Ant Lion Optimization and Grey Wolf Optimizer to Optimally Locate Single and Multiple Distributed Generation Units and Capacitor Shunts in Power Distribution Networks

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Abstract **Power supply challenges continue to be a significant issue, necessitating ongoing efforts to enhance power generation, network infrastructure, and system configurations. Notably, the integration of distributed generation (DG) units and capacitor shunts (CSs) has emerged as a key advancement. With the escalating complexity and scale of power systems, optimizing these components to maximize benefits and mitigate drawbacks has become essential. Consequently, optimization has become a crucial element in the development of algorithms. This study proposes the utilization of the Grey Wolf Optimizer (GWO) and Ant Lion Optimization (ALO) methods for determining the optimal sizing of capacitor shunts and distributed generation units within distribution systems. The Reconfiguration Method (RM) is employed to identify the optimal location for single-generation units and capacitor shunts, while the Loss Sensitivity Factor (LSF) is utilized to determine the optimal placement for multiple DG units and CSs. The primary objective is to minimize real power losses across the entire system by selecting the optimal sizes with GWO and ALO, while also optimizing their placement using LSF and RM. The performance of the proposed algorithms, GWO and ALO, was evaluated using the IEEE 33-bus power system. Four distinct scenarios were employed to demonstrate the superiority and effectiveness of these optimization methods.**

Index Terms **— Capacitor shunt, distributed generation, Grey Wolf Optimizer, Ant Lion Optimization, optimal allocation, real power loss minimization, IEEE 33-bus system.**

I. Introduction

The increasing global demand for energy, driven by social, economic, and industrial developments, makes efficient power supply a critical concern. Distribution networks, which represent a significant investment and directly connect with consumers, are particularly susceptible to power losses, with approximately 70% of real power losses occurring within these networks [1]. Traditional solutions, such as building new generation stations, are often costly and time-consuming. Consequently, modern approaches focus on optimizing existing infrastructure through network reconfiguration and the strategic integration of devices like distributed generation (DG) units and capacitor shunts (CSs).

DG units, which can be renewable (e.g., solar, wind) or conventional (e.g., fuel cells), are strategically placed near consumption points to enhance system reliability, reduce power losses, improve network performance, and defer the need for new distribution feeders. The integration of DG also transforms traditional unidirectional power flow into bidirectional flow, introducing new complexities and opportunities [2]. However, the unpredictable nature of renewable energy sources necessitates careful planning to avoid negative impacts such as overvoltage or exceeding feeder load limits. Similarly, the installation of CSs is crucial for optimizing voltage profiles, increasing voltage

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stability, decreasing real power loss, and improving power factor and quality by injecting reactive power into the system. Both DG and CS placement and sizing require meticulous study to maximize their benefits and avoid adverse effects [3]. Various optimization techniques, including heuristic, analytical, and hybrid methods, are proposed for the optimal allocation of DG units and CSs in power systems [4]. For instance, enhanced Ant Lion Optimization (ALO) and Particle Swarm Optimization (PSO) are used for DG allocation in IEEE 69-bus systems [5]. The Grey Wolf Optimizer (GWO) is also widely applied for optimal DG placement and sizing [6, 7]. Other metaheuristic algorithms, such as Harris Hawks Optimization (HHO) [8] and Wild Horse Optimizer (WHO) [9], are explored for similar purposes. The optimal planning of PV sources and D-STATCOM devices, incorporating network reconfiguration using a Modified Ant Lion Optimizer, is investigated in [10]. Similarly, [11] proposes a modified Ant Lion Optimization algorithm for efficient distributed generation allocation in power distribution networks. Furthermore, [12] utilizes an Ant Lion Optimizer-based multi-objective approach for the simultaneous optimal allocation of distributed generations and synchronous condensers in distribution networks. Hybrid approaches combining analytical techniques with optimization algorithms show promise in minimizing power loss and improving voltage profiles [13–16]. A fuzzy genetic approach for network reconfiguration is applied to enhance voltage stability in radial distribution systems [17]. A hybrid of ant colony optimization and artificial bee colony algorithm is employed for probabilistic optimal placement and sizing of distributed energy resources [18].

This paper introduces a novel hybrid optimization strategy for the simultaneous optimal placement and sizing of DG units and CSs in radial distribution networks, specifically targeting the minimization of real power losses. While the application of metaheuristic algorithms to this problem is not new, our work distinguishes itself through a rigorous and direct comparative performance analysis of two prominent nature-inspired algorithms, GWO and ALO, within a unified hybrid framework. We employ a two-step process: the Reconfiguration Method (RM) for single-unit placement and the Loss Sensitivity Factor (LSF) for multiple-unit placement, which effectively streamlines the search space. This allows the powerful GWO and ALO algorithms to focus solely on determining the optimal component sizes, thereby significantly enhancing computational efficiency and the quality of the solution. The study evaluates the performance of this hybrid approach on the IEEE 33-bus system under four distinct and practical scenarios, providing a comprehensive understanding of how these optimization tools perform under various system planning conditions. This direct comparison, coupled with the systematic evaluation across diverse scenarios, offers valuable insights into the strengths and weaknesses of GWO and ALO for real-world power system optimization challenges.

The primary contributions of this study are summarized as follows:

Novel Hybrid Optimization Framework: Development and application of a hybrid methodology that combines deterministic placement strategies (RM for single units, LSF for multiple units) with metaheuristic sizing algorithms (GWO and ALO) to efficiently minimize real power losses in distribution networks.

Direct Comparative Performance Analysis: A rigorous and direct comparison of GWO and ALO for minimizing real power loss through DG and CS integration, tested on the identical IEEE 33-bus system under four distinct and practical scenarios.

Comprehensive Scenario Evaluation: Unlike studies that may focus on a single type of installation, our research evaluates the problem across a comprehensive set of four scenarios (single CS, single DG, multiple CSs and multiple DG units). This provides a broader understanding of how these optimization tools perform under different system planning conditions and demonstrates that the installation of multiple DG units yields the most significant reduction in power losses among the tested configurations.

Improved System Performance: The proposed optimization approach consistently leads to significant reductions in real power losses, alongside improvements in voltage profiles and an enhanced voltage stability index across all evaluated scenarios.

The remainder of this paper is organized as follows: Section 2 details the problem formulation, including objective functions, constraints, the Reconfiguration Method, and the Loss Sensitivity Factor. Section 3 presents the mathematical models and overviews of the proposed GWO and ALO algorithms. Section 4 discusses the simulation results for optimal location and size of single DG units, single CSs, multiple DG units, and multiple CSs on the IEEE 33-bus system. Finally, Section 5 provides the conclusions and outlines avenues for future research.

Convergence Analysis: The convergence characteristics of both algorithms were analyzed by plotting the best fitness value against the number of iterations. The analysis reveals GWO typically converges faster than ALO, reaching near-optimal solutions within 60–70 iterations ALO shows more exploration in the early iterations but may require more iterations to converge. Both algorithms demonstrate good convergence characteristics without premature stagnation. These statistical results provide strong evidence for the effectiveness and reliability of the proposed optimization approach, with GWO showing superior performance in terms of solution quality and consistency.

II. Problem Formulation

The proposed approach aims to determine the optimal locations and sizes of DG units and CSs to minimize total real power losses in a multi-constrained radial distribution network (RDN).

