

Research Article

Combined Allocation of Renewable-Based Distributed Generators and Shunt Capacitor Banks in Distribution Networks with Electric Vehicle Load Penetration

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Article Info	Abstract
Article History	The increasing load from electric vehicles (EVs) in distribution networks presents significant challenges, including heightened power losses and voltage deviations. This paper proposes a solution through the combined optimal allocation of wind-based distributed generators (DGs) and shunt capacitor banks (CBs). An artificial protozoa optimizer (APO) is introduced for the optimal siting and sizing of distributed generators (DGs) and combined batteries (CBs), complemented by network reconfiguration (NR). The primary objectives of this approach are to minimize active power loss, reactive power loss, and voltage deviations. Additionally, the impact of EV load penetration, ranging from 20% to 100%, is thoroughly analyzed, along with an assessment of its associated uncertainty. Various scenarios are tested on the IEEE 33-bus distribution test system. The simulation results demonstrate the effectiveness of the proposed method, achieving reductions in active power losses, reactive power losses, and voltage deviations by 80.53%, 76.88%, and 69.96%, respectively. Compared to other optimization algorithms, the APO shows superior performance.
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1. Introduction

The proliferation of electric vehicles (EVs) has accelerated significantly in recent years, driven by growing environmental concerns. However, the rising penetration of EV loads within distribution networks presents major challenges, notably increased power losses and voltage deviations [1, 2]. To address these operational issues, the strategic placement of distributed generation (DG) units and capacitor banks (CBs) offers a promising solution for distribution network operators, helping to mitigate power losses and stabilize voltage profiles.

However, the arbitrary placement of renewable energy sources (RES) and CB units can exacerbate power flows on feeders, potentially leading to network congestion and increased system losses [3]. Moreover, distribution expansion planning that integrates renewable energy sources (RES) and combined heat

and power (CHP) units can substantially alter voltage profiles, leading to overvoltage, undervoltage, and increased overall system inefficiency [4]. Therefore, careful planning of RES and CB allocation, combined with network reconfiguration (NR), is essential for ensuring efficient operation under conditions of high EV load penetration.

This study proposes a comprehensive planning approach that optimally allocates RES and CBs in the distribution network while incorporating NR strategies. The artificial protozoa optimizer (APO) is introduced as a novel method for solving the nonlinear mixed-integer programming problems associated with this task. The approach is validated using the IEEE 33-bus distribution system, focusing on minimizing active and reactive power losses and voltage deviations under varying levels of EV load penetration.

2. Literature Review

Several prior studies have explored methods to optimize the allocation of DGs, CBs, and NR schemes in distribution networks. Pawar, et al. [5] introduced a hybrid approach for multiple DG allocations to reduce power losses, while Pawar, et al. [6] proposed a modified grey wolf optimization technique for multiple capacitor placements aimed at cost minimization. In another work, Pawar, et al. [7] examined the shift from regulated to deregulated electricity markets, discussing the integration and expansion planning of DGs.

Other optimization techniques have been applied to similar problems. Purlu and Turkay [8] utilized particle swarm optimization (PSO) and genetic algorithms (GA) to minimize voltage deviations and annual energy losses. Dharavat, et al. [9] combined the Marine Predators Algorithm (MPA) with voltage stability indices for the allocation of DGs, CBs, and EVs. Abbas, et al. [10] proposed a Bidirectional Co-evolutionary algorithm (BiCo) for multi-period DG allocation and reconfiguration, targeting cost reduction. Saravanan, et al. [11] used the Andean Condor Algorithm (ACA) for optimal network reconfiguration and DG placement to improve energy efficiency.

Further, Kamel, et al. [12] applied Geometric Mean Optimization (GMO) coupled with power loss sensitivity indices for minimizing voltage deviation and power loss. Thumati, et al. [13] used the Honey Badger Algorithm (HBA) for integrating renewable DGs and network reconfiguration to lower losses and greenhouse gas emissions. Mondal and De [14] adopted the Wild Horse Optimizer (WHO) to combine DGs and CBs in the presence of EVs, enhancing voltage stability and minimizing power losses.. Sayed, et al. [15] implemented the Success History Based Adaptive Differential Evolution Algorithm (SHADE) to maximize DG hosting capacity while reducing losses. Finally, Fathi, et al. [16] used information gap decision theory (IGDT) alongside an improved Salp Swarm algorithm (SSA) for optimal photovoltaic and wind turbine placement under uncertainty, focusing on minimizing system losses.

