



Performance Enhancement of Distribution System using Grey Wolf Optimizer for Capacitor Placement and Sizing Considering Load Variations

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Abstract

This research introduces a Grey Wolf Optimizer (GWO) strategy for determining the optimal placement and sizing of shunt capacitors in radial distribution networks under different load scenarios. The task is structured as a multi-scenario optimization model aimed at reducing active power loss, voltage deviation, and annual compensation expenses, all while adhering to bus voltage and line current limitations. Unlike traditional methods that focus on capacitor allocation for a single operating condition, this approach explicitly accounts for light, normal, and heavy load conditions to ensure solutions are effective throughout daily demand fluctuations. The method is tested on the IEEE 33-bus distribution system and benchmarked against several existing metaheuristic techniques. Findings reveal that GWO consistently provides viable capacitor configurations across all load conditions and offers enhanced technical and economic outcomes. During normal load conditions, the method decreases active power loss from 202.69 kW to 131.83 kW, and under heavy load, it achieves the highest annual net savings of \$97,588. In summary, the results suggest that GWO is a reliable and economical solution for reactive power compensation planning in distribution systems with variable loads.

Keywords: annual cost; capacitor; grey wolf optimizer; load variations; power loss

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1. Introduction

Electric power distribution systems frequently experience considerable active power losses and voltage profile degradation due to inefficient reactive power flow management, particularly under daily load fluctuations. In radial distribution systems (RDS), the long feeder structure and relatively high R/X ratio make downstream buses more vulnerable to voltage drops and higher copper losses, especially when reactive power demand increases under heavy loading. Shunt capacitor compensation is widely recognized as an effective and economical solution for reducing line losses, improving voltage profiles, and enhancing overall operating efficiency. However, determining the optimal locations and sizes of capacitor banks remains a nonlinear optimization problem whose solution is highly dependent on the system loading level [1]. Distribution systems generally have a radial topology with relatively long lines from the substation to the customer and a high

R/X ratio. This characteristic causes load current to flow through conductors with relatively high resistance, increasing copper losses. When the load is inductive (induction motors, distribution transformers, conventional lighting), the reactive power requirement (RPR) causes the total current to increase, resulting in higher losses and voltage drops along the feeder. This condition is exacerbated by daily load variations (light, normal, and heavy), which cause current profiles and RPR requirements to fluctuate. Meanwhile, equipment capacity (conductors, transformers, tap changers) is limited and cannot always maintain voltage within the standard range during all operating hours. On long feeders, lateral branches farthest from the source are most susceptible to low voltage, especially during heavy loads [2]. SC placement and sizing should not be optimized solely for a single load condition (e.g., nominal load), as distribution network characteristics and reactive power requirements change with the daily

load profile. Load current, RPR requirements, losses, and voltage profiles are all nonlinear with load levels. Consequently, optimal solutions at 100% load are often no longer optimal and may even violate operating limits when the system is at light or heavy load [3].

Numerous studies have investigated SC placement and sizing together with the assessment of penetration levels in RDS. The primary objective is to mitigate active power losses and improve bus-voltage profiles under operational constraints. To this end, optimization-based approaches have been widely adopted, and several population based metaheuristics have been implemented, including Bacterial Foraging Optimization (BFO) [2], arithmetic optimization algorithm (AOA) [4], diffusion and update techniques based algorithm (DUTA)[5] and Genetic Algorithm (GA) [6]. In [7] SC placement and sizing in RDS were optimized using three approaches gravitational search algorithm (GSA), interior point (IP), simulated annealing (SA), flower pollination algorithm (FPA), monkey search optimization (MSO) [8], and multi-objective water cycle algorithm (MOWCA) [9], and sine cosine algorithm (SCA) [10]. The study analyzed the annual cost with the following components: (i) power loss, (ii) number of installed SC, and (iii) capacity of the SC banks. The evaluation was conducted on conditions before and after SC installation, thus obtaining net savings [11-13]. Prior research has demonstrated that strategically placing and sizing capacitors can greatly decrease power loss and enhance voltage performance, two important limitations still remain. First, many earlier works mainly emphasize comparative numerical results without providing a sufficiently critical explanation of why a particular optimization algorithm is more suitable than others for this problem. Second, only a limited number of studies simultaneously assess technical, economic, and voltage-quality performance under multiple loading scenarios. As a result, the robustness of many reported

solutions under varying operating conditions is still not fully clarified. Therefore, a more comprehensive and better-justified optimization framework is needed for capacitor placement and sizing in practical RDS with time-varying load demand. Table 1 provides a comprehensive comparison between the proposed method and recent literature reviews based on various technical and economic assessment metrics. GWO is particularly attractive for this problem because its hierarchical leadership mechanism and position updating process provide a natural balance between exploration and exploitation. Unlike methods that rely heavily on velocity control, mutation tuning, or multiple internal parameters, GWO has a relatively simple structure and fewer control parameters, which can improve implementation stability. For capacitor placement and sizing under load variation, such characteristics are beneficial because the optimization problem is highly nonlinear, constrained, and sensitive to changes in reactive power demand across different scenarios. Therefore, this study does not merely apply another metaheuristic to a standard test system. Its main contribution lies in formulating capacitor placement and sizing as a multi-scenario optimization problem under light, normal, and heavy load conditions, and in evaluating whether GWO can provide a technically feasible and economically attractive solution that remains robust across these varying operating states.

This paper presents an optimization of SC placement and sizing in RDS using the metaheuristic GWO. The goals include minimizing active power losses in the network, enhancing voltage profiles at the bus, and reducing the annual cost in a coordinated approach. Unlike studies that evaluate a single operating point, this work explicitly accounts for load variations, namely light, normal, and heavy load so the resulting solution remains effective across operating hours and avoids over or under compensation.

