Optimization of Distributed Generation Planning to Maximize the Absorption Rate of Renewable Energy in Distribution Networks

Trieu Ngoc Ton
Thu Duc College of Technology, Ho Chi Minh City, Vietnam
tonngoctrieu@gmail.com (corresponding author)

Hai Hoang Lai
Thu Duc College of Technology, Ho Chi Minh City, Vietnam
hoanghailai10@gmail.com

Loi Van Pham
Thu Duc College of Technology, Ho Chi Minh City, Vietnam
phamvanloi@tdc.edu.vn

Tuyen Ngoc Hoang
Thu Duc College of Technology, Ho Chi Minh City, Vietnam
hoangngoctuyen@tdc.edu.vn

Received: 12 March 2025 | Revised: 4 April 2025 | Accepted: 9 April 2025

 DOI: https://doi.org/10.48084/etasr.10921

ABSTRACT

This paper presents a multi-objective optimization approach for optimal Distributed Generation (DG) placement and sizing, optimizing power loss reduction, cost efficiency, voltage stability, and Renewable Energy Source (RES) absorption. The Gray Wolf Optimizer (GWO) was chosen for its strong global search, fast convergence, and ability to avoid local optima. Simulations on IEEE 33-bus and IEEE 69-bus systems compared GWO against the Cuckoo Search Algorithm (CSA), Multi-Objective Particle Swarm Optimization (MOPSO), and Genetic Algorithm (GA). The results showed that GWO achieved the least power loss and highest RES absorption, enhancing efficiency, stability, and sustainability. This study demonstrates the effectiveness of nature-inspired optimization in DG planning and RES integration.

Keywords-distributed generation; renewable energy absorption; multi-objective optimization; grey wolf optimizer; distribution network

I. INTRODUCTION

The growth of Distributed Generation (DG), especially Renewable Energy Sources (RES) such as solar and wind, is reshaping distribution networks [1, 2]. DG integration reduces grid load, minimizes power losses, and enhances reliability while supporting sustainability. However, RES intermittency can cause voltage fluctuations, power imbalances, and stability issues. Thus, optimal DG placement and size must ensure efficiency and maximize RES integration for effective utilization [3, 4].

In recent years, the optimization of DG planning has gained significant attention from the research community due to its potential to improve energy efficiency, improve power system reliability, and facilitate large-scale integration of RES. Numerous studies have explored traditional optimization techniques such as Genetic Algorithm (GA) [5], Particle Swarm Optimization (PSO) [6], Search Algorithm (CSA) [7], and Nondominated Sorting Genetic Algorithm II (NSGA-II) [8] to solve this problem. However, these methods often face limitations such as susceptibility to local optima, poor global search capabilities, and slow convergence rates when dealing with complex search spaces. To overcome these limitations, advanced metaheuristic algorithms, such as the Gray Wolf Optimizer (GWO) [9], have been developed, providing an effective balance between exploitation and exploration, leading to more accurate solutions. Moreover, although some studies have focused on improving voltage quality and improving system stability with DG integration, they have not fully addressed optimizing RES absorption rates [4, 10]. Recent multi-objective optimization approaches have been proposed to simultaneously optimize criteria such as power loss reduction, investment cost, and voltage quality [11, 12]. However, most of these studies have not deeply focused on maximizing RES utilization efficiency, resulting in suboptimal DG integration outcomes [13, 14].

This paper presents a multi-objective optimization model using the GWO to enhance DG planning in distribution networks, maximizing RES utilization while ensuring efficient power system operation. The model optimizes four key criteria: minimizing power losses, reducing DG investment costs, improving voltage quality, and maximizing RES absorption. The GWO algorithm is chosen for its strong global search, ability to avoid local optima, and faster convergence compared to traditional methods such as GA, PSO, and NSGA-II. Simulations on IEEE 33-bus and 69-bus systems compare GWO with CSA [15], Multi-Objective Particle Swarm Optimization (MOPSO) [16], and GA [17], demonstrating that GWO achieves superior optimization, reduces power losses, maintains voltage stability, and maximizes RES utilization more effectively, contributing to a more sustainable and efficient distribution network.