A. Power Flow

The radial distribution network (RDN) single-line diagram is shown in Fig. 1. The real and reactive power will be supplied from bus a and received at bus b. The real and reactive powers of buses a and b can be calculated as follows [4]:

$$P_a = P_b + P_{l,b} + R_{ab}\left(\frac{\left(P_{l,a}+P_{l,b}\right)^2+\left(Q_{l,b}+Q_{l,b}\right)^2}{\left|V_b\right|^2}\right), \quad (1)$$

$$Q_a = Q_b + Q_{l,b} + X_{ab}\left(\frac{\left(P_{l,a}+P_{l,b}\right)^2+\left(Q_{l,a}+Q_{l,b}\right)^2}{\left|V_b\right|^2}\right), \quad (2)$$

$$V_b = \left(V_a^2 - 2\left(P_a R_a + Q_a X_{ab}\right) + \left(R_{ab}{}^2 + X_{ab}{}^2\right)\left(\frac{P_a^2+Q_a^2}{V_a^2}\right)\right), \quad (3)$$

where P_a and P_b are the real powers at buses a and b, respectively; $P_{l,a}$ and $P_{l,b}$ are real load powers at buses a and b, respectively; Q_a and Q_b are the reactive powers at buses a and b, respectively; $Q_{l,a}$ and $Q_{l,b}$ are reactive load powers at buses a and b, respectively; R_a and R_{ab} are the resistance and reactance of lines a and b, respectively; V_b is the voltage at bus b; V_a is the voltage at bus a; X_{ab} is the line impedance.

The real power loss in lines between buses a and b can be computed as follows:

$$P_{loss(a,b)} = R_{a,b}\left(\frac{P_a{}^2 + jQ_a{}^2}{\left|V_a\right|^2}\right). \quad (4)$$

The reactive power loss in lines connecting buses a and b is calculated as follows:

$$Q_{loss(a,b)} = X_{a,b}\left(\frac{P_a{}^2 + jQ_a{}^2}{\left|V_a\right|^2}\right), \quad (5)$$

where j in this context, is not a variable but the imaginary unit.

Therefore, the total real and reactive power losses in radial distribution network are the following:

$$TP_{loss} = \sum_{a,b}^{Nb_r} P_{loss(a,b)}, \quad (6)$$

$$TQ_{loss} = \sum_{a,b}^{Nb_r} Q_{loss(a,b)}, \quad (7)$$

where TP_{loss} is total real power loss, TQ_{loss} is total reactive power loss, Nb_r is the total number of branches in the network (IEEE 33-Bus system).

B. Objective Function

The primary objective of this study is to minimize the total real power losses in the distribution network. Minimizing real power losses also leads to improved voltage profiles and a higher voltage stability index. The objective function can be expressed in the following

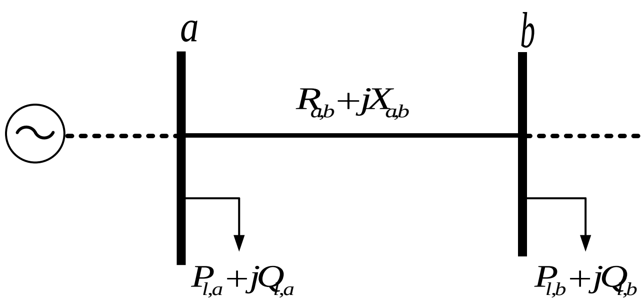

Fig. 1. Single line diagram for two buses of radial distribution network.

manner:

$$P_{loss} = \sum_{a=1}^{N}\sum_{b=1}^{N}\alpha_{ab}(P_a P_b + Q_a Q_b) + \beta_{ab}(Q_a P_b - P_a Q_b), \quad (8)$$

where N represents the total number of busses in the system, α_{ab} and β_{ab} can be calculated as follows:

$$\alpha_{ab} = \frac{R_{ab}}{V_a V_b}\cos\left(\alpha_a - \alpha_b\right), \quad (9)$$

$$\beta_{ab} = \frac{R_{ab}}{V_a V_b}\sin\left(\alpha_a - \alpha_b\right). \quad (10)$$

Here α_a, α_b are the voltage phase angles (in radians) at bus *a* and *b* respectively.

C. Problem Constraints

The optimization problem is subject to both equality and inequality constraints to ensure a realistic and stable operation of the power system.

1) Equality Constraints

The equality constraints represent the balance between generation and load with the power losses in lines, and can be expressed through as follows:

$$\sum_{i=1}^{N_G} P_{Gen}(i) + \sum_{i=1}^{N_{DG}} P_{DG}(i) - \sum_{i=1}^{N_{load}} P_{Demand}(i) - \sum_{i=1}^{N_{line}} P_{Loss}(i) = 0, \quad (11)$$

$$\begin{gathered}\sum_{i=1}^{N_G} Q_{Gen}(i) + \sum_{i=1}^{N_{DG}} Q_{DG}(i) + \sum_{i=1}^{N_{CS}} Q_{CS}(i) - \\ - \sum_{i=1}^{N_{load}} Q_{Demand}(i) - \sum_{i=1}^{N_{line}} Q_{Loss}(i) = 0,\end{gathered}, \quad (12)$$

where P_{Gen}, P_{DG}, P_{Demand}, and P_{Loss} denote to real power of generators, distributed generations, demand, and losses, respectively; Q_{Gen}, Q_{DG}, Q_{CS}, Q_{Demand}, and Q_{Loss} refer to reactive power of generators, distributed generations, capacitor shunt, demand, and losses, respectively; N_G, N_{DG}, N_{CS}, N_{load}, and N_{line}, denote to the number of generators, distributed generations, capacitors shunts, loads, and lines, respectively.

2) Inequality Constraints

Inequality constraints provide limits or bounds on specific variables or expressions. Usually, they specify areas or requirements that the variables need to meet. One way to characterize the inequality constraints is as follows:

a) *Bus voltage:* Due to the inequality constraint, voltage at each bus must fall within the given bounds.

$$V_q^{\min} \le V_q \le V_q^{\max}, \quad (13)$$

where $V_q^{\min}$ and $V_q^{\max}$ indicate the lowest and highest voltage values at bus q represented as the range of 0.95 to 1.05.

b) *Line current:* Every branch's current flow cannot exceed its thermal limit due to the inequality constraint

$$I_{ab} \le I_{ab}^{rated}, \quad (14)$$

where I_{ab}^{rated} represents the thermal limit between nodes a and b, and I_{ab} is the line current between nodes a and b.

c) *DG capacity:* A particular percentage of the total feeder load cannot be exceeded by distributed generation capacity, according to the inequality constraint

$$\sum\sqrt{\left(P_{DG}\right)^2 + \left(Q_{DG}\right)^2} = \sum\sqrt{\left(P_L\right)^2 + \left(Q_L\right)^2}. \quad (15)$$

where P_L, Q_L represents the total system active and reactive load demand respectively.

d) *DG capacity:* A particular percentage of the network's total feeder load cannot be exceeded by distributed generation capacity, according to the inequality constraint

$$\sum Q_C = \sum Q_L. \quad (16)$$

where Q_C is the total reactive power compensation from all capacitor shunts.

III. Overview of the Proposed Methodology

System performance in distribution networks is highly dependent on the optimal selection of bus locations for DG and CS integration. This study employs a hybrid approach that combines deterministic methods for identifying candidate locations with metaheuristic algorithms for determining optimal sizing. The Reconfiguration Method (RM) is utilized for the placement of single capacitor shunts (CSs) and distributed generation (DG) units, while the Loss Sensitivity Factor (LSF) guides the placement of multiple units. Subsequently, the Grey Wolf Optimizer (GWO) and Ant Lion Optimization (ALO) algorithms are employed to determine the optimal sizes of these components at the identified locations, with the overarching objective to minimize real power losses.

A. Reconfiguration Method (RM)

Reconfiguration method is the suggested strategy for determining the best placement of single CS and DG connection. By positioning the source (CS or DG) at each bus and figuring out the actual power losses there, the reconfiguration method determines which bus is optimal. The bus that has the lowest real power loss value is the ideal bus, and all of the bus losses combined will be ranked. The primary actions that need to be taken while using distinct single DG unit and CS are:

- Calculating the real power loss at each bus after connecting DG unit and CS, thus selecting the optimal size based on GWO and ALO.
- Identifying the bus that has the lowest real power loss to link the CS and the DG unit.
- Determining the size of DG unit and CS unit according to GWO and ALO.