Table 1. Comparison with the literature review

Method	APL	Techno	Economic	Load Variation	VDI	VSI	Test System	Year
Jelly Fish [14]	✓	-	-	-	-	-	33 bus	2024
HPSO [15]	✓	-	-	-	-	-	33 bus	2024
IPSO [16]	✓	-	-	✓	-	-	33 bus and 69 bus	2025
WAR [17]	✓	-	-	✓	-	-	33 bus	2024
Cuckoo [1]	✓	-	-	✓	-	-	34 bus and 69 bus	2024
GA [6]	✓	-	-	-	-	-	33 bus	2024
MOWCA[9]	✓	✓	✓	-	-	✓	33 bus and 94 bus	2023
This Work	✓	✓	✓	✓	✓	✓	33 bus	2025

2. Methods

In this study, the GWO method is proposed as a solution to the problems in placement and sizing capacitors in RDS. The stages for solving the problem will include:

2.1 Power Flow Formulation

Figure 1 illustrates a simple 3-bus RDS. Bus 1 serves as the slack bus with a reference voltage of $V_1 = 1.0 \angle 0^\circ$, while buses 2 and 3 are load buses with complex power

demands $S_2 = P_2 + jQ_2$ and $S_3 = P_3 + jQ_3$, respectively. Branch 1 connects Bus 1 to Bus 2 with impedance $Z_{12} = R_{12} + jX_{12}$, and branch 2 connects Bus 2 to Bus 3 with impedance $Z_{23} = R_{23} + jX_{23}$.

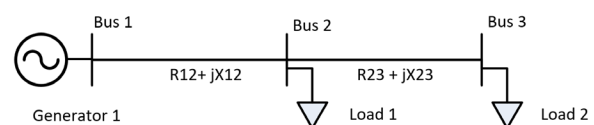


Figure 1. Single line diagram 3-bus distribution system

The injected current at each load bus is calculated using Equation 1.

$$I_i^k = \left(\frac{S_i^*}{V_i^{(k-1)}} \right)^*, i = 2, 3 \quad (1)$$

$V_i^{(0)} = 1.0 \angle 0^\circ$ pu is the initial voltage guess. The branch currents are related to bus injection by Equation 2.

$$\begin{bmatrix} I_{12} \\ I_{23} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} I_2 \\ I_3 \end{bmatrix} \quad (2)$$

The matrix equation represents the BIBC relationship in a RDS. It maps load bus current injections (I_2, I_3) to branch currents (I_{12}, I_{23}). Therefore, the branch currents are obtained in Equations 3 and 4.

$$I_{12} = I_2 + I_3 \quad (3)$$

$$I_{23} = I_2 + I_3 \quad (4)$$

The voltage drops are computed using Equation 5 [16].

$$\begin{bmatrix} \Delta V_2 \\ \Delta V_3 \end{bmatrix} = \begin{bmatrix} Z_{12} & Z_{12} \\ Z_{12} & Z_{12} + Z_{23} \end{bmatrix} \begin{bmatrix} I_{12} \\ I_{23} \end{bmatrix} \quad (5)$$

The BCBV matrix correctly relates branch currents to bus voltage drops in the 3-bus radial system. It accounts for the cumulative impedance from the slack bus to each load bus. The bus voltages are then updated using Equations 6 and 7.

$$V_2^k = V_1 - \Delta V_2 \quad (6)$$

$$V_3^k = V_1 - \Delta V_3 \quad (7)$$

In the 3-bus RDS, power losses occur along the feeders due to the resistance of the lines carrying current from the slack bus to the load buses. These losses are inherently higher in branches that supply more downstream load, active and reactive power losses in a branch with series impedance $Z_{12} = R + jX$ [18], are expressed in Equations 8 and 9.

$$P_{loss} = I^2 R \quad (8)$$

$$Q_{loss} = I^2 X \quad (9)$$

For a network with N_b branches, the total system losses are obtained by summing the contributions of all branches as expressed in Equations 10 and 11 [19].

$$APL = \sum_{k=1}^{N_b} |I_k|^2 R_k \quad (10)$$

$$RPL = \sum_{k=1}^{N_b} |I_k|^2 X_k \quad (11)$$

APL stands for active power loss, representing the total real power dissipated as heat in the network due to conductor resistance, RPL denotes reactive power loss [20].

2.2 Objective Functions

In this work, the objective of capacitor placement optimization is redefined to minimize a composite cost function J , which encapsulates both operational and investment expenditures [21]. The total cost is described by the following Equation 12.

$$\min J = K_p * APL * T + K_i * C_B + K_c * \sum_{i=1}^{N_c} Q_{c,i} \quad (12)$$

K_p is cost per kWh, K_c is cost per kVAr, K_i is cost per installation, C_B is the number of compensated busses and $Q_{c,i}$ is the value of installed reactive power in kVAr.

Table 2. Parameter Cost Function

Parameter	Value
K_p	0.06 \$/kWh
K_c	3 \$/kVAr
K_i	1000 \$
T	8760 hours

2.3 Voltage Deviation

Voltage deviation serves as a critical metric for evaluating the operational integrity and power quality of distribution networks. Mathematically, the aggregate voltage deviation V_D across all load buses is quantified using Equation 13 [22].

$$V_D = \sum_{i=1}^{n_b} \frac{V_{base} - V_i}{V_{base}} \quad (13)$$

V_{base} denotes the reference voltage in per unit at the system, V_i represents the actual voltage magnitude at bus i and n_b is the total number of load buses considered.