II. PROBLEM DESCRIPTION

A. Distribution Network Model with Integrated Distributed Generation

Traditional distribution networks operate with a unidirectional power flow from substations to consumers. However, DG integration introduces bidirectional power flows, posing challenges in optimally placing and sizing DG units to maintain safe, efficient, and stable operation (Figure 1) [18]. The integration of DG leads to complexities such as voltage regulation issues, power flow imbalances, and protection system coordination challenges. Therefore, it is essential to develop optimization models that can effectively address these challenges while maximizing the benefits of DG integration, such as reduced power losses, enhanced voltage stability, and increased renewable energy utilization.

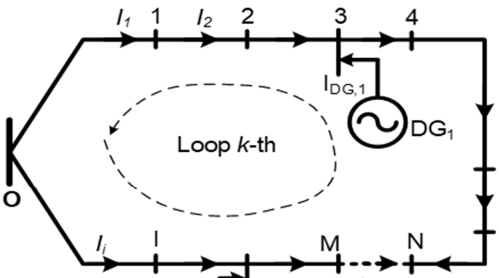

Fig. 1. Distribution network with DG.

B. Objective Function

The DG optimization problem is a multi-objective function optimizing performance, costs, and RES utilization, expressed as:

$$F = w_1 P_{\text{loss}} + w_2 C_{\text{DG}} + w_3 \Delta V + w_4 \frac{P_{\text{total}}}{\max(P_{\text{RES}}, k_{\min})} \quad (1)$$

where P_{loss} is the total power loss in the system (kW), C_{DG} is the total investment cost of DG units (USD), ΔV is the voltage deviation at nodes compared to the nominal voltage (p.u.), $P_{\text{RES}}/P_{\text{total}}$ is the ratio of RES to the total load power, which needs to be maximized, $k_{\min}$ is a small threshold to avoid division by zero when there is no RES ($k_{\min}$=0.01), and w_1, w_2, w_3, and w_4 are weighting factors to adjust the priority level of each criterion.

C. Problem Constraints

1) Power Balance at Each Node

The system must ensure power balance at each node.

$$P_{\text{gen},i} + P_{\text{DG},i} = P_{\text{load},i} + P_{\text{loss},i}, \ \forall i \in N \quad (2)$$

where $P_{\text{gen},i}$ is the power generated from the main grid at node i, $P_{\text{DG},i}$ is the power generated from DG at node i, $P_{\text{load},i}$ is the load demand at node i, and $P_{\text{loss},i}$ is the power loss on the branch connected to node i.

2) Voltage Limits at Each Node

The voltage at each node must remain within safe operating limits to prevent damage to electrical equipment:

$$V_{\min} - V_{\max} = 0.95\text{-}1.05 \text{ p.u.}$$

$$V_{\min} \le V_i \le V_{\max}, \quad \forall i \in N \quad (3)$$

3) DG Power Capacity Limits

The output power of DG units must not exceed their allowable capacity to avoid overloading. The maximum DG power output, $P_{\text{DG},i}^{\max}$, is determined based on the RES availability at node i:

$$P_{\text{DG},i}^{\min} \le P_{\text{DG},i} \le P_{\text{DG},i}^{\max}, \quad \forall i \in N_{\text{DG}} \quad (4)$$

4) Total System Power Constraint

This constraint ensures that the total power generated from both DG units and the main grid equals the total load demand and system power losses, helping maintain the balance and stability of the power system. The maximum total system capacity, denoted as $P_{\text{total}}^{\max}$, represents the upper limit of the system's allowable power output.

$$\sum_{i=1}^{N_{\text{DG}}} P_{\text{DG},i} \le P_{\text{total}}^{\max} \quad (5)$$

D. Decision Variables

In this optimization problem, the decision variables are: x_i (the location of the DG unit, representing the node i in the distribution network where the DG is installed) and $P_{\text{DG},i}$ (the power output of the DG at node i, representing the optimal generation capacity assigned to each selected location).

