binary variable handling and constraint processing

The binary decision variable x_i (DG placement) is derived from the continuous domain using a sigmoid function:

$$\mathrm{x_i} = \begin{cases} 1, & \text{if } \sigma(\mathrm{X_i}) > \mathrm{rand}(0,1) \\ 0, & \text{otherwise} \end{cases} \quad \text{where } \sigma(\mathrm{z}) = \frac{1}{1+\mathrm{e}^{-\mathrm{z}}} \quad (12)$$

Constraints on power output, voltage levels, and harmonic limits are handled by adding a penalty to the objective function when violated.

3.5. Steps of the run algorithm

The steps of the run algorithm are as follows:

Step 1: Initialize a population of N individuals. Each individual represents a candidate solution, including DG placement vector x_i and corresponding output powers $P_{\mathrm{DG},i}$.

Step 2: Evaluate the objective function F for each individual, which includes:
- f_1: total power loss in the network,

– f_2: THD at DG buses,
– A penalty term applied if THD exceeds the IEEE 519 limit.

Step 3: Identify the initial global best solution X_{best} from the evaluated population.

Step 4: For each iteration $t = 1$ to T, perform the following steps:
– Determine the search phase:
  + If $t < T/2$, apply the exploration phase to enhance global search;
  + If $t \geq T/2$, apply the exploitation phase to refine local solutions.
– Update the position of each individual using the corresponding update formula based on the selected phase.
– Apply a sigmoid transfer function to convert continuous decision variables to binary form for DG placement decisions.
– Re-evaluate the objective function F for each updated individual.
– Update X_{best} if a new individual yields a better solution.

Step 5: Repeat step 4 until the maximum number of iterations T is reached.

Step 6: Output the final optimal solution X_{best}, which includes: optimal DG placement (bus locations), optimal DG sizing at each selected node, total system power loss, and the final THD levels across the system.

To further clarify the RUN implementation, the algorithmic steps are summarized as in Figure 1.

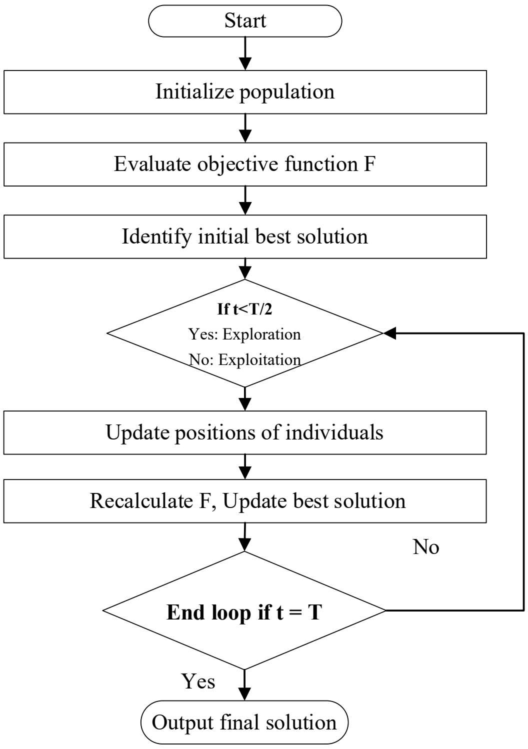

Figure 1. RUN for DG planning

4. RESULTS AND DISCUSSION

This section presents and discusses the simulation results obtained by applying the proposed model on 33-bus and 69-bus DPS. Performance is evaluated based on three metrics: power loss, THD compliance, and convergence behavior. Comparative results with MOPSO, MOGWO, and MOWOA are included to validate the effectiveness of the RUN algorithm. In this simulation, DGs are modeled as inverter-based sources, which inherently introduce harmonic distortion particularly at the 3rd, 5th, and 7th orders. The amplitude of each harmonic component is defined as a percentage of the DG's output power at the corresponding bus, following the model:

$$V_h(i) = k_h \cdot P_{dg,i}, \quad h \in \{3,5,7\} \tag{13}$$

The voltage quality at each bus is evaluated using the THD, calculated as (14):

$$\mathrm{THD_i} = \sqrt{\sum_h \left(\frac{V_h(i)}{V_1(i)}\right)^2} \quad (14)$$

The maximum allowable THD threshold is set to 5%, as recommended by the IEEE 519 standard. The maximum number of DGs installed is set to 3 for the 33-bus system and 5 for the 69-bus system. The output power of each DG is constrained between 0 and 500 kW. The potential installation sites are selected from load buses only (excluding the main source bus). All optimization algorithms (RUN, MOPSO, MOGWO, and MOWOA) are configured with the same parameters to ensure fair comparison (maximum number of iterations: 100, population size: 50, number of independent runs: 20). Each algorithm utilizes a weighted objective function with $w_1 = 0.5$ and $w_2 = 0.5$ to simultaneously minimize power losses and harmonic distortion. A penalty function based on THD violations is also incorporated across all approaches.