2.4 Voltage Stability Index

In this study, the voltage stability index (VSI) is reinterpreted not merely as a computational artifact, but as a sensitivity indicator that quantifies the vulnerability of each load node to voltage collapse under increasing power demand. The VSI at any non-slack node m is defined using Equation 14.

$$VSI_{(m)} = |V_m|^4 - 4\{P_{(m)} * x_{jj} - Q_{(m)} * r_{jj}\}^2 - 4\{P_{(m2)} * r_{jj} + Q_{(m2)} * x_{jj}\} |V_{(m1)}|^2 \quad (14)$$

2.5 Loss Sensitivity Factor

The Loss Sensitivity Factor (LSF) quantifies how much total system losses change in response to an incremental injection of reactive power at a specific bus. The real power dissipated in the branch connecting buses i and j arises from resistive losses and is fundamentally expressed as $I^2 R_{ij}$ in Figure 2, by substituting the line current with equivalent power and voltage quantities, this loss can be equivalently represented using Equations 15 and 16.

$$P_{ij-loss} = \frac{(P_j^2 + Q_j^2) R_{ij}}{(V_j)^2} \quad (15)$$

$$Q_{ij-loss} = \frac{(P_j^2 + Q_j^2) X_{ij}}{(V_j)^2} \quad (16)$$

The LSF is obtained by evaluating the equations presented in Equations 17 and 18.

$$\frac{\partial P_{ij-loss}}{\partial Q_j} = \frac{2 Q_j * R_{ij}}{(V_j)^2} \quad (17)$$

$$\frac{\partial Q_{ij-loss}}{\partial Q_j} = \frac{2 Q_j \cdot X_{ij}}{(V_j)^2} \quad (18)$$

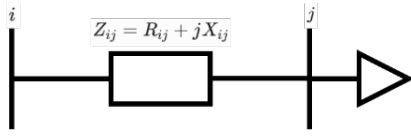


Figure 2. Single line diagram 3-bus distribution system

2.6 Voltage Constraints

Each bus in the system is required to maintain its voltage magnitude within defined boundaries, as expressed in Equation 19.

$$V_{\min} \leq V_i \leq V_{\max} \quad (19)$$

This means the voltage magnitude at bus must not fall below or exceed, ensuring stable and secure operation of the power system

2.7 Total Reactive Power Constraint

For a power system functioning with a lagging power factor to remain stable, the injected reactive power should be limited to no more than 75% of the overall reactive power requirement. This relationship is mathematically represented using Equation 20.

$$\sum_{b=1}^{CB} Q_c(b) \leq 0.75 \sum_q Q_a(q) \quad (20)$$

2.8 Power Factor Constraint

The overall power factor of the system must stay between a minimum and a maximum value using Equation 21. This ensures the system runs efficiently without causing voltage problems.

$$PF_{\text{minimum}} \leq PF_{\text{system}} \leq PF_{\text{maximum}} \quad (21)$$

2.9 Capacitor Rating Constraint

The reactive power output of the capacitor bank can take any value within the allowed range from 10 kVAR to 1200 kVAR. Unlike systems with fixed step controls, here is treated as a continuous variable, meaning any real number in this interval is admissible, as defined in Equation 22.

$$Q_{\text{minimum}} \leq Q_c \leq Q_{\text{maximum}} \quad (22)$$

2.10 Load Variations

To evaluate the robustness and adaptability of the capacitor placement and sizing strategy under realistic operating conditions, this study considers three distinct load levels: light load (60% of nominal demand), normal load (100% of nominal demand), and heavy load (160% of nominal demand).

These scenarios represent typical daily or seasonal variations in consumer demand such as nighttime (low consumption), daytime (average consumption), and peak evening hours (high consumption) which significantly affect voltage profiles and power losses in distribution networks [23].

2.11 Grey Wolf Optimizer Equation

The GWO is a metaheuristic algorithm for optimization, introduced by Seyedali Mirjalili, Seyed Mohammad Mirjalili, and Andrew Lewis in 2014. This algorithm draws inspiration from the natural social order and hunting tactics of grey wolf [24]. In the GWO framework, the wolf pack is structured into four main roles based on a dominance hierarchy: alpha (α), beta (β), delta (δ), and omega (ω). The alpha represents the leader (i.e., the best solution), while beta and delta are the second- and third-best solutions, respectively. Wolves update their positions relative to the prey (i.e., the current best solution) using Equations 23 and 24.

$$\vec{D} = |\vec{C} * \vec{X}_p(t) - \vec{X}(t)| \quad (23)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} * \vec{D} \quad (24)$$

$\vec{X}_p(t)$ is the position vector of the prey (best solution) at iteration t , $\vec{X}(t)$ is the position vector of a grey wolf, $\vec{A}$ and $\vec{C}$ are coefficient vectors computed using Equations 25 and 26.

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (25)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (26)$$

here, is $\vec{a}$ linearly decreasing vector from 2 to 0 over the course of iterations and $\vec{r}_1, \vec{r}_2$ are random vectors in $[0, 1]$. Since the optimal solution (prey location) is unknown, the algorithm assumes that the α, β , and δ the three best solutions have knowledge of the prey's location. The position update is guided by these three leaders is expressed in Equations 27 – 32.

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \quad (27)$$

$$\vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \quad (28)$$

$$\vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \quad (29)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \quad (30)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_1 \cdot \vec{D}_\beta \quad (31)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_1 \cdot \vec{D}_\delta \quad (32)$$

The new position wolf is then calculated as the average of these three estimates using Equation 33.

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (33)$$

2.12 Computational Procedure for Capacitor Placement and Sizing GWO

To solve the allocation problem, the presented framework applies to GWO for the concurrent selection of shunt capacitor sites and ratings within radial distribution systems. This approach targets total power loss minimization while strictly keeping bus voltages inside bounded limits across different loading conditions. The computational steps are as follows:

Step 0: Input system data. load data at each bus for all considered load levels, line data, base values, and operational constraints.