The GWO algorithm optimizes DG placement and capacity to balance power loss reduction, cost minimization, voltage improvement, and renewable energy absorption.

$$F = w_1 P_{\text{loss}} + w_2 C_{\text{DG}} + w_3 \Delta V + w_4 \frac{P_{\text{total}}}{\max(P_{\text{RES}}, k_{\min})} \quad (6)$$

Power loss (kW):

$$P_{\text{loss}} = \sum_{(i,j)\in\mathcal{B}} R_{ij} \frac{|S_{ij}|^2}{|V_i|^2} \quad (7)$$

DG investment and operational cost (USD):

$$C_{\text{DG}} = \sum_{i=1}^{N_{\text{DG}}} C_{\text{install},i} \quad (8)$$

Voltage deviation (p.u.):

$$\Delta V = \sum_{i=1}^{N} | V_i - V_{ref} | \quad (9)$$

RES utilization factor:

$$\frac{P_{\text{total}}}{\max(P_{\text{RES}}, k_{\min})} = \frac{\sum_{i=1}^{N} P_{\text{load},i}}{\max\left(\sum_{i=1}^{N_{\text{RES}}} P_{\text{RES},i}, k_{\min}\right)} \quad (10)$$

III. PROPOSED METHOD

This study proposes an optimization method for DG placement and sizing to maximize RES absorption, minimize power losses, maintain voltage quality, and optimize costs. GWO is chosen for its fast convergence, strong global search, and ability to avoid local optima. The fitness function combines the main objective with penalty terms to ensure compliance with network constraints, expressed as:

$$Fitness = F + P_V + P_{\text{DG}} + P_{\text{bal}} \quad (11)$$

where F is the main objective function value, as defined in (1), and P_V, P_{DG}, and P_{bal} are penalty functions corresponding to voltage constraints, DG power output limits, and power balance constraints, respectively.

- Voltage constraint penalty: The voltage at each node must be within the allowable range $[V_{\min}, V_{\max}]$. If the node voltage V_i falls outside this range, a penalty is applied. The penalty function is defined as:

  $$P_V = \lambda_1 \sum_{i=1}^{N}\left(\max(0, V_{\min} - V_i) + \max(0, V_i - V_{\max})\right) \quad (12)$$

  where λ_1 is the voltage penalty coefficient.

- DG power output penalty: The power output of each DG unit must be within its technical limits. If $P_{\text{DG},i}$, exceeds the allowed range, a penalty is imposed:

  $$P_{\text{DG}} = \lambda_2 \sum_{i=1}^{N_{\text{DG}}} \left(\max\left(0, P_{\text{DG},i}^{\min} - P_{\text{DG},i}\right) + \max\left(0, P_{\text{DG},i} - P_{\text{DG},i}^{\max}\right)\right) \quad (13)$$

  where λ_2 is the DG power output penalty coefficient.

- Power balance penalty: The total power generated from DG and the grid must equal the sum of the load demand and system losses. Any imbalance incurs a penalty:

  $$P_{\text{bal}} = \lambda_3 \mid P_{\text{gen}} + P_{\text{DG}} - (P_{\text{load}} + P_{\text{loss}}) \mid \quad (14)$$

  where λ_3 is the power balance penalty coefficient.

- Adding these penalty functions to the objective function helps guide the optimization algorithm to find solutions that are not only optimal in terms of performance but also maintain system stability and reliability. The GWO algorithm mimics the hunting behavior of gray wolves, where the top three wolves, Alpha, Beta, and Delta, lead the search process. Each wolf represents a potential solution, corresponding to a combination of DG locations and capacities. The positions of the wolves are updated iteratively based on the following formula:

$$X(t+1) = \frac{X_\alpha + X_\beta + X_\delta}{3} \quad (15)$$

where $X(t+1)$ is the updated position of a solution at iteration t+1, and X_α, X_β and X_δ are the positions of the best three solutions (wolves) in the current population.

This ensures global convergence while avoiding local optima, making it ideal for DG planning. Figure 2 outlines the GWO process, including initialization, evaluation, updates, and convergence checks.