B. Loss Sensitivity Factor (LSF)

LSF is the indicator used to determine the best location of CSs and DG sources (candidate buses). The bus will be selected by determining which buses have the most sensitive active and reactive power injection. LSFs help minimize the search area and optimize the process by reducing the time required for optimization. Using LSF calculations based on load flow, buses are arranged in declining order. The active power loss in this line can be defined as $I_{ab}^2 R_{ab}$, where:

$$P_{loss(a,b)} = \frac{\left(P_a^2 + Q_a^2\right) R_{ab}}{\left(V_a\right)^2} . \quad (17)$$

LSFs can be computed using the following equation [4]:

$$LSFP(p) = \frac{2 P_{loss} R_{ab}}{\left|V_m\right|^2} , \quad (18)$$

$$LSFQ(p) = \frac{2 Q_{loss} X_{ab}}{\left|V_m\right|^2} , \quad (19)$$

where Q_{loss}, P_{loss} are the losses on the branch for which the sensitivity is being computed; p denotes the bus number at which the sensitivity factor is being calculated; *LSFP* the loss sensitivity factor with respect to active power injection at bus p; *LSFQ* the loss sensitivity factor with respect to reactive power injection at bus p; P_a the real power flow in the line connected to the bus p; R_{ab}, X_{ab} the resistance and reactance of line connected to bus p; V_m the voltage magnitude at bus p.

C. Grey Wolf Optimizer (GWO)

GWO is a nature-inspired metaheuristic algorithm that mimics the social hierarchy and hunting behavior of grey wolves. The algorithm models the leadership hierarchy among wolves, which consists of alpha (α), beta (β), delta (δ), and omega (ω) wolves. The alpha wolf represents the best solution found so far, guiding the search process. Beta and delta wolves assist the alpha in hunting, while omega wolves follow the dominant wolves. This hierarchical structure facilitates a collaborative search for the optimal solution through iterative updates of wolf positions [19].

The main phases of GWO include:

• **Encircling Prey**: Wolves adjust their positions to encircle the prey, mathematically represented by updating their current positions based on the position of the prey.

• **Hunting**: The hunting process is guided by the three best solutions (alpha, beta, and delta wolves). Other wolves update their positions based on the positions of these three leaders.

• **Attacking Prey** (Exploitation): As the hunting progresses, the wolves converge towards the prey. This phase is characterized by a decreasing parameter that controls the exploration and exploitation balance, allowing the algorithm to narrow down the search to promising regions.

• **Searching for Prey** (Exploration): Wolves also diverge to explore new areas in the search space, preventing premature convergence. This exploration phase is crucial for finding globally optimal solutions.

In the context of this problem, the positions of the wolves correspond to the sizes of the DG units and CSs. The alpha wolf represents the combination of DG and CS sizes that yields the minimum real power loss. The iterative updates of the wolf positions allow the algorithm to efficiently search for the optimal sizing configuration.

D. Ant Lion Optimizer (ALO)

ALO is another metaheuristic algorithm inspired by the hunting mechanism of ant lions in nature. Ant lions dig cone-shaped traps in the sand to catch ants. The algorithm simulates the interactions between ants (representing candidate solutions) and ant lions (representing search agents) in the search space. The movement of ants is modeled as a random walk, while ant lions are responsible for constructing traps and capturing ants [20].

The key stages of ALO are:

• **Random Walks of Ants:** Ants move randomly in the search space, representing the exploration phase. The random walk is influenced by the ant lion's position.

• **Trap Construction:** Ant lions build traps, which are essentially the fitness landscapes around their current positions. Fitter ant lions (better solutions) have larger and more effective traps.

• **Ants Sliding Towards Ant lion:** When an ant falls into an ant lion's trap, its random walk is adjusted to simulate sliding towards the ant lion at the bottom of the cone. This represents the exploitation phase.

• **Catching Prey and Rebuilding the Trap:** Once an

TABLE 1. The Bus and Line Data of IEEE 33-Bus System

Bus Data			Line Data			
Bus	Load		Bus		R, p.u.	X, p.u.
	P, kW	Q, kVAr	From	To		
1	0	0	1	2	0.005753	0.002932
2	100	60	2	3	0.030760	0.015667
3	90	40	3	4	0.022836	0.011630
4	120	80	4	5	0.023778	0.012110
5	60	30	5	6	0.051099	0.044112
6	60	20	6	7	0.011680	0.038608
7	200	100	7	8	0.044386	0.014668
8	200	100	8	9	0.064264	0.046170
9	60	20	9	10	0.065138	0.046170
10	60	20	10	11	0.012266	0.004056
11	45	30	11	12	0.023360	0.007724
12	60	35	12	13	0.091592	0.072063
13	60	35	13	14	0.033792	0.044480
14	120	80	14	15	0.036874	0.032818
15	60	10	15	16	0.046564	0.034004
16	60	20	16	17	0.080424	0.107378
17	60	20	17	18	0.045671	0.035813
18	90	40	2	19	0.010232	0.009764
19	90	40	19	20	0.093851	0.084567
20	90	40	20	21	0.025550	0.029849
21	90	40	21	22	0.044230	0.058481
22	90	40	3	23	0.028152	0.019236
23	90	50	23	24	0.056028	0.044243
24	420	200	24	25	0.055904	0.043743
25	420	200	6	26	0.012666	0.006451
26	60	25	26	27	0.017732	0.009028
27	60	25	27	28	0.066074	0.058256
28	60	20	28	29	0.050176	0.043712
29	120	70	29	30	0.031664	0.016128
30	200	600	30	31	0.060795	0.060084
31	150	70	31	32	0.019373	0.022580
32	210	100	32	33	0.021276	0.033081

ant is caught, the ant lion's position is updated to that of the captured ant if it represents a better solution. The ant lion then rebuilds its trap, reflecting the improved solution.

In this study, the ants represent different combinations of DG and CS sizes, and the ant lions represent the potential optimal solutions. The algorithm iteratively refines the sizes by simulating the ant lion's hunting behavior, aiming to find a combination of DG and CS sizes that minimizes real power losses.

E. Algorithm Parameters

For the implementation of the Grey Wolf Optimizer (GWO) and Ant Lion Optimization (ALO) algorithms, specific parameters were carefully selected to ensure optimal performance and fair comparison. The following parameters were used in this study:

Grey Wolf Optimizer (GWO) Parameters: Population Size: 30 wolves. Maximum Iterations: 100. Search Space Dimension: Variable (depends on the

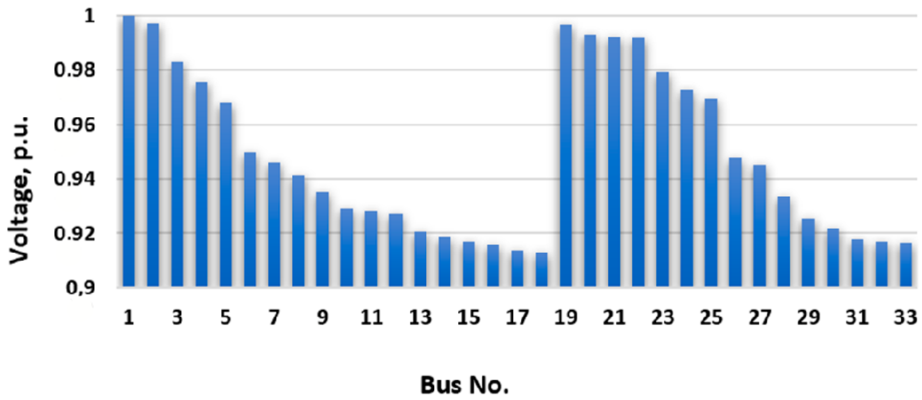

Fig. 3. Voltage profiles for initial case on IEEE 33-bus system.