Step 1: define decision variables and generate of initial population: each candidate solution in GWO is encoded as a vector, as shown in Equation 34.

$$X = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^N \end{bmatrix} = \begin{bmatrix} L_2^1 & L_2^1 & L_3^1 & Q_1^1 & Q_2^1 & Q_3^1 \\ L_2^2 & L_2^2 & L_3^2 & Q_1^2 & Q_2^2 & Q_3^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ L_2^N & L_2^N & L_3^N & Q_1^N & Q_2^N & Q_3^N \end{bmatrix} \quad (34)$$

X^i denotes the i -th wolf (candidate solution), N is the maximum number of capacitor banks allowed in the system, for each solution (L_2^1, L_2^1, L_3^1) represent the bus locations where capacitors are placed. The remaining elements (Q_1^1, Q_2^1, Q_3^1) represent the reactive power ratings assigned to the corresponding capacitor locations.

Step 3: Evaluate initial population for each wolf, decode the placement and sizing information, run a load flow analysis, check constraints, compute power loss each load scenario.

Step 4: Identify α, β, δ wolves, Select the three wolves with the best (lowest) objective function values as $\vec{X}_\alpha, \vec{X}_\beta$, and $\vec{X}_\delta$.

Step 5: Update positions using Equation 33.

Step 6: Repeat Evaluation and Update $\vec{X}_\alpha, \vec{X}_\beta$, and $\vec{X}_\delta$,

decrease $\vec{a}$, repeat steps 5-6 until maximum iteration

Step 7: Output solution optimal.

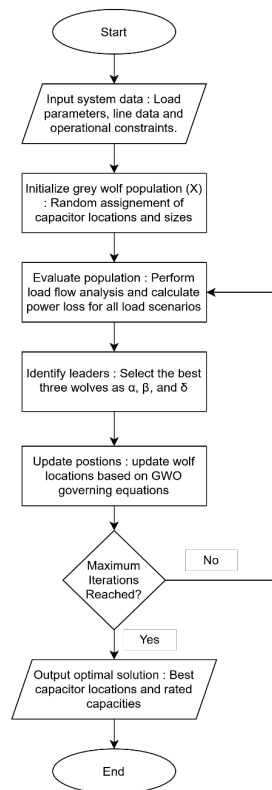


Figure 3. Flowchart of the GWO algorithm for optimal capacitor placement and sizing

The systematic implementation of the proposed GWO for optimal shunt capacitor placement and sizing is illustrated in the flowchart in Figure 3. The process begins with data acquisition (Step 0) and population encoding according to Equation 33 (Step 1). The iterative cycle involves rigorous evaluation via load flow analysis (Step 3) and leader identification (Step 4). The movement of the pack is governed by position updates (Step 5) until the convergence criteria are met (Step 6), ultimately yielding the optimal system configuration (Step 7).

3. Results and Discussions

An aggregate load of 3,715 kW and 2,300 kVAR, spread across 32 distinct load buses, characterizes the IEEE 33-bus radial test system evaluated in this study. Operating at a base voltage of 12.66 kV, the network designates its first bus (bus 1) as the slack reference [25]. To verify the accuracy of the executed power flow method, a comparative analysis was performed against ETAP 19 using the identical IEEE 33-bus RDS model. The minimal deviation between the base-case load flow outputs from both approaches confirms that the developed computation is reliable for subsequent capacitor placement and sizing optimization.

This research considers a fixed setup of exactly three shunt capacitor banks for installation in the network. To find the most efficient positions, candidate buses are pre-selected using the LSF, a sensitivity index evaluating how reactive power injection at each node impacts overall active power losses. The LSF is evaluated across all load buses. Subsequently, the GWO algorithm searches this candidate set to determine the three ideal locations and optimal sizes. The target is minimizing total power loss under three distinct operating states: light (60%), nominal (100%), and peak (160%) loads. This strategy ensures effective capacitor allocation while enabling the optimizer to adapt to varying demand levels. Under normal loading conditions, the performance of the proposed GWO was evaluated against several well-established metaheuristic algorithms, namely GA, PSO, AOA, and GSA. All algorithms were tested on the IEEE 33-bus distribution system under the same optimization objective, namely minimizing total active power loss through the optimal placement and sizing of three shunt capacitors selected from an LSF-based candidate set. As presented in Table 3, the base case resulted in a total power loss of 202.69 kW with a minimum bus voltage of 0.9131 p.u. After optimization, all methods significantly improved system performance by reducing power losses in the range of 15%–35% and increasing the minimum voltage to above 0.93 p.u. Among the compared methods, GWO achieved the best overall performance, yielding the lowest power loss of 131.83 kW and the highest minimum bus voltage of 0.9337 p.u., outperforming GA (143.60 kW), PSO (136.15 kW), AOA (139.41 kW), and GSA (134.50 kW).