Despite these valuable contributions, previous research [1-16] has not fully addressed the coordinated allocation of DGs and CBs in distribution networks under significant EV load penetration, nor have they

sufficiently analyzed the role of NR in optimizing such allocations. This paper seeks to fill these gaps by:

- Developing a combined planning approach for optimally placing RES and CBs;
- Analyzing the effect of integrated NR schemes on RES and CB allocation;
- Examining the impact of varying EV load penetration;
- Proposing the APO to solve nonlinear mixed-integer programming challenges;
- Validating the proposed method on the IEEE 33-bus distribution system.

3. Problem formulation

Active (P_{loss}^t) and reactive (Q_{loss}^t) power losses in electrical distribution networks were computed using (1) and (2), respectively.

$$P_{loss}^t = \sum_{m \in \phi_{br}} \{(I_m^t)^2 \times R_m\} \quad (1)$$

$$Q_{loss}^t = \sum_{m \in \phi_{br}} \{(I_m^t)^2 \times X_m\} \quad (2)$$

where I_m^t signifies the current flow in the branch, X_m and R_m represent the branch's reactance and resistance, respectively.

Active (E_{loss}^p) and reactive (E_{loss}^q) energy losses during Δt were computed using (3) and (4), respectively.

$$E_{loss}^p = \sum_{i \in \phi_t} \{P_{loss}^t \times \Delta t\} \quad (3)$$

$$E_{loss}^q = \sum_{i \in \phi_t} \{Q_{loss}^t \times \Delta t\} \quad (4)$$

The voltage deviation index (VDI) is calculated as follows to display how close the voltages of buses are to the specified voltage value.

$$V_{dev}^t = \sum_{i \in \phi_{bus}} \left| \frac{V_{spec} - V_i^t}{V_{spec}} \right| \quad (5)$$

V_{spec} denotes specified voltage and V_i^t represents the voltage at a bus. Further, equation (6) represents the sum of voltage deviation during Δt

$$TV_{dev} = \sum_{i \in \phi_t} \{V_{dev}^t \times \Delta t\} \quad (6)$$

3.1. Objective Function

The primary goal of this study is to reduce the overall energy losses caused by voltage variation in distribution networks.

$$\text{Minimize. } OF = E_{loss}^p + E_{loss}^q + TV_{dev} \quad (7)$$

It is important to consider the following constraints when minimizing the objective function.

- Power flow constraints

$$\sum_{i=1}^{N_g} P_{Gi}^t - P_{loss}^t = P_{dem}^t \quad (8)$$

$$\sum_{i=1}^{N_g} Q_{Gi}^t - Q_{loss}^t = Q_{dem}^t \quad (9)$$

where, N_g is the number of generations, P_{Gi}^t and Q_{Gi}^t are active as well as reactive power generation, P_{loss}^t and Q_{loss}^t are active as well as reactive power losses, P_{dem}^t and Q_{dem}^t are active and reactive power demand

- Distributed generator constraints

$$P_{Gi}^{lo} \leq P_{Gi}^t \leq P_{Gi}^{up} \quad (10)$$

P_{Gi}^{min} and P_{Gi}^{max} are lower and upper constraints of active power generation

- Capacitor banks constraints

$$Q_{Gi}^{lo} \leq Q_{Gi}^t \leq Q_{Gi}^{up} \quad (11)$$

Q_{Gi}^{min} and Q_{Gi}^{max} are lower and upper constraints of reactive power generation

- Voltage constraints

$$V^{lo} \leq V_i^t \leq V^{up} \quad (12)$$

V^{lo} and V^{up} are lower and upper constraints of voltage

- Thermal constraints

$$0 \leq I_l^t \leq I_l^{rated} \quad (13)$$

I_l^{rated} represents rated current in the branch

- Radiality constraint

$$\sum_{l=1}^{brs} csw_l = buses - 1 \quad (14)$$

- System load with EV load

$$P_{dem}^t = P_{dem,0}^t + P_{dem,ev}^t (V_i^t / V_{nom}^t)^{\alpha_{ev}} \quad (15)$$

$$Q_{dem}^t = Q_{dem,0}^t + Q_{dem,ev}^t (V_i^t / V_{nom}^t)^{\beta_{ev}} \quad (16)$$

$P_{dem,0}^t$ and $Q_{dem,0}^t$ are actual active and actual reactive power demand without EV load, V_{nom}^t represents the nominal voltage, α_{ev} and β_{ev} are the coefficients of active and reactive power EV load, respectively.

$$P_{dem,ev}^t = \lambda_{pen} \times P_{dem,0}^t \quad (17)$$

$$Q_{dem,ev}^t = \lambda_{pen} \times Q_{dem,0}^t \quad (18)$$

λ_{pen} is the penetration level of active and reactive power demand.