4.1. 33-BUS DPS

Figure 2 presents the single line diagram of the 33-bus DPS, comprising 37 branches, and clearly depicting the connectivity between the main substation, load buses, feeder lines, and candidate nodes for DG integration. The system topology and electrical parameters are adopted from reputable sources [25], [26] to ensure the credibility and reproducibility of the simulation results.

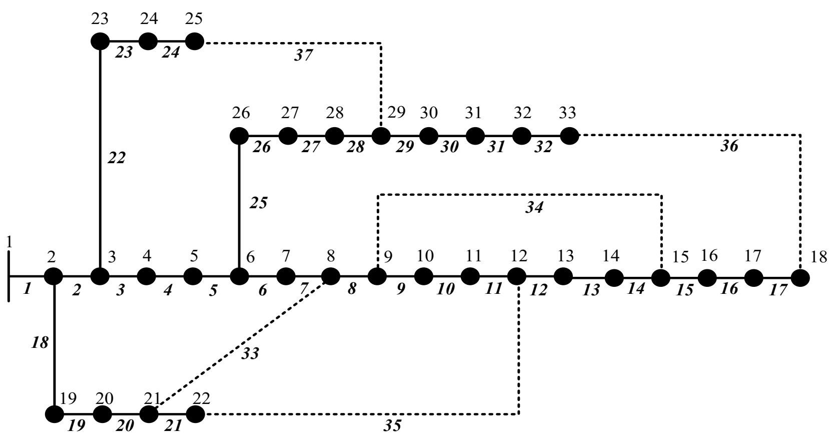

Figure 2. Single line diagram of the 33-bus DPS

The simulation results presented in Table 2 clearly indicate that the proposed RUN algorithm outperforms the benchmark methods (MOPSO, MOGWO, and MOWOA) in terms of three critical performance indicators: total power loss, THD, and DG allocation effectiveness. Specifically, RUN achieves the lowest total power loss of 139.2 kW, representing a reduction of 4.2%, 2.0%, and 3.7% compared to MOPSO (145.3 kW), MOGWO (142.1 kW), and MOWOA (144.6 kW), respectively. In terms of power quality, RUN maintains the total harmonic distortion at 2.78%, significantly below the IEEE 519 threshold (5%) and lower than the corresponding results of MOPSO (3.46%), MOGWO (3.02%), and MOWOA (3.11%).

Table 2. Optimization results on the 33-bus DPS

Method	L_{DG} (node)	P_{DG} (MW)	P_{loss} (kW)	THD (%)	Time (s)
RUN	6, 14, 30	0.4, 0.25, 0.33	139.2	2.78	16.2
MO-PSO	6, 18, 29	0.38, 0.2, 0.34	145.3	3.46	12.7
MO-GWO	7, 13, 28	0.37, 0.21, 0.32	142.1	3.02	14.9
MO-WOA	5, 15, 27	0.36, 0.23, 0.31	144.6	3.11	13.5

This improvement can be attributed to RUN's effective balance between exploration and exploitation, enabling it to identify well distributed DG placements. In particular, RUN selects buses [6, 14, 30] with output powers [0.4, 0.25, 0.33] MW, closely aligned with the system's load profile. This configuration ensures both voltage support and harmonic mitigation. In contrast, the alternative algorithms tend to allocate DGs with lower capacities or less strategic placement, leading to suboptimal compensation for power losses and harmonic suppression.

Although the execution time of RUN (16.2 seconds) is marginally higher than that of the other methods, the added computational effort is acceptable considering the substantial gains in solution quality and the fact that DG planning is an offline, non-real time task. The convergence behavior illustrated in Figure 3 further validates RUN's superiority: it achieves the most stable and rapid convergence, reaching near optimal fitness within approximately 40 iterations. While MOPSO converges faster initially, it suffers from slight oscillations, whereas MOGWO and MOWOA converge more slowly with less consistency. Overall, these findings confirm the robustness, efficiency, and practical applicability of the RUN algorithm for high quality DG planning under harmonic constraints.