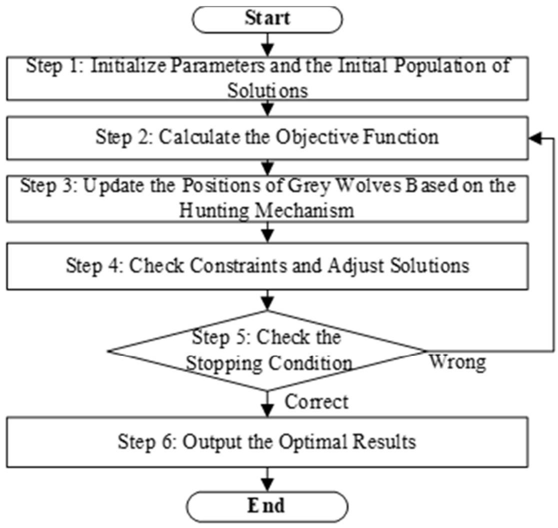

Fig. 2. GWO flowchart for DG optimization.

1) *Step 1: Initialize Parameters and the Initial Population of Solutions*

This step defines the number of individuals (gray wolves) in the population, the maximum number of iterations, and initializes the DG locations and capacities randomly within the constraint limits. It also sets the weighting factors w_1, w_2, w_3, and w_4 based on the priority of each optimization criterion.

2) *Step 2: Calculate the Objective Function*

For each individual in the population, this step calculates the values of P_{loss}, C_{DG}, ΔV, and P_{RES}. The three best solutions, X_α, X_β, and X_δ, are identified based on the objective function values.

3) *Step 3: Update the Positions of Gray Wolves Based on the Hunting Mechanism*

This step updates the position of each individual according to the hunting behavior equation:

$$X(t+1) = X_\alpha - A \cdot D$$

where $D = \mid C \cdot X_\alpha - X \mid$ represents the distance between the current wolf and the prey, and A, C are random adjustment vectors that help expand or narrow the search space.

4) Step 4: Check Constraints and Adjust Solutions

This step verifies that node voltages are within allowable limits, DG power outputs do not exceed their capacity limits, and the total DG generation does not surpass the total load demand. If any solution violates the constraints, it is adjusted to the nearest valid value.

5) Step 5: Check Stopping Criteria

The algorithm stops if the maximum number of iterations is reached or if there is no significant improvement in the objective function. If the stopping criteria are not met, the process returns to Step 2 to continue updating the solutions.

6) Step 6: Output the Optimal Results

Once the optimal solution X_α is found, this step outputs the final optimal results, including DG locations and capacities, power losses, voltage quality, and the achieved RES utilization rate.

IV. TEST RESULTS

The IEEE 33-bus and 69-bus systems were simulated using the backward-forward sweep method combined with optimization algorithms to determine the optimal placement and sizing of DG units. The simulations were carried out on a computer with an Intel Core i7 CPU 5.0 GHz, 32GB RAM, running Windows 11 and utilizing MATLAB R2023a. GWO uses 30 individuals for the 33-bus system and 50 individuals for the 69-bus system, with maximum iterations of 100 and 150, respectively. A control coefficient was set to decrease from 2 to 0 to balance between exploitation and exploration. For comparison, the CSA employed 30 nests with an abandonment probability of $p_a = 0.25$ and Levy flight characterized by $\lambda = 1.5$. The MOPSO used 30 particles with an inertia weight of $w = 0.7$ and acceleration coefficients $c_1 = c_2 = 1.5$. Meanwhile, the GA operates with a population of 30 individuals, a crossover rate of 0.8, and a mutation rate of 0.02. These parameters were optimized to ensure fast convergence and effective global search.

TABLE I. PARAMETERS OF THE 33-BUS AND 69-BUS DISTRIBUTION NETWORKS

Parameter	33-bus	69-bus
V_{nominal}	12.66 kV	12.66 kV
Total load capacity	(3.715 + j2.30) MVA	(3.80 + j2.69) MVA
$P_{\text{DG},k}$	0.5 - 2.0 MW	0.5 - 2.0 MW
C_{DG}	1500 USD/kW	1500 USD/kW
Number of DGs	3	3
$V_{\min} - V_{\max}$	0.90 - 1.05 p.u.	0.90 - 1.05 p.u.
w_1, w_2, w_3, w_4	0.2; 0.2; 0.1; 0.5	0.2; 0.2; 0.1; 0.5
Max iterations	100	150
Population size	30	50