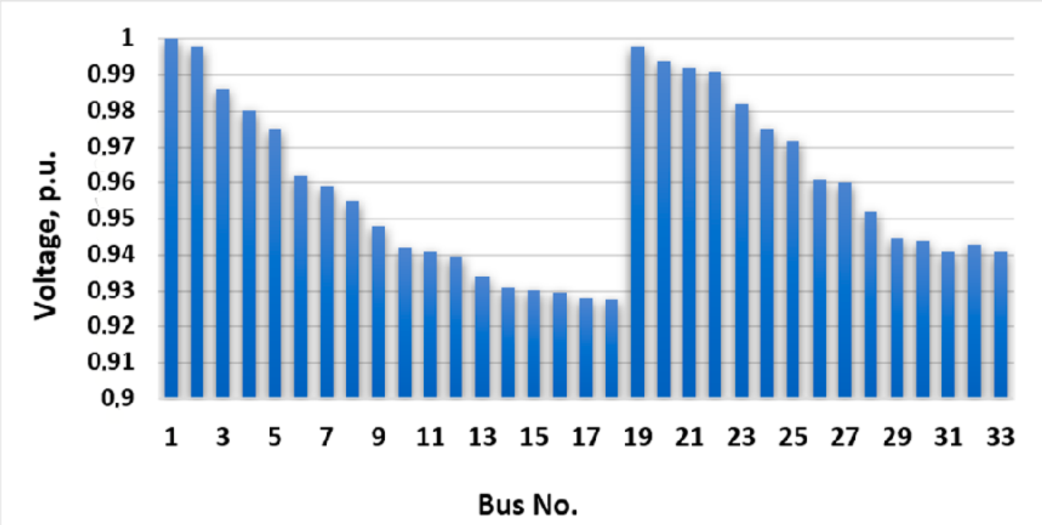

Fig. 4. Voltage profiles for Case 1: a single CS placed in IEEE 33-bus system using the ALO algorithm.

number of DG and CS units to be optimized). Convergence Parameter (a): Linearly decreases from 2 to 0 over the iterations. Random Vectors (r1, r2): Uniformly distributed random numbers in [0, 1]. Position Update Mechanism: Based on alpha, beta, and delta wolves' positions.

Ant Lion Optimization (ALO) Parameters: Population Size: 30 ants. Maximum Iterations: 100. Number of Ant Lions: 30. Random Walk Steps: 500. Elite Selection: Best ant lion is selected as elite. Roulette Wheel Selection: Used for ant lion selection. Random Walk Boundaries: Dynamically updated based on ant lions' positions.

IV. Simulation Results

This section presents the simulation results obtained applying the proposed hybrid optimization methodology to the IEEE 33-bus radial distribution network. The IEEE 33-bus system is a widely recognized benchmark for power system studies. The IEEE 33-bus power system's single line diagram is shown in Fig. 2. The Bus and Line data of IEEE 33-bus system are presented in Table 1.

The system comprises 33 buses and 32 lines, with base voltage and apparent power set at 12.66 kV and 10 MVA, respectively. The objective of these simulations is to demonstrate the efficacy of the GWO and ALO algorithms in minimizing real power losses through optimal placement and sizing of DG units and CSs under various scenarios.

The investigated scenarios include:

- **Initial Case (Base Case):** Represents the system without any DG or CS integration.
- **Case 1: Single source (CS):** Evaluates the impact of optimally placing and sizing a single CS.
- **Case 2: Single source (DG unit):** Assesses the effect of optimally placing and sizing a single DG unit.
- **Case 3: Multiple sources (CSs):** Examines the performance with multiple optimally placed and sized CSs.
- **Case 4: Multiple sources (DG units):** Investigates the impact of multiple optimally placed and sized DG units.

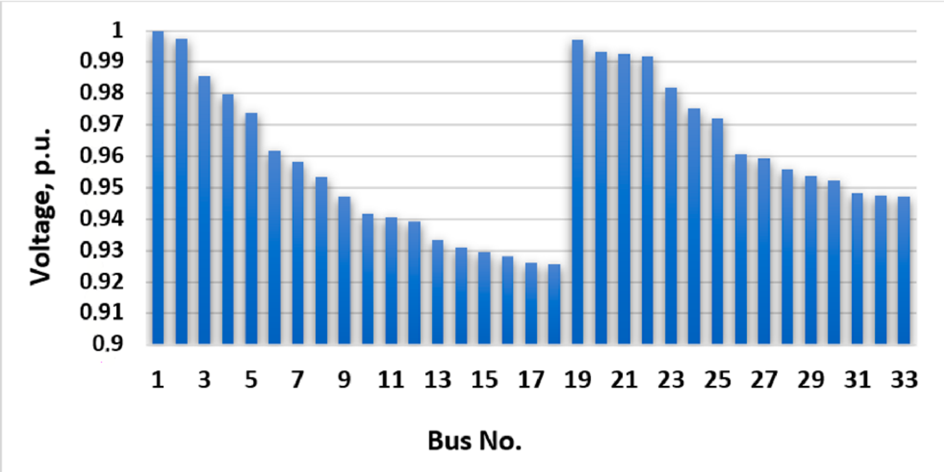

Fig. 5. Voltage profiles for Case 1: a single CS placed in IEEE 33-bus system using the GWO algorithm.

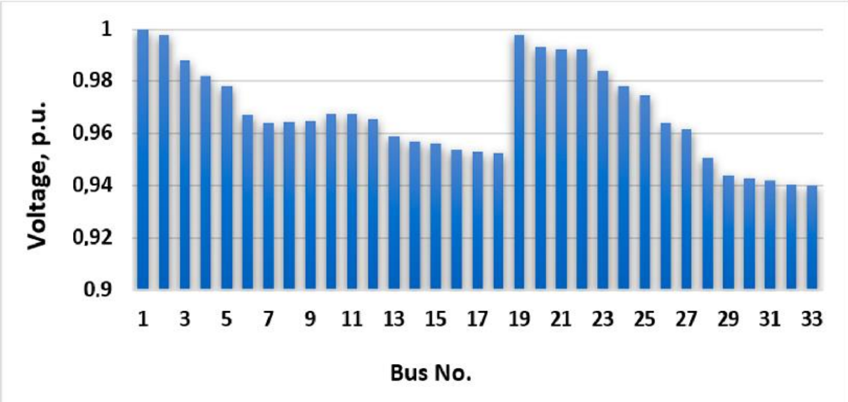

Fig. 6. Voltage profiles for Case 2: a single DG unit placed in IEEE 33-bus system using the ALO algorithm.

A. Initial Case (Base Case)

In this case, power flow calculations are performed using the Newton-Raphson method. The total loads for the active and reactive power are 3.715 MW and 2.3 MVAr, respectively. Reactive power losses total 0.1343 MVAr and active power losses amount to 0.2015 MW. The voltage magnitude reaches its minimum at 0.913 p.u. at bus 18 and its maximum at 0.997 p.u. at bus 2, as shown in Fig. 3. The voltage stability index (VSI) has minimum and highest values of 0.696 and 0.9883 on buses 18 and 2, respectively.

B. Case 1: Single Source (Capacity Shunt)

This case explores the optimal placement and sizing of a single CS unit using both ALO and GWO algorithms in conjunction with the Reconfiguration Method (RM).

1) Use of the ALO algorithm

With the ALO algorithm, the optimal location for the single CS is identified as bus 31, with an optimal size of 1.308 MVAr. This integration reduces the real power losses from the initial 0.2015 MW to 0.1515 MW, representing a 24.81% reduction. Figure 4 shows the voltage profile at each bus after installing a single CS. The minimum VSI at bus 18 improves from 0.6960 to 0.736 and reactive power losses decrease from 0.1343 MVAr to 0.1041 MVAr.