Table 3. Result for Normal Load

Method	Losses (kW)	Vmin (p.u)	Capacitor Location	Capacitor Capacity (kVAR)	Reduction Losses (%)	Annual cost (\$)	Net Saving (\$)	Net Saving (%)
Base	202.69	0.9131	-	-	-	106534		
GWO (proposed)	131.83	0.9337	30, 24, 13	1042, 549, 377	34.96	78192	28342	26.60
AOA [4]	139.41	-	8, 24, 30	556, 513, 965	31.22	82376	24158	22.68
BFO [2]	144.04	0.9361	18, 30, 33	349.6, 820.6, 277.3	28.95	83050	23484	22.04
SA [7]	151.75	0.9591	10, 30, 14	450, 350, 900	25.13	87860	18674	17.53
IP [7]	171.78	0.9501	9, 29, 30	450, 800, 900	15.25	99738	6796	6.38
GSA[7]	134.50	0.9511	26, 13, 15	350, 450, 800	33.64	78493	28041	26.32
BA [11]	138.35	-	13, 25, 30	380, 490, 990	31.74	81297	25237	23.69
MPSO [12]	137.37	0.9451	8, 16, 24, 30, 32	320, 340, 500, 660, 380	32.22	83802	22732	21.34
TSM [12]	144.04	0.9416	7, 29, 30	850, 25, 900	28.93	84032	22501	21.12
MMS [12]	135.77	0.9416	9, 13, 29	300, 300, 900	33.01	78861	27673	25.98
FPA [22]	134.47	0.9365	6, 9, 30	250, 400, 900	33.66	78477	28056	26.34
NSGA[9]	142.70	0.9449	6, 8, 30, 13	137, 359, 1035, 430	29.59	84886	21648	20.32
MOWCA [9]	150.61	0.9504	30, 13, 10	1211, 396, 480	25.69	88422	18112	17.00
MOWGO[9]	148.78	0.9456	30, 13, 10	400, 1150, 500	26.59	87349	19185	18.01
SCA [10]	138.07	0.9286	6, 30	577.6, 916.8	33.96	79053	27481	25.78
MRFO [10]	140.22	0.9284	6, 29	600, 900	30.82	80200	26334	24.72
MPSO [10]	142.21	0.9400	6, 28, 29, 8, 30, 9, 13	300, 300, 250, 300, 350, 300, 300	29.84	87746	18788	17.64
GA [6]	143.60	0.9256	30	1252.7	29.15	80234	26300	24.69

Figure 4 presents a radar chart comparing the voltage profiles across all 33 buses of the IEEE 33-bus RDF under normal load conditions, for five optimization methods GWO, MRFO, PSO, IEDO, EDO and the base case (without capacitors). While the concentric circles indicate voltage magnitude in per-unit (p.u.), ranging from 0.91 to 1.00 p.u.

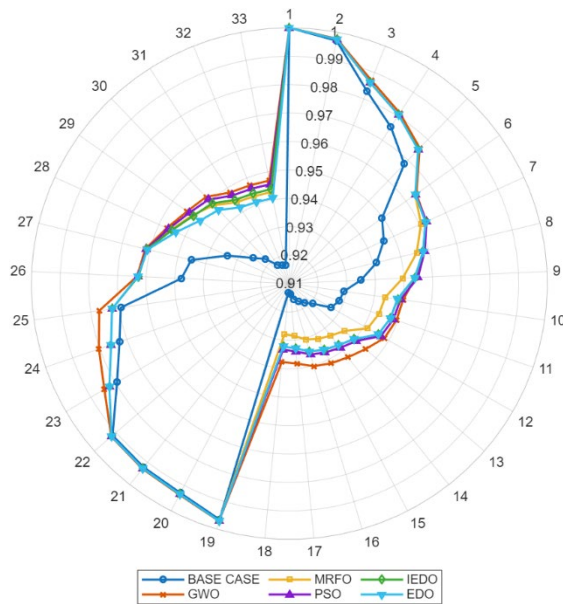


Figure 4. Voltage Profile Under Normal Load

As clearly illustrated, the base case exhibits the poorest voltage profile, with several buses falling below 0.92 p.u., particularly in the downstream sections (e.g., buses 18–25 and 30–33), reflecting significant voltage drop due to high line losses.

Based on Figure 5, the VSI for all 33 buses under normal load shows a clear and consistent improvement under the GWO optimized scenario compared to the base case. The orange line (GWO) forms a larger, more outward polygon than the blue line (Base), indicating

that the VSI values are higher across nearly all buses after optimization particularly notable at critical buses such as 2, 19, and 22, where the index approaches or exceeds 0.96.

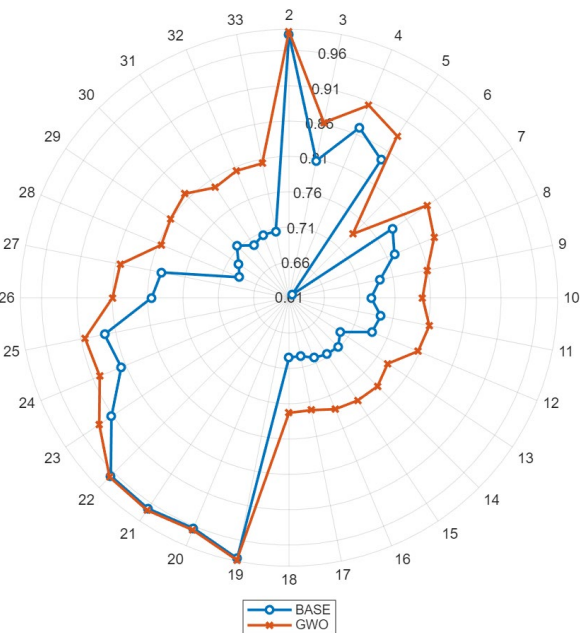


Figure 5. Voltage Stability Index under Normal Load

Figure 6 illustrates VDI values for all buses under normal load show a consistent and significant reduction after applying the GWO compared to the base case, indicating improved voltage profiles across the entire system. Buses that initially exhibited the largest deviations such as buses 5, 8, 15, and 25 demonstrate the most substantial improvements (approximately 29–30% reduction in VDI), highlighting GWO's effectiveness in mitigating critical voltage issues. As illustrated in Figure 7, evaluating the voltage profiles across the 33 buses demonstrates a uniform enhancement in grid performance through the

deployment of optimization algorithms. The GWO approach achieves the most superior overall voltage levels relative to both the uncompensated scenario and alternative PSO variants. For the uncompensated base case, the lowest voltage drops to 0.9583 pu at bus 18, indicating significant voltage drop toward the end of the feeder. Among the compared methods, GWO consistently maintains the highest voltages across both the first and second laterals of the network, particularly improving critical buses such as 17–18 and 31–33.