GWO simulates the hunting behavior of gray wolves, effectively avoiding local optima and maintaining solution diversity. CSA enhances global search capabilities but can become unstable due to its inherent randomness. MOPSO shows fast convergence but is prone to get stuck in local optima, while the GA tends to reduce population diversity over time, lowering its optimization efficiency. Assigning a weight of $w_4 = 0.5$ to maximize RES absorption helps achieve a balance between environmental objectives and technical efficiency. The simulation results demonstrate that increasing this weight allows the algorithm to prioritize solutions with higher RES absorption rates without significantly increasing power losses or investment costs. Meanwhile, weights $w_1 = 0.2$ and $w_2 = 0.2$ ensure that power loss reduction and investment cost optimization are not overlooked, maintaining the system's overall performance. A smaller weight of $w_3 = 0.1$ allows the system to maintain stable voltage within safe limits without over-optimizing this factor. In the DG planning optimization problem, prioritizing maximum RES absorption is essential to reduce dependence on traditional energy sources. Therefore, the highest weight $w_4 = 0.5$ is assigned to ensure the algorithm favors solutions that maximize RES utilization. At the same time, weights w_1 and w_2 help balance operational performance and investment costs, while w_3 ensures that the system operates within safe voltage limits.

A. 33-Bus Distribution System

Figure 3 illustrates the single-line diagram of the 33-bus distribution network with 37 transmission branches, showing the interconnection structure between the main substation, load nodes, distribution lines, and potential locations for integrating RES. The node and branch data are referenced from [19, 20] to ensure accuracy for the simulation study.

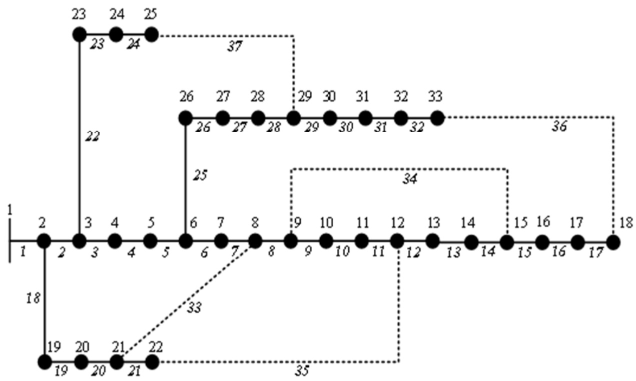

Fig. 3. Single-line diagram of the 33-bus system.

TABLE II. SIMULATION RESULTS ON THE 33-BUS SYSTEM

Algorithm	DG location and capacity (MW)	P_{loss} (kW)	C_{DG} (million USD)	ΔV (p.u.)	P_{RES} %
GWO	6 (1.2), 18 (0.8), 30 (1.0)	85.4	1.45	0.028	88
CSA [15]	7, (1.1), 17 (0.9), (29, 1.0)	88.7	1.50	0.034	85
MOPSO [16]	5 (1.0), 16 (0.85), 28 (0.95)	92.1	1.53	0.039	82
GA [17]	8 (1.05), 19 (0.9), 31 (0.92)	96.0	1.58e6	0.043	79

Table II shows that the GWO algorithm outperforms other methods, achieving the lowest power loss (85.4 kW) and the highest RES absorption rate (88%). This result demonstrates GWO's superior global search capability due to its effective balance between exploitation and exploration, which helps avoid local optima and optimize system performance.

Compared to GWO, CSA achieves relatively good results with a power loss of 88.7 kW and a RES absorption rate of 85%, but its performance is less effective due to slower convergence and a limited search range. Meanwhile, MOPSO exhibits faster convergence but is prone to getting stuck in local optima, leading to higher power losses (92.1 kW) and a lower RES absorption rate (82%). GA produces the least favorable results, with the highest power loss (96.0 kW) and the lowest RES absorption rate (79%), mainly due to the reduction in population diversity after multiple generations of crossover and mutation, which limits its ability to find optimal solutions. Thus, GWO not only minimizes power losses but also optimizes RES utilization efficiency while ensuring more stable and sustainable operation of the distribution network. Figure 4 presents a comparative analysis of the simulation results of different algorithms applied to the 33-bus system.