2) Use of the GWO algorithm

When employing the GWO algorithm, the optimal location for the single CS is determined to be bus 30, with an optimal size of 1.2527 MVAr. This results in a decrease in real power losses from 0.2015 MW to 0.1436 MW, achieving a 28.74% reduction. Figure 5 shows the voltage profile at each bus after installing a single CS. The minimum VSI at bus 18 improves from 0.6960 to 0.735 and reactive power losses decrease from 0.1343 MVAr to 0.0959 MVAr.

C. Case 2: Single Distributed Generation (DG) Source

This case investigates the optimal placement and sizing of a single DG unit using ALO and GWO with the

Reconfiguration Method (RM).

1) Use of the ALO algorithm

For the ALO algorithm, the optimal DG placement is at bus 10, with an ideal size of 1.92 MW. This leads to a significant decrease in real power losses from 0.2015 MW to 0.1255 MW, achieving a reduction of 37.73%. Figure 6 illustrates the voltage profile at each bus after installing a single DG unit. The minimum VSI at bus 18 increases from 0.6960 to 0.813 and reactive power losses decrease from 0.1343 MVAr to 0.0867 MVAr.

2) Use of the GWO algorithm

For the GWO algorithm, the optimal DG unit placement is at bus 6, with an ideal size of 2.575 MW. This results in a substantial power loss reduction from 0.2015 MW to 0.1037 MW, achieving a 48.54% reduction. Figure 7 illustrates the voltage profile at each bus after installing a single DG unit. The minimum VSI at bus 18 improves from 0.6960 to 0.8191 and reactive power losses decrease from 0.1343 MVAr to 0.0746 MVAr. Table 2 presents the comparison of the results obtained by GWO and ALO with other methods after installing a single DG unit.

D. Case 3: Multiple Capacitor Shunts (CSs)

This case investigates the optimal placement and sizing of multiple CS units using both ALO and GWO algorithms, guided by the Loss Sensitivity Factor (LSF).

1) Use of the ALO algorithm

Based on LSF values, the optimal candidate buses for multiple CS placement are 25, 2, 9, and 31. The ALO algorithm determines the optimal sizes for these CS units as 0.575 MVAr (bus 25), 0.6 MVAr (bus 2), 0.465 MVAr (bus 9), and 0.575 MVAr (bus 31). This configuration minimizes real power losses to 0.1382 MW, achieving a 31.41% reduction. Figure 8 presents the convergence characteristics of reactive power loss after installing multiple CS units using the ALO algorithm, given the number of populations is 50 and number of iterations is 50. Figure 9 illustrates the voltage profile at each bus after installing multiple CS units. The minimum VSI at bus 18 increases to 0.757.

2) Use of the GWO algorithm

For the GWO algorithm, the LSF also identifies buses 31, 25, 2, and 9 as optimal candidate locations. The optimal

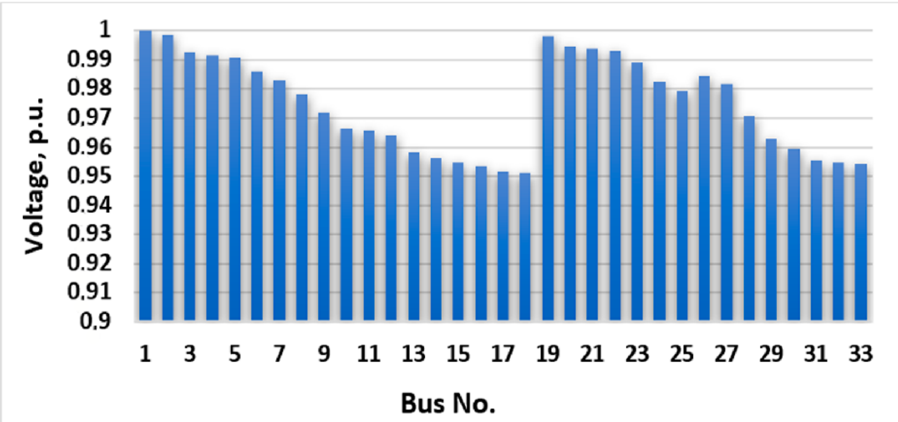

Fig. 7. Voltage profiles for Case 2: a single DG unit placed in IEEE 33-bus system using the GWO algorithm.

TABLE 2. Comparison of the Results Obtained by GWO and ALO with Other Methods after Installing a Single DG Unit

Method	Initial loss, MW	With a DG unit installed			Reduction %
		Loss, MW	Size, MW	Bus	
IWD [21]	0.2112	0.1110	2.49	6	47.46
BB-BC [22]	0.2110	0.1082	2.58	5	48.70
MINLP [23]	0.2110	0.1110	2.59	6	47.39
Analy. [24]	0.2112	0.1112	2.49	6	47.33
PSO [25]	0.2110	0.1153	3.15	6	45.36
PSO [26]	0.2110	0.1188	2.49	6	43.68
GWO	**0.2015**	**0.1037**	**2.575**	**6**	**48.54**
ALO	**0.2015**	**0.1255**	**1.92**	**6**	**37.73**

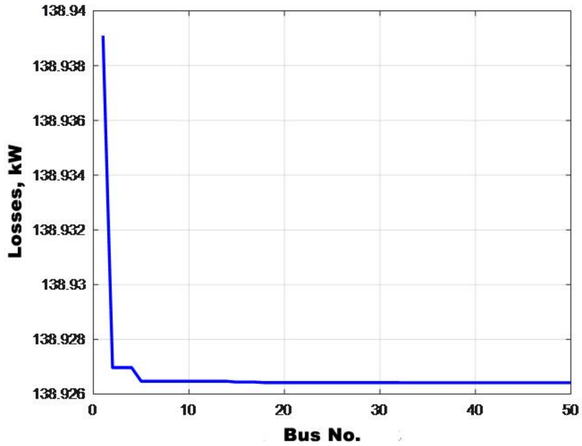

Fig. 10. The convergence characteristics of RPL after installation of multiple CSs using the GWO algorithm.

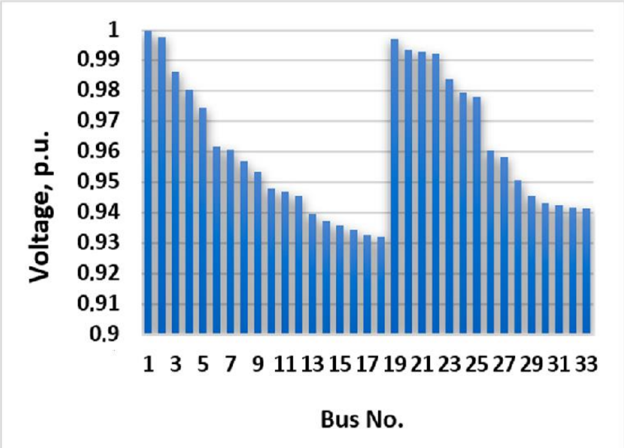

Fig. 11. Voltage profiles for Case 3: multiple CSs placed in IEEE 33-bus system using the GWO algorithm.

sizes for the multiple CS units are determined as 0.575 MVAr (bus 31), 0.4703 MVAr (bus 25), 0.575 MVAr (bus 2), and 0.575 MVAr (bus 9). This configuration results in real power losses minimized to 0.1384 MW, with a 31.31% reduction. Figure 10 presents the convergence characteristics of RPL after installing multiple CSs using the GWO algorithm, given the number of populations is 50 and the number of iterations is 50. Figure 11 presents the voltage profile at each bus. The minimum VSI at bus 18 increases to 0.755.

E. Case 4: Multiple Distributed Generation (DG) Sources

This case examines the optimal placement and sizing of multiple DG units using the ALO and GWO algorithms based on the Loss Sensitivity Factor (LSF).