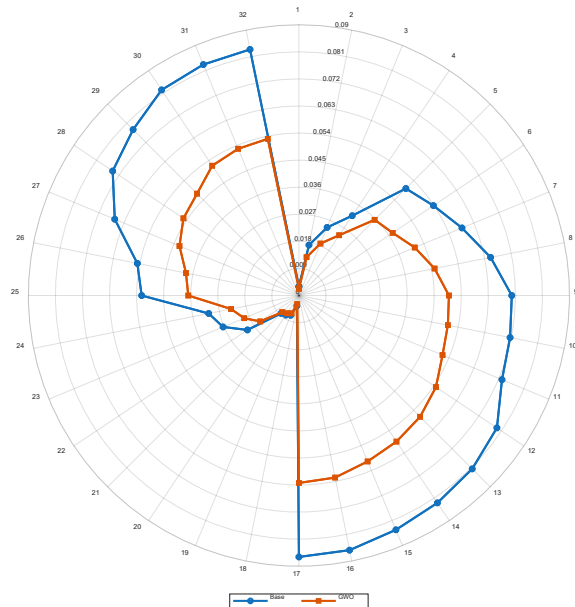


Figure 6. Voltage Deviation Index under Normal Load

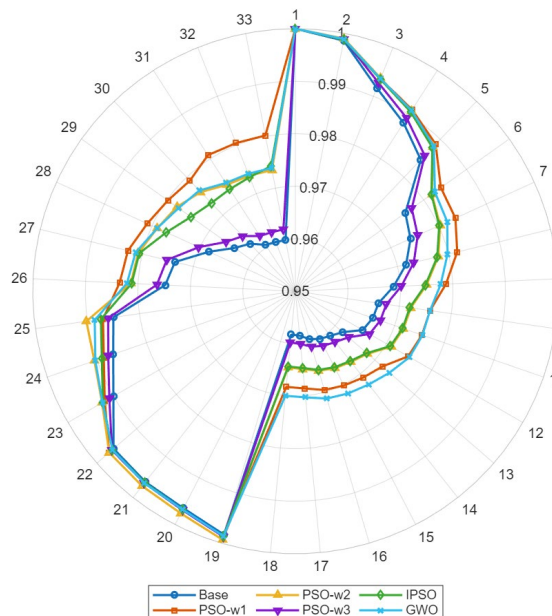


Figure 7. Voltage Profile under Light Load

Based on Figure 8 the VSI, represented here by the per unit voltage magnitudes at buses 2 through 33, shows a marked improvement under the GWO optimized scenario compared to the base case. In the base case, several buses particularly in the later sections of the network exhibit critically low voltages, with values as low as 0.8433 p.u.

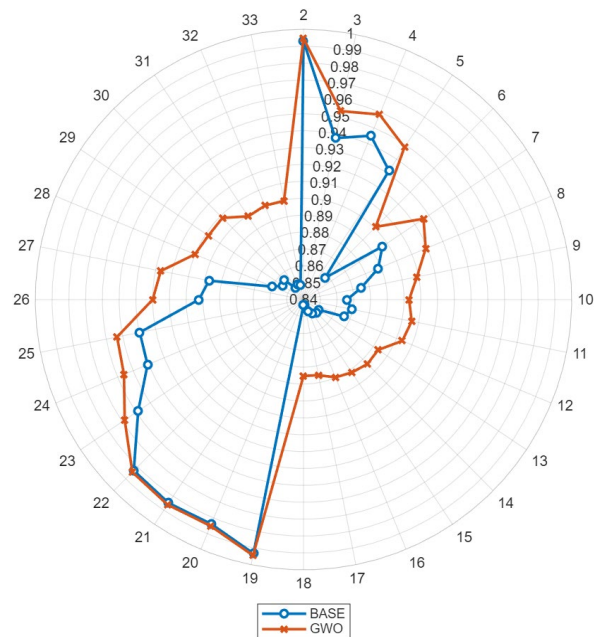


Figure 8. Voltage Stability Index under Light Load

Figure 9 illustrates that the proposed GWO method significantly reduces the Voltage Deviation Index (VDI) under light load conditions. Compared with the base case, the GWO curve is positioned closer to the center of the radar chart, particularly at downstream buses, indicating that voltage magnitudes are closer to the nominal value. Therefore, the optimized capacitor placement and sizing obtained by GWO can improve voltage regulation and enhance the overall voltage profile of the distribution system.

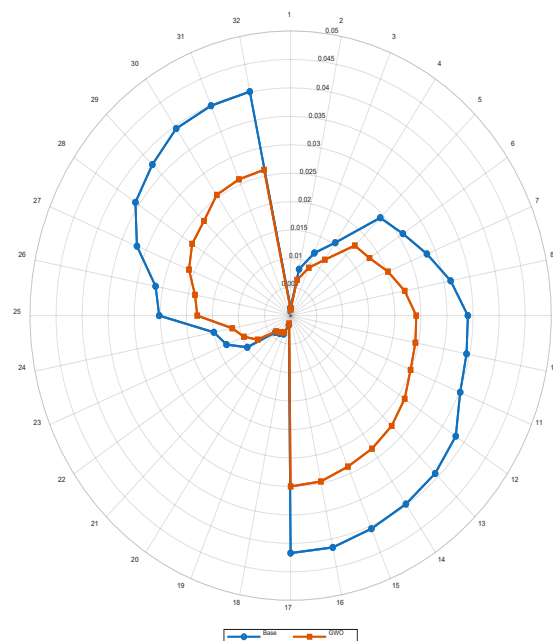


Figure 9. Deviation Index under Light Load

Under light load conditions, as shown in Table 4, the GWO method demonstrates superior performance compared to other optimization techniques (PSO-w1, PSO-w2, PSO-w3, and IPSO), achieving the lowest active power losses of 31.47 kW and the highest

minimum voltage of 0.9701 pu indicating improved voltage stability with capacitor placement at buses 13, 24, and 30 with capacities of 200, 263, and 504.5 kVAR, respectively. It also delivers the greatest loss reduction (33.14%) and the most favorable economic

outcome, with the lowest annual cost (\$22,443) and the highest net saving (\$2,297 or 9.28%), underscoring its effectiveness in both technical enhancement and cost efficiency under light load scenarios.