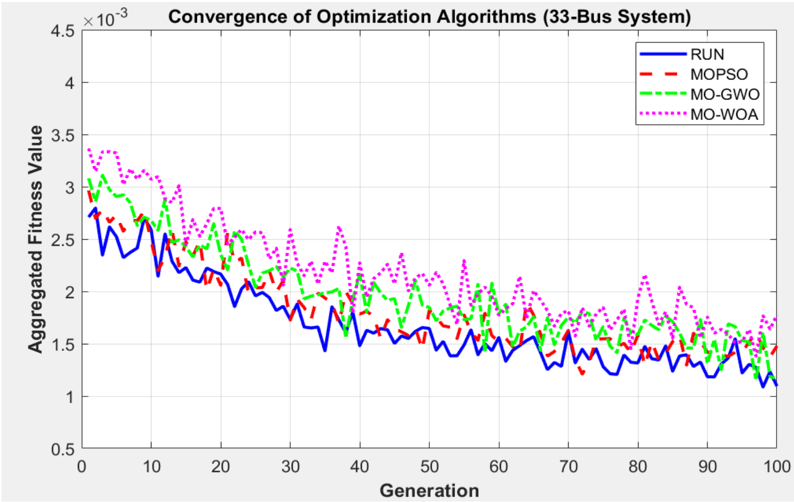

Figure 3. Convergence curves of the optimization algorithms on the 33-bus DPS

4.2. 69-BUS DPS

Figure 4 shows the single-line diagram of the 69-bus DPS, comprising 73 branches and a more complex topology than the 33-bus system. It depicts the connections among the main substation, load buses, feeders, and potential sites for renewable integration. The network structure and data are based on trusted sources [25], [26] ensuring consistency in simulation. This configuration provides a robust testbed for evaluating optimization algorithms in reducing power losses and improving voltage profiles in large scale DPS.

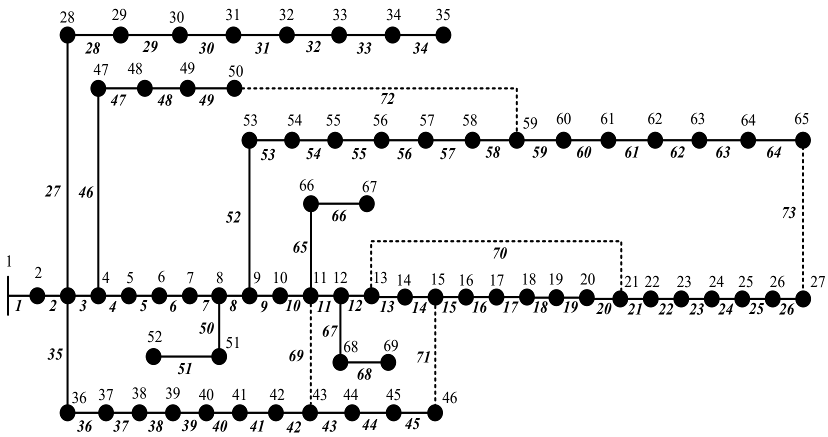

Figure 4. Single-line diagram of the 69-bus DPS

The simulation outcomes on the IEEE 69-bus DPS, as summarized in Table 3 and illustrated in Figure 5, further reinforce the superior performance of the proposed RUN algorithm over the benchmark methods. In terms of power loss minimization, RUN achieved the best result with a total loss of 212.7 kW, improving upon MOPSO (223.5 kW), MOGWO (218.3 kW), and MOWOA (221.6 kW) by 4.8%, 2.6%, and 4.0%, respectively. Regarding power quality, RUN also recorded the lowest THD of 3.15%, well within the IEEE 519 standard and lower than MOPSO (3.91%), MOGWO (3.41%), and MOWOA (3.57%).