1)Use of the ALO algorithm

Based on LSF values, the optimal candidate buses for placing multiple DG units are 25, 2, 9, and 31. The ALO algorithm determines the optimal sizes for these DG units as 0.9288 MW (bus 25), 0.9288 MW (bus 2), 0.8456 MW (bus 9), and 0.8994 MW (bus 31). This configuration minimizes real power losses to 0.0754 MW, achieving a substantial 62.59% reduction. Figure 12 presents the convergence characteristics of RPL after installation of multiple DG units using the ALO algorithm, given the number of populations is 50 and number of iterations is 50. Figure 13 presents the voltage profile at each bus. The minimum VSI at bus 18 increases to 0.8374.

2) Use of the GWO algorithm

For the GWO algorithm, the LSF also identifies buses 25, 2, 9, and 31 as optimal candidate locations. The optimal sizes for the multiple DG units are determined as 0.8558 MW (bus 25), 0.9288 MW (bus 2), 0.9288 MW (bus 9), and 0.9093 MW (bus 31). This configuration results in real power losses minimized to 0.0754 MW, with a 62.6% reduction. Figure 14 presents the convergence characteristics of RPL after installation of multiple DG units using the GWO algorithm, with a population size of 50 and 50 iterations. The voltage profiles at each bus are illustrated in Figure 15. The minimum VSI at bus 18 increases to 0.839.

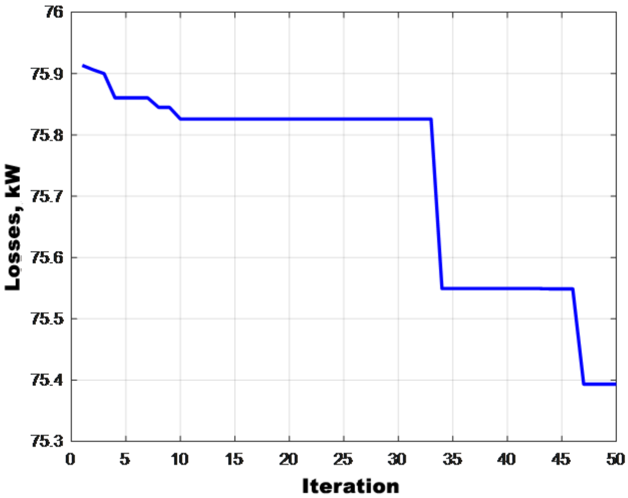

Fig. 12. The convergence characteristics of RPL after installation of multiple DG units using the ALO algorithm.

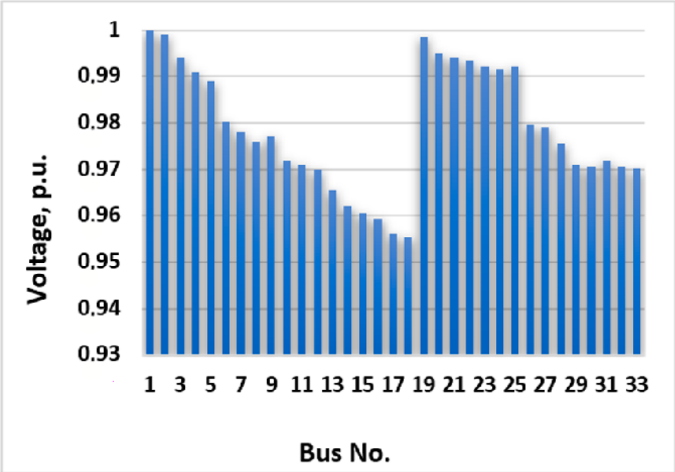

Fig. 13. Voltage profiles for Case 4: multiple DG units placed in IEEE 33-bus system using the ALO algorithm.

Table 3 represents the optimal results achieved through the application of the proposed Grey Wolf Optimizer (GWO) and Ant Lion Optimization (ALO) algorithms to the IEEE 33-bus system. Figures 16 and 17 further illustrate a comparative analysis of real and reactive power losses across the initial case and four distinct scenarios: installation of 1) a single capacitor shunt (CS), 2) a single distributed generation (DG) unit, 3) multiple CSs, and 4) multiple DG units, utilizing both ALO and GWO algorithms. Complementing these findings, Table 4 provides a comprehensive statistical analysis of GWO and ALO performance across these four scenarios, based on 30 independent runs. This analysis evaluates the best, worst, and mean power loss (in kW), alongside the standard deviation (σ) and coefficient of variation (CV), to rigorously assess the reliability and consistency of the generated solutions. The statistical findings consistently demonstrate the superior performance of the GWO algorithm across all evaluated scenarios, achieving lower mean power loss compared to ALO. This research introduces a hybrid optimization strategy for the integration of Distributed Generation (DG) and Capacitor Shunt (CS) into power systems, primarily aimed at minimizing real power loss. The methodology employs deterministic approaches, specifically the Reconfiguration Method (RM) for single-unit placement and the Loss Sensitivity Factor (LSF) for multiple-unit placement, which are then coupled with the metaheuristic GWO and ALO algorithms to determine optimal sizing. This two-step process significantly enhances computational efficiency by streamlining the search space. The study rigorously compares the performance of GWO and ALO algorithms when applied to the IEEE 33-bus system under four diverse

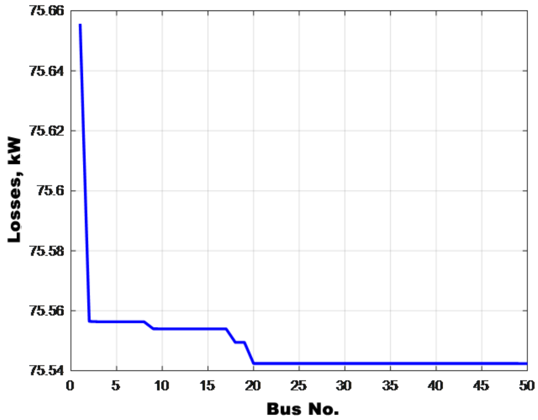

Fig. 14. The convergence characteristics of RPL after installation of multiple DG units using the GWO algorithm.

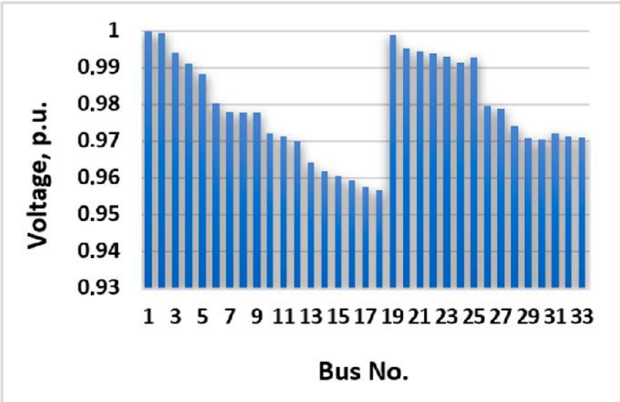

Fig. 15. Voltage profiles for Case 4: multiple DG units placed in IEEE 33-bus system using the GWO algorithm.