Table 4. Result for Light Load

Method	Losses (kW)	Vmin	Capacitor Location	Capacitor Capacity (kVAR)	Reduction Losses (%)	Annual cost (\$)	Net Saving (\$)	Net Saving (%)
Base	47.07	0.9583	-	-	-	24740	-	-
GWO	31.47	0.9701	13, 24, 30	200, 263, 504.5	33.14	22443	2297	9.28
PSO-w1 [16]	34.65	0.9681	19, 31, 8	600, 600, 300	26.38	25712	-972	-3.93
PSO-w2 [16]	33.84	0.9645	25, 29, 19	300, 600, 600	28.10	25286	-546	-2.21
PSO-w3 [16]	34.82	0.9598	3, 28, 2	300, 600, 900	26.03	26701	-1961	-7.93
IPSO [16]	33.50	0.9645	23, 33, 27	300, 300, 300	28.84	23308	1432	5.79

Under heavy load conditions, as shown in Table 5, the GWO method outperforms all other optimization techniques (PSO-w1, PSO-w2, PSO-w3, and IPSO) by achieving the lowest active power losses of 367.08 kW and the highest minimum voltage of 0.8967 pu indicating superior voltage stability and system efficiency. It strategically places capacitors at buses 13, 30, and 24 with capacities of 746.4, 1200, and 1025.9 kVAR, respectively, resulting in a remarkable 36.09%

loss reduction the highest among all methods. Economically, GWO also delivers the greatest net saving of \$97,588 (32.27%), despite higher initial capacitor costs, due to significantly reduced energy losses over time. This combination of technical excellence and cost-effectiveness makes GWO the most robust solution for capacitor placement under heavy load scenarios, ensuring both enhanced grid performance and maximum financial return.

Table 5. Result for Heavy Load

Method	Losses (kW)	Vmin (p.u)	Capacitor Location	Capacitor Capacity (kVAR)	Reduction Losses (%)	Annual cost (\$)	Net Saving (\$)	Net Saving (%)
Base	575.41	0.8528	-	-	-	302444	-	-
GWO	367.08	0.8967	13, 30, 24	746.4, 1200, 1025.9	36.09	204850	97588	32.27
PSO-w1 [16]	426.84	0.8682	3, 27, 20	600, 600, 600	25.82	232750	69688	23.04
PSO-w2 [16]	408.37	0.8701	4, 30, 5	900, 900, 600	29.03	224840	77596	25.66
PSO-w3 [16]	427.99	0.8670	24, 33, 5	900, 600, 900	25.62	235150	67284	22.25
IPSO [16]	404.54	0.8698	24, 30, 5	600, 900, 900	29.70	222830	79609	26.32

Based on Figure 10 showing the voltage profiles across all 33 buses under heavy load conditions, the GWO-optimized case consistently maintains the highest voltage magnitudes compared to the base case and all PSO-based methods (PSO-w1, PSO-w2, PSO-w3, and IPSO). The base case exhibits the lowest voltages, particularly at the tail ends of both feeders dropping to 0.8528 pu at bus 18 and 0.8588 pu at bus 33 indicating significant voltage stress. Based on Figure 11, which presents the VSI for all 32 load buses (bus 2 to 33), the GWO-optimized case (orange curve) demonstrates a substantial and consistent improvement over the base case (blue curve) across the entire distribution network. In the base case, several buses particularly in the later sections of both feeders exhibit critically low VSI values (e.g., as low as 0.1735 at bus 5 and below 0.55 at buses 8–17 and 27–33), indicating high vulnerability to voltage collapse under stressed conditions.

Based on Figure 12, which illustrates VDI across all 32 load buses (bus 2 to 33), the GWO-optimized case (orange curve) exhibits a clear and consistent reduction in voltage deviation compared to the base case (blue curve). In the base scenario, VDI values rise sharply toward the end of both feeders reaching as high as 0.1472 at bus 17 and 0.1412 at bus 33 indicating significant departure from the nominal voltage and poor voltage regulation. In contrast, the GWO method effectively suppresses these deviations, lowering the

peak VDI to just 0.1033 at bus 17 and 0.0982 at bus 33, representing a reduction of approximately 30% across the most stressed locations.

The comparative results across light, normal, and heavy load conditions demonstrate that GWO possesses a strong capability to maintain solution quality under changing operating requirements. At light load, the method avoids over-compensation by selecting moderate capacitor ratings while still achieving the best technical and economic performance. At normal load, GWO maintains an effective balance between loss minimization and annual cost reduction, indicating that the selected capacitor configuration is not only electrically beneficial but also economically justified. Its advantage becomes most evident under heavy load, where higher reactive power demand and larger voltage drops make the optimization problem more challenging; in this case, GWO produces the lowest losses, the highest minimum voltage, and the greatest net saving. These findings suggest that the strength of GWO lies in its ability to coordinate capacitor location and sizing decisions across different loading scenarios through a balanced search process, allowing it to remain robust when system stress increases.