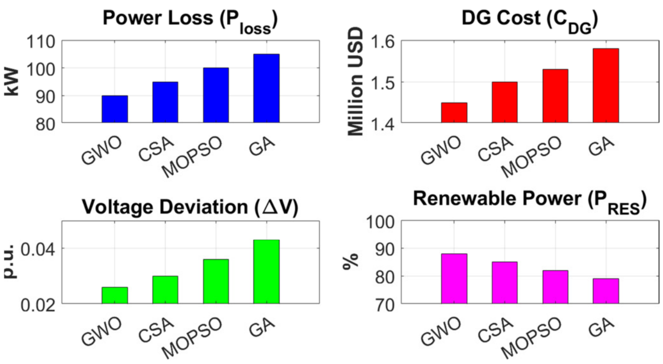

Fig. 4. Parameter comparison for the 33-bus network.

B. 69-Bus Distribution System

Figure 5 illustrates the single-line diagram of the 69-bus distribution network with 73 branches, showing the interconnection structure between the main substation, load nodes, distribution lines, and potential locations for integrating RES. The node and branch data are referenced from [19, 20] to ensure accuracy for the simulation study. This diagram features a more complex structure, providing a basis for evaluating the effectiveness of optimization algorithms in terms of reducing power losses, improving voltage quality, and maximizing RES utilization in large-scale distribution networks.

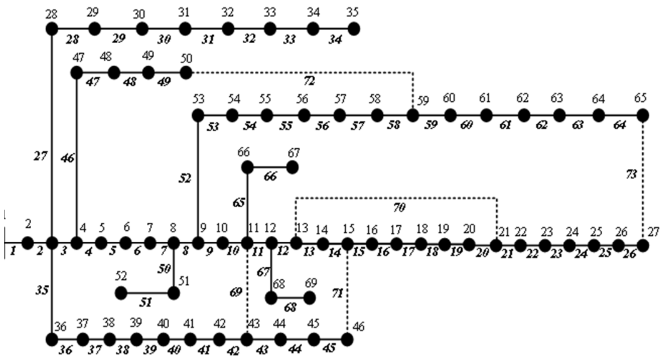

Fig. 5. Single-line diagram of the 69-bus system.

Table III further confirms the superior performance of the GWO algorithm in optimizing the placement and sizing of DG units in the 69-bus distribution network. The algorithm achieves the lowest power loss (78.3 kW) and the highest RES absorption rate (89%), demonstrating its ability to maintain optimal performance even as the system becomes more complex. Compared to GWO, CSA shows higher power loss (82.5 kW) and a lower RES absorption rate (86%) due to its less effective search capability in larger solution spaces. Although MOPSO is a swarm-based algorithm with the advantage of fast convergence, it is still limited by the tendency to get trapped in local optima, resulting in a power loss of 87.0 kW and a RES absorption rate of only 83%. The GA continues to produce the least favorable results, with the highest power loss (91.5 kW) and the lowest RES absorption rate (80%), clearly reflecting its limitations when handling multi-objective optimization problems in large-scale power systems. Thus, GWO exhibits strong adaptability to complex distribution systems, optimizing performance, reducing energy losses, and maximizing RES utilization. This contributes to the development of a greener and more sustainable distribution network.

TABLE III. SIMULATION RESULTS ON THE 69-BUS SYSTEM

Algorithm	DG location and capacity (MW)	P_{loss} (kW)	C_{DG} (million USD)	ΔV (p.u.)	P_{RES} %
GWO	11 (1.5), 27 (1.2), 50 (1.3)	78.3	1.42	0.026	89
CSA [15]	10 (1.4), 28 (1.1), 49 (1.25)	82.5	1.47	0.032	86
MOPSO [16]	9 (1.35), 26 (1.15), 48 (1.2)	87.0	1.51	0.037	83
GA [17]	12 (1.3), 29 (1.1), 51 (1.2)	91.5	1.55	0.041	80

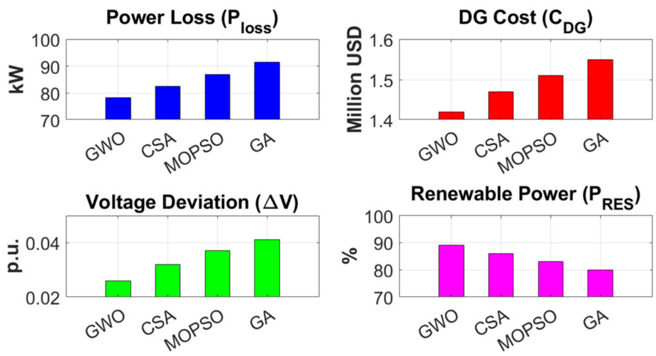

Fig. 6. Parameter comparison for the 69-bus network.