TABLE 3. The Optimal Results Obtained for IEEE 33-Bus System with the Proposed ALO and GWO Algorithms

Items	Initial	Using ALO (After Installation)				Using GWO (After Installation)			
		Single CS	Single DG unit	Multiple CSs	Multiple DG units	Single CS	Single DG unit	Multiple CSs	Multiple DG units
Total RPL, MW	0.2015	0.1515	0.1255	0.1382	0.0754	0.1436	0.1037	0.1384	0.0754
Total QPL, MVar	0.1343	0.1041	0.0867	0.0925	0.0517	0.0959	0.0746	0.0959	0.0518
RPL loss reduction rate %	-	24.81	37.73	31.41	62.59	28.74	48.54	31.31	62.6
Minimum VSI	0.696	0.736	0.813	0.757	0.835	0.735	0.819	0.755	0.839
Sum of VSI	27.155	27.273	28.72	27.32	28.15	27.166	28.87	27.30	29.36
Optimal size of CSs, MVAr	-	1.308		0.575 0.6 0.465 0.575		1.253		0.575 0.4703 0.575 0.575	
Optimal size of DG, MW			1.92		0.9288 0.9288 0.8456 0.8994		2.575		0.8558 0.9288 0.9288 0.9093
Location (bus No.)		31	10	25,2,9,31	25, 2, 9, 31	30	6	31, 25, 2, 9	25, 2, 9, 31

TABLE 4. Statistical Analysis Results for Different Scenarios

CV %	Std Dev (σ)	Mean (kW)	Worst (kW)	Best (kW)	Algorithm	Scenario
0.77	1.23	159.87	162.15	158.42	GWO	Single CS
1.03	1.67	161.45	164.33	159.12	ALO	Single CS
0.76	1.08	141.22	143.21	139.55	GWO	Single DG unit
1.01	1.45	142.89	145.67	140.33	ALO	Single DG unit
1.08	1.56	144.78	147.89	142.67	GWO	Multiple CSs
1.29	1.89	146.12	149.23	143.45	ALO	Multiple CSs
1.05	1.34	127.45	129.67	125.34	GWO	Multiple DG units
1.30	1.67	128.89	131.45	126.78	ALO	Multiple DG units

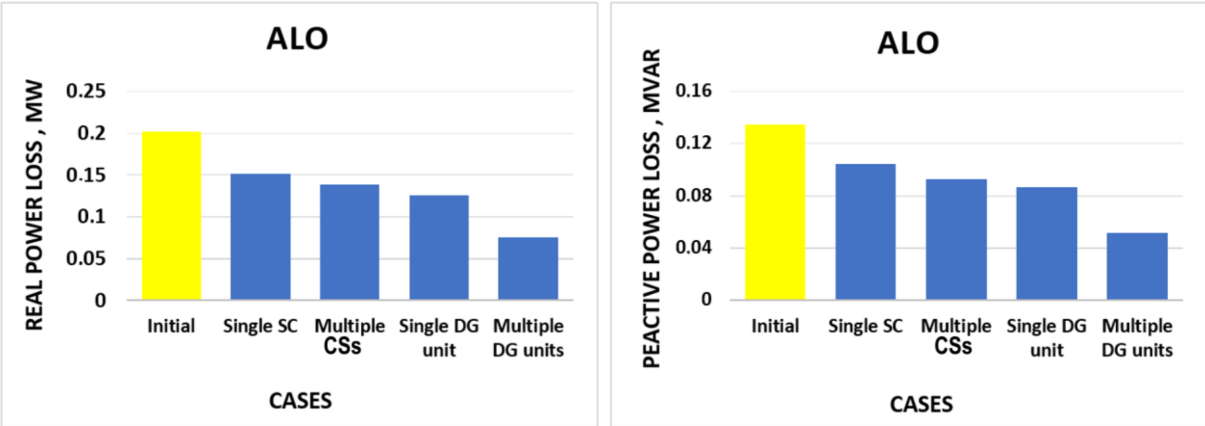

Fig. 16. Comparison results of real power losses and reactive power loss using the ALO for each case.

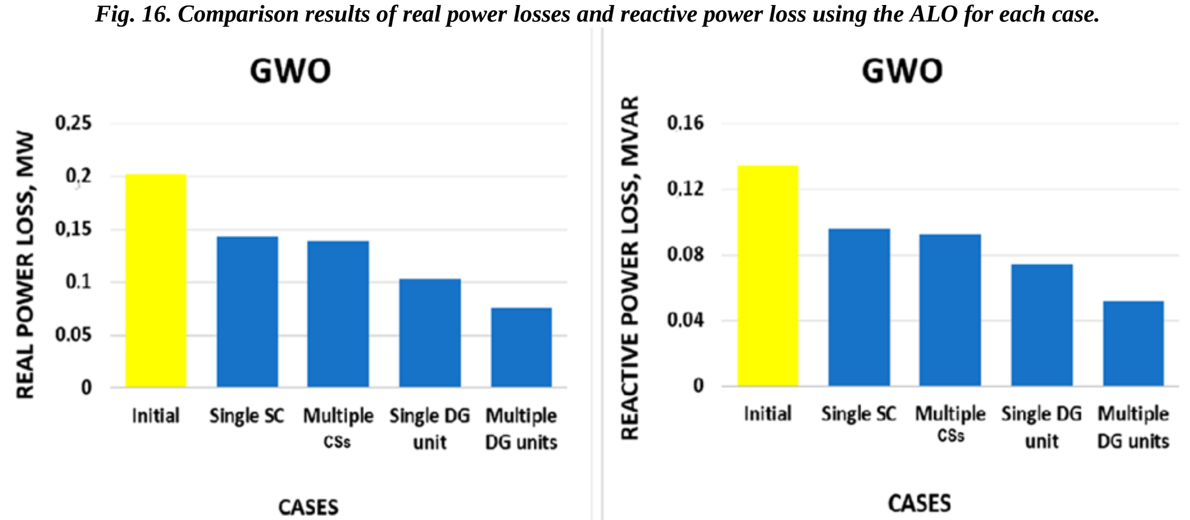

Fig. 17. Comparison results of real power losses and reactive power loss using GWO for each case.

scenarios, confirming that the installation of multiple DG units yields the most substantial reduction in power losses. Key limitations identified for future research include the imperative to incorporate the inherent uncertainty of load demands and renewable energy generation; to adopt a multi-objective optimization framework encompassing economic costs, environmental emissions, and system reliability; and to conduct a comprehensive techno-economic analysis to provide a more pragmatic basis for decision-making in utility planning.

V. CONCLUSION

In this study, we successfully developed and applied a novel hybrid optimization technique for determining the optimal size and location of Distributed generation (DG) units and Capacitor shunts (CSs) within the IEEE 33-bus radial distribution system. The proposed methodology effectively combines deterministic placement strategies – the Reconfiguration Method (RM) for single units and the Loss Sensitivity Factor (LSF) for multiple units – with two powerful metaheuristic algorithms, the Grey Wolf Optimizer (GWO) and Ant Lion Optimization (ALO), for optimal sizing. The primary objective was to minimize the total real power losses, which, as demonstrated, concurrently led to significant improvements in voltage profiles and an enhanced voltage stability index across the system.

Our comprehensive evaluation across four distinct scenarios (single CS, single DG unit, multiple CSs, and multiple DG units) provided valuable insights into the performance of both GWO and ALO. The results consistently indicated that the integration of distributed generation (both single and multiple units) yields a more substantial reduction in real power losses compared to the installation of capacitor shunts. This highlights the significant potential of DG units in enhancing the efficiency and stability of distribution networks. Furthermore, while both GWO and ALO proved to be highly effective in identifying optimal solutions for the sizing of CS and DG units, the Grey Wolf Optimizer consistently demonstrated a more favourable balance of computational efficiency and robustness. GWO often achieved faster convergence and produced results that were more consistent across multiple runs, as evidenced by its lower standard deviation and coefficient of variation in the statistical analysis. Although ALO can find highly competitive solutions and, in some specific instances, might even attain a slightly lower absolute minimum, the superior consistency and reliability of GWO make it a preferable choice for practical applications where rapid and dependable decision-making is paramount.

Building upon the findings of this study, future research endeavours can further enhance the proposed optimization framework by addressing several key areas. These include incorporating the inherent uncertainties of load demands and renewable energy generation through probabilistic or possibility models; expanding the optimization to a multi-objective framework that considers economic costs, environmental impacts, and system reliability; and conducting comprehensive techno-economic analysis to provide a more practical basis for decision-making.