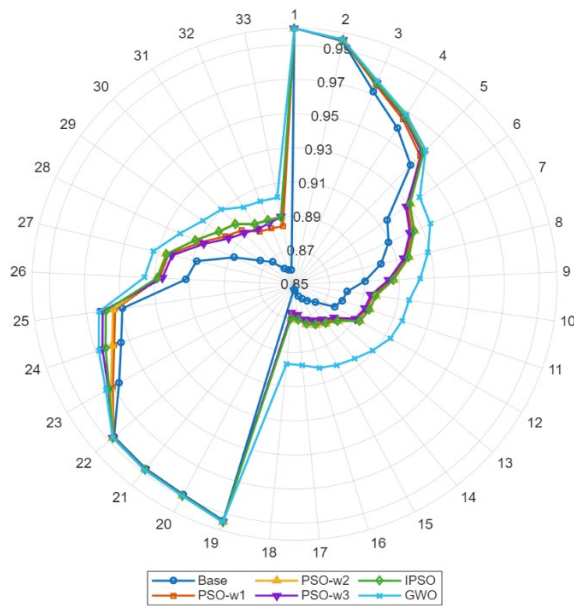


Figure 10. Voltage Profile under Heavy Load

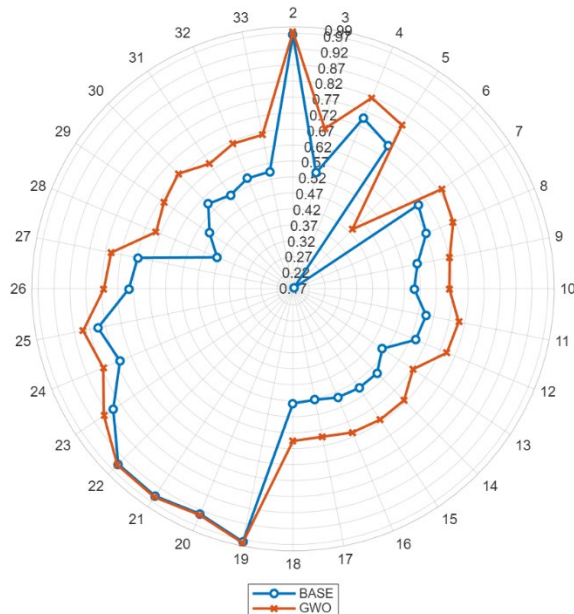


Figure 11. Voltage Stability Index under Heavy Load

Compared with PSO and GA, GWO provides a more stable search mechanism for the capacitor placement and sizing problem because candidate solutions are guided by three leaders, namely alpha, beta, and delta, instead of relying mainly on a single global-best direction or stochastic crossover and mutation operators alone. This characteristic helps maintain population diversity during the search process and reduces the risk of premature convergence. In the present study, such a mechanism is particularly beneficial because the optimization involves both bus-location selection and capacitor-size determination under light, normal, and heavy load conditions, leading to a highly nonlinear and constrained search space. Consequently, GWO is better able to maintain solution quality across different loading scenarios, which explains why its technical and

economic performance remains more consistent than that of the compared methods.

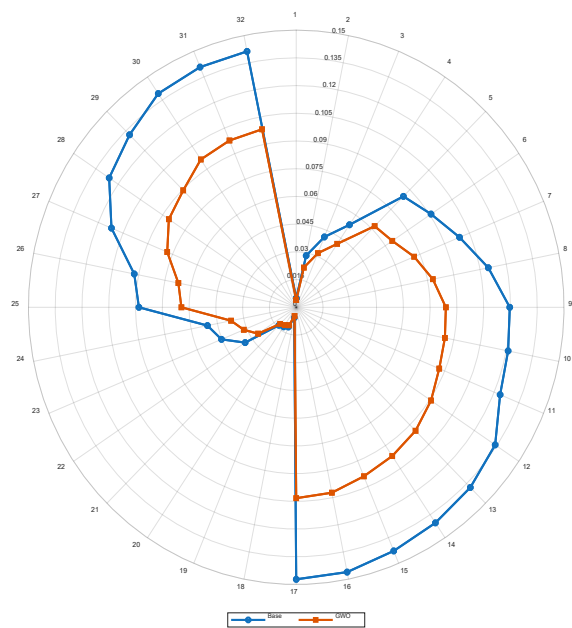


Figure 12. Voltage Deviation Index under Heavy Load

From a practical planning perspective, this result indicates that the capacitor configuration obtained by GWO is less likely to become over-compensated during low-demand periods or under-compensated during peak-demand periods. This is important for real distribution systems, where loading conditions vary continuously and a solution that performs well only at one operating point may not remain technically or economically effective in actual operation.

4. Conclusions

The GWO proves highly effective for the ideal allocation and sizing of shunt capacitors within the IEEE 33-bus RDS across diverse loading states—specifically light (60%), nominal (100%), and peak (160%) demands. Throughout all cases, GWO uniformly delivers the minimal active power losses, superior lowest bus voltages, and maximum mitigation in voltage deviation over the uncompensated network and competing metaheuristics (e.g., PSO variants, IPSO, AOA, BFO, GA, etc.). Specifically, under normal load, GWO reduces losses by 34.96% and improves the minimum voltage to 0.9337 pu; under light load, it attains a 33.14% loss reduction with a minimum voltage of 0.9701 pu; and under heavy load, it delivers the most significant improvement 36.09% loss reduction and a minimum voltage of 0.8967 p.u., well above the base case's 0.8528 p.u. Economically, GWO yields the highest net annual savings (\$28,342 at normal load and \$97,588 at heavy load) and the lowest total annual cost, confirming its cost-effectiveness. Furthermore, GWO enhances both the VSI and VDI across all buses, indicating robust voltage security and improved power quality. These results validate that GWO is a technically and economically effective

solution for reactive power planning in distribution systems with dynamic load profiles.

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