Table 3. Optimization results on the 69-bus DPS

Method	L_{DG} (node)	P_{DG} (MW)	P_{loss} (kW)	THD (%)	Time (s)
RUN	17, 24, 61, 65, 66	0.45, 0.39, 0.3, 0.26, 0.31	212.7	3.15	28.5
MOPSO	16, 26, 60, 67, 68	0.44, 0.35, 0.29, 0.25, 0.3	223.5	3.91	22.2
MOGWO	18, 25, 59, 64, 69	0.43, 0.36, 0.28, 0.24, 0.31	218.3	3.41	25.6
MOWOA	20, 27, 62, 63, 66	0.42, 0.37, 0.27 0.23, 0.32	221.6	3.57	24.0

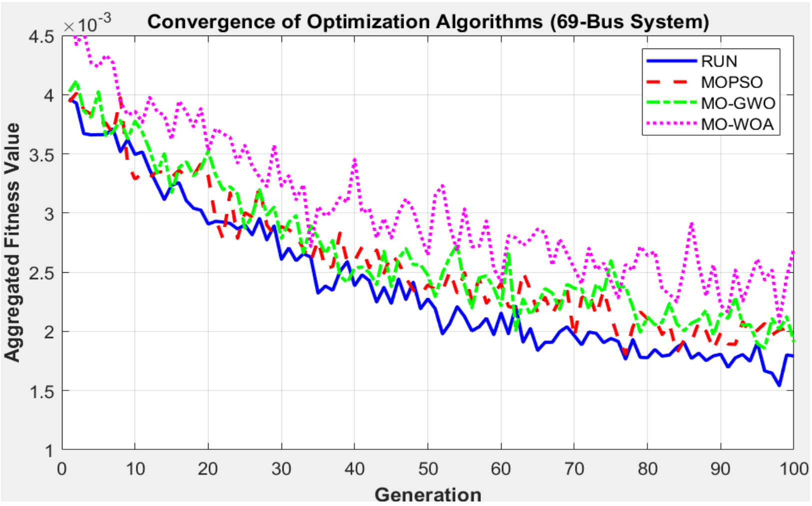

Figure 5. Convergence curves of the optimization algorithms on the 69-bus DPS

The enhanced performance of RUN can be attributed to its balanced exploration-exploitation mechanism, which leads to more effective DG allocations. In particular, RUN selected buses [17, 24, 61, 65, 66] with power outputs [0.45, 0.39, 0.30, 0.26, 0.31] MW, reflecting a well distributed configuration aligned with key load nodes. This configuration results in better support for voltage profiles and harmonic suppression. In contrast, the alternative algorithms showed less effective sizing and positioning strategies, contributing to higher losses and greater harmonic distortion. Although RUN required a slightly longer execution time (28.5 seconds) compared to MOPSO (22.2 seconds), MOGWO (25.6 seconds), and MOWOA (24.0 seconds), this overhead is reasonable given the improved solution quality and the offline nature of DG planning. Figure 5 shows the convergence profiles of the four algorithms. RUN consistently exhibits the most stable and rapid convergence, attaining the lowest aggregated fitness value within approximately 40 iterations. MOPSO also converges quickly but displays noticeable oscillations in later generations. In contrast, MOGWO and MOWOA converge more slowly and present greater fluctuations throughout the optimization process, reflecting weaker stability and reliability. These observations validate the scalability, robustness, and practical applicability of the RUN algorithm in solving large scale DG planning problems under power quality constraints.

5. CONCLUSION

This paper presented a multi-objective optimization model for determining the optimal placement and sizing of inverter-based DG units in active DPS, explicitly addressing the impact of harmonic distortion, an issue often underestimated in previous studies. The model was designed to simultaneously minimize total power losses and THD, in compliance with IEEE 519 standards, thereby ensuring both technical efficiency and power quality. To solve this complex optimization problem, the RUN, a recent metaheuristic inspired by reptilian hunting strategies, was adopted and benchmarked against three established algorithms: MOPSO, MOGWO, and MOWOA. Simulation experiments on the IEEE 33-bus and 69-bus test systems demonstrated that RUN consistently outperformed the alternatives in terms of loss reduction, THD minimization, and convergence stability. These results validate the algorithm's robustness and effectiveness in solving nonlinear, constraint intensive planning problems in distribution networks. The findings also revealed a clear correlation between DG output power and harmonic amplitudes, underscoring the importance of incorporating harmonic distortion explicitly into DG planning frameworks. From a practical perspective, the proposed approach offers a more comprehensive tool for network operators to improve system reliability and power quality while integrating renewable energy sources. Future research directions may include extending the model to unbalanced three phase systems, integrating dynamic load profiles, and exploring hybrid frameworks that combine metaheuristics with machine learning techniques for faster convergence and better generalization in real-time smart grid applications.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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