The simulation results on both the 33-bus and 69-bus systems show that GWO consistently achieves the best optimization performance, demonstrating its strong scalability when applied to distribution networks of varying sizes. Specifically, GWO achieves the lowest power loss (85.4 kW) and the highest RES absorption rate (88%) on the 33-bus network, while continuing to lead on the 69-bus network with a power loss of just 78.3 kW and an RES absorption rate of 89%. This confirms GWO's strong global search capability, even in complex systems. In contrast, GA performs worst due to local optima trapping, leading to higher power losses and lower RES absorption. Although CSA and MOPSO perform relatively well, they remain limited in global search. GWO's superiority lies in its flexible search, avoidance of local optima, and balanced exploration-exploitation, making it the most effective method for DG planning, ensuring efficient and sustainable operation, and maximizing RES utilization.

V. CONCLUSION

This paper presents an optimized DG planning approach using GWO to maximize RES absorption, minimize power losses, maintain voltage quality, and optimize investment costs. The proposed method was applied to IEEE 33-bus and 69-bus systems, where GWO consistently outperformed CSA, MOPSO, and GA, achieving the lowest power losses (85.4 and 78.3 kW) and the highest RES absorption rates (88% and 89%). These results highlight the GWO's strong optimization capability, effectively balancing exploitation and exploration to enhance power system sustainability, reduce dependence on fossil fuels, and improve the overall efficiency and stability of distribution networks. Furthermore, compared to other heuristic methods, GWO proves to be a more reliable choice in multi-objective DG planning due to its high accuracy and strong adaptability. The study demonstrates that GWO is a highly effective tool for DG planning, providing superior performance compared to traditional optimization algorithms.

ACKNOWLEDGMENT

The authors sincerely acknowledge The Thu Duc College of Technology, Vietnam, for its support, which has greatly contributed to the success of this research.

REFERENCES

[1] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, and R. Seethapathy, "Optimal Renewable Resources Mix for Distribution System Energy Loss Minimization," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 360–370, Oct. 2010, https://doi.org/10.1109/TPWRS.2009.2030276.

[2] P. S. Georgilakis and N. D. Hatziargyriou, "A review of power distribution planning in the modern power systems era: Models, methods and future research," *Electric Power Systems Research*, vol. 121, pp. 89–100, Apr. 2015, https://doi.org/10.1016/j.epsr.2014.12.010.

[3] W. Zhang, F. Li, and L. M. Tolbert, "Review of Reactive Power Planning: Objectives, Constraints, and Algorithms," *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 2177–2186, Aug. 2007, https://doi.org/10.1109/TPWRS.2007.907452.

[4] B. Singh and J. Sharma, "A review on distributed generation planning," *Renewable and Sustainable Energy Reviews*, vol. 76, pp. 529–544, Sep. 2017, https://doi.org/10.1016/j.rser.2017.03.034.

[5] A. A. Abou El-Ela, S. M. Allam, and M. M. Shatla, "Maximal optimal benefits of distributed generation using genetic algorithms," *Electric Power Systems Research*, vol. 80, no. 7, pp. 869–877, Jul. 2010, https://doi.org/10.1016/j.epsr.2009.12.021.

[6] M. H. Moradi and M. Abedini, "A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 34, no. 1, pp. 66–74, Jan. 2012, https://doi.org/10.1016/j.ijepes.2011.08.023.

[7] M. Ghosh, S. Kumar, S. Mandal, and K. Mandal, "Optimal sizing and placement of DG units in radial distribution system using cuckoo search algorithm," *International Journal of Applied Engineering Research*, vol. 12, no. 1, 2019, Art. no. 2017.