References

[1] M. G. Hemeida, A. Ahmed, A. A. Mohamed, S. Alkhalaf, A. M. B. El-dine, "Optimal allocation of distributed generators DG based Manta Ray Foraging Optimization algorithm (MRFO)," Ain Shams Eng. J., vol. 12, no. 1, pp. 609–619, 2021. DOI: 10.1016/j.asej.2020.07.009.

[2] K. S. Sambaiah, "A Review on Optimal Allocation and Sizing Techniques for DG in Distribution Systems," International Journal of Renewable Energy Research, vol. 8, no. 3, pp. 1236–1256, 2018.

[3] M. M. Sayed, M. Y. Mahdy, S. H. E. A. Aleem, H. K. M. Youssef, T. A. Boghdady, "Simultaneous Distribution Network Reconfiguration and Optimal Allocation of Renewable-Based Distributed Generators and Shunt Capacitors under Uncertain Conditions," Energies, vol. 15, no. 6, Art. no. 2299, 2022. DOI: 10.3390/en15062299.

[4] A. Selim, S. Kamel, A. A. Mohamed, E. E. Elattar, "Optimal Allocation of Multiple Types of Distributed Generations in Radial Distribution Systems Using a Hybrid Technique," Sustainability, vol. 13, no. 12, Art. no. 6644, 2021. DOI: 10.3390/su13126644 2021.

[5] A. R. Ali, A. Abdul, R. Altahir, S. Alwash, M. Al-Kaabi, "Investigation Study of Injecting Numerous DGs in IEEE 69 – bus Radial Networks Using Enhanced PSO and Ant Lion Optimization Algorithms," in 2023 3rd International Conference on Electrical Machines and Drives (ICEMD), Tehran, Iran, Islamic Republic of, 2023, pp. 1–7. DOI: 10.1109/ICEMD60816.2023.10429267.

[6] B. Hussein, A. Igeb, M. Al-Kaabi, P. P. Oshchepkov, M. Muhssin, "Grey Wolf Optimizer Algorithm to Solve Optimal Placement and Sizing of the Distributed Generation Sources in Distribution Radial Networks," in 2023 International Symposium on Fundamentals of Electrical Engineering (ISFEE), Bucharest, Romania, 2023, pp. 1–6. DOI: 10.1109/ISFEE60884.2023.10637122.

[7] J. Al Hasheme, M. Al-Kaabi, L. Toma, "Optimal allocation of distribution generator for radial distribution network using grey wolf optimizer," U.P.B. Sci. Bull., ser. C, vol. 86, no. 3, pp. 371–390, 2024.

[8] A. Naeem, A. Saheb, D. Nazarpour, M. Al-kaabi, "Economic Dispatch Using Harris Hawks Optimization with Renewable Energy Source and Capacitor Shunt," in *2024 16th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, Iasi, Romania, 2024, pp. 1–8. DOI: 10.1109/ECAI61503.2024.10607530.

[9] Almoataz Y. Abdelaziz, Mirna Fouad Ali, Eman Beshr, "Hybrid Siting and Sizing of Distributed Generators and Shunt Capacitors with System Reconfiguration using Wild Horse Optimizer," J. Adv. Res. Applied Sciences and Eng. Technol., vol. 38, no. 2, pp. 196–213, 2024.

[10] B. C. Sujatha, A. Usha, R. S. Geetha, "Optimal Planning of PV Sources and D-STATCOM Devices with Network Reconfiguration Employing Modified Ant Lion Optimizer," Energies, vol. 17, no. 10, Art. no. 2238, 2024. DOI: 10.3390/en17102238.

[11] B. P. Nanda, D. P. Mishra, S. R. Salkuti, “A modified ant lion optimization algorithm for efficient distributed generation allocation in power distribution networks,” Electric Power Systems Research, vol. 246, Art. no. 111705, 2025. DOI: 10.1016/j.epsr.2025.111705.

[12] A. R. A. Wafa, “Ant-lion optimizer-based multi-objective optimal simultaneous allocation of distributed generations and synchronous condensers in distribution networks,” Int. Trans. Electr. Energy Syst., vol. 29, pp. 1–14, 2019. DOI: 10.1002/etep.2755.

[13] R. A. Lone, S. J. Iqbal, A. S. Anees, “Optimal location and sizing of distributed generation for distribution systems: An improved analytical technique,” Int. J. Green Energy, vol. 21, no. 3, pp. 682–700, 2024. DOI: 10.1080/15435075.2023.2207638.

[14] M. Alqahtani, P. Marimuthu, V. Moorthy, B. Pangedaiah, C. R. Reddy, M. K. Kumar, M. Khalid, “Investigation and Minimization of Power Loss in Radial Distribution Network Using Gray Wolf Optimization,” Energies, vol. 16, no. 12, Art. no. 4571, 2023. DOI: 10.3390/en16124571.

[15] M. K. Das, “Optimal Placement of Distributed Generation in Distribution Networks Using Grey Wolf Optimization,” Master's Thesis, Dept. of Electrical Engineering, Tribhuvan University, Pulchowk Campus, Lalitpur, Nepal, Jun. 2023.

[16] M. Varan, A. Erduman, F. Menevşeoğlu, “A Grey Wolf Optimization Algorithm-Based Optimal Reactive Power Dispatch with Wind-Integrated Power Systems,” Energies, vol. 16, no. 13, Art. no. 5021, 2023. DOI: 10.3390/en16135021.

[17] N. C. Sahoo, K. Prasad, “A fuzzy genetic approach for network reconfiguration to enhance voltage stability in radial distribution systems,” vol. 47, pp. 3288–3306, 2006. DOI: 10.1016/j.enconman.2006.01.004.

[18] M. Kefayat, A. L. Ara, S. A. N. Niaki, “A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources,” Energy Conversion and Management, vol. 92, pp. 149–161, 2015. DOI: 10.1016/j.enconman.2014.12.037.

[19] S. Mirjalili, S. Mohammad, A. Lewis, “Advances in Engineering Software Grey Wolf Optimizer,” Adv. Eng. Softw., vol. 69, pp. 46–61, 2014. DOI: 10.1016/j.advengsoft.2013.12.007.

[20] A. S. Assiri, A. G. Hussien, M. Amin, “Ant Lion Optimization: Variants, Hybrids, and Applications,” IEEE Access, vol. 8, pp. 77746–77764, 2020. DOI: 10.1109/ACCESS.2020.2990338.

[21] D. R. Prabha, T. Jayabarathi, R. Umamageswari, S. Saranya, “Optimal location and sizing of distributed generation unit using intelligent water drop algorithm,” Sustainable Energy Technologies and Assessments, vol. 11, pp. 106–113, 2015.

[22] M. M. Othman, W. El-Khattam, Y. G. Hegazy, A. Y. Abdelaziz, “Optimal Placement and Sizing of Distributed Generators in Unbalanced Distribution Systems Using Supervised Big Bang-Big Crunch Method,” IEEE Transactions on Power Systems, vol. 30, no. 2, pp. 911–919, 2015.

[23] S. Kaur, G. Kumbhar, J. Sharma, “A MINLP technique for optimal placement of multiple DG units in distribution systems,” Electrical Power and Energy Systems, vol. 63, pp. 609–617, 2014.

[24] N. Acharya, P. Mahat, N. Mithulananthan, “An analytical approach for DG allocation in primary distribution network,” Electrical Power and Energy Systems, vol. 28, no. 10, pp. 669–678, 2006.

[25] S. Kansal, V. Kumar, B. Tyagi, “Optimal placement of different type of DG sources in distribution networks,” Electrical Power and Energy Systems, vol. 53, pp. 752–760, 2013.

[26] M. P. Lalitha, V. C. V. Reddy, V. Usha, “Optimal DG placement for minimum real power loss in radial distribution systems using PSO,” Journal of Theoretical and Applied Information Technology, vol. 13, no. 2, pp. 107–114, 2010.

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