[8] W. Sheng, K. Y. Liu, Y. Liu, X. Meng, and Y. Li, "Optimal Placement and Sizing of Distributed Generation via an Improved Nondominated Sorting Genetic Algorithm II," *IEEE Transactions on Power Delivery*, vol. 30, no. 2, pp. 569–578, Apr. 2015, https://doi.org/10.1109/TPWRD.2014.2325938.

[9] A. Tyagi, A. Verma, and L. K. Panwar, "Optimal placement and sizing of distributed generation in an unbalance distribution system using grey wolf optimisation method," *International Journal of Power and Energy Conversion*, vol. 10, no. 2, pp. 208–224, Jan. 2019, https://doi.org/10.1504/IJPEC.2019.098621.

[10] N. Dharavat, S. K. Sudabattula, and S. Velamuri, "Review on the integration of distributed generations (solar, wind) and electric vehicles connected to the distribution system to minimize power loss and voltage profile enhancement," *AIP Conference Proceedings*, vol. 2455, no. 1, Oct. 2022, Art. no. 020001, https://doi.org/10.1063/5.0100957.

[11] S. Zhang, H. Cheng, K. Li, N. Tai, D. Wang, and F. Li, "Multi-objective distributed generation planning in distribution network considering correlations among uncertainties," *Applied Energy*, vol. 226, pp. 743–755, Sep. 2018, https://doi.org/10.1016/j.apenergy.2018.06.049.

[12] D. Q. Hung and N. Mithulananthan, "Multiple Distributed Generator Placement in Primary Distribution Networks for Loss Reduction," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 4, pp. 1700–1708, Apr. 2013, https://doi.org/10.1109/TIE.2011.2112316.

[13] J. A. P. Lopes, N. Hatziargyriou, J. Mutale, P. Djapic, and N. Jenkins, "Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities," *Electric Power Systems Research*, vol. 77, no. 9, pp. 1189–1203, Jul. 2007, https://doi.org/10.1016/j.epsr.2006.08.016.

[14] P. Astero and L. Söder, "Improvement of RES hosting capacity using a central energy storage system," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Turin, Italy, Sep. 2017, pp. 1–6, https://doi.org/10.1109/ISGTEurope.2017.8260102.

[15] X. S. Yang and S. Deb, "Cuckoo Search via Levy flights," in *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC)*, Coimbatore, India, 2009, pp. 210–214, https://doi.org/10.1109/NABIC.2009.5393690.

[16] A. Zeinalzadeh, Y. Mohammadi, and M. H. Moradi, "Optimal multi objective placement and sizing of multiple DGs and shunt capacitor banks simultaneously considering load uncertainty via MOPSO approach," *International Journal of Electrical Power & Energy Systems*, vol. 67, pp. 336–349, May 2015, https://doi.org/10.1016/j.ijepes.2014.12.010.

[17] Y. Alinejad-Beromi, M. Sedighizadeh, M. R. Bayat, and M. E. Khodayar, "Using genetic alghoritm for distributed generation allocation to reduce losses and improve voltage profile," in *2007 42nd International Universities Power Engineering Conference*, Brighton, UK, Sep. 2007, pp. 954–959, https://doi.org/10.1109/UPEC.2007.4469077.

[18] A. V. Truong, T. N. Ton, T. T. Nguyen, and T. L. Duong, "Two States for Optimal Position and Capacity of Distributed Generators Considering Network Reconfiguration for Power Loss Minimization Based on Runner Root Algorithm," *Energies*, vol. 12, no. 1, Jan. 2019, Art. no. 106, https://doi.org/10.3390/en12010106.

[19] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Transactions on Power Delivery*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989, https://doi.org/10.1109/61.25627.

[20] T. N. Ton, T. T. Nguyen, A. V. Truong, and T. P. Vu, "Optimal Location and Size of Distributed Generators in an Electric Distribution System based on a Novel Metaheuristic Algorithm," *Engineering, Technology & Applied Science Research*, vol. 10, no. 1, pp. 5325–5329, Feb. 2020, https://doi.org/10.48084/etasr.3372.