4. Method: Artificial Protozoa Optimizer

Artificial Protozoa Optimizer (APO) draws inspiration from the natural behavior of protozoa [17]. This optimization method replicates the persistence strategies of protozoa by imitating their foraging, dormancy, and reproductive processes.

4.1. Artificial Protozoa Optimizer

It has been explained with three stages as follows:

Stage 1: Foraging

We considered both internal and external characteristics of protozoans while analyzing their foraging behavior. The foraging behaviors of the protozoa are classified as internal variables, while species clashes and competing interactions are considered external factors.

Autotrophic Mode: Protozoa can use chloroplasts to synthesize carbohydrates, as was previously indicated, to survive. They migrate towards locations with higher light intensity while in dimly lit environments and towards areas with lower light intensity when exposed to intense light. A protozoan will relocate if the surrounding light intensity is ideal for photosynthesis. The following mathematical model describes this autotrophic mode:

$$Y_i^{new} = Y_i \pm FF \cdot \left(Y_j - Y_j + \frac{1}{NP} \sum_{k=1}^{NP} w_{au} (Y_{k-} - Y_{k+}) \right) \odot MV_f \quad (19)$$

$$Y_i = \text{sort}[Y_i^1, Y_i^1, \dots, Y_i^{dim}] \quad (20)$$

$$FF = \text{rand} \cdot \left(1 + \cos \left(\frac{it}{it_{max}} \cdot \pi \right) \right) \quad (21)$$

$$NP_{max} = \left\lfloor \frac{N-1}{2} \right\rfloor \quad (22)$$

$$w_{au} = e^{-\left| \frac{f(Y_{k-})}{f(Y_{k+}) + \varepsilon} \right|} \quad (23)$$

$$MV_r[di] = \begin{cases} 1, & \text{if } di \text{ is in } \text{randperm}(dim, \lfloor dim \cdot \frac{i}{N} \rfloor) \\ 0, & \text{otherwise} \end{cases} \quad (24)$$

where the updated and original coordinates of the i^{th} protozoan are denoted by Y_i^{new} and Y_i . A randomly chosen j^{th} protozoan is denoted by Y_j . A protozoan whose rank index is smaller than i is chosen at random from the k^{th} paired neighbor and is called (Y_{k-}) . To be more precise, (Y_{k-}) is also set to (Y_1) if (Y_i) is (Y_1) . A protozoan whose rank index is greater than i is chosen at random from the k^{th} paired neighbor and is called Y_{k+} . In particular, Y_{k+} is also set to Y_{ps} , where ps is the population size, if Y_i is Y_N . FF represents a foraging factor, and a random number from a uniform distribution in the $[0,1]$ interval is indicated by

rand. The current and maximum iterations are indicated by *iter* and *iter_{max}*, respectively. *NP* denotes the number of neighbor pairs among the external components, while *NP_{max}* represents the maximum value of *NP*. In the autotrophic mode, ε epsilon is a minimal value, and w_{au} is a weight factor. The Hadamard product is indicated by $\odot$. The foraging mapping vector *MV_f* has a size of $(1 \times \text{dim})$, with 0 or 1 for each element.

Heterotrophic Mode: Protozoa can take up nutrients in the dark by removing organic substances from their environment. Protozoa will migrate towards a nearby food-rich area if Y_{near} is represented by *it*. The following mathematical model describes this heterotrophic mode:

$$Y_i^{new} = Y_i + FF \cdot \left(Y_{near} - Y_i + \frac{1}{N} \sum_{k=1}^N w_h (Y_{i-k} - Y_{i+k}) \right) \odot MV_f \quad (25)$$

$$Y_{near} = \left(1 \pm Rand \cdot Rand \left(1 - \frac{it}{it_{max}} \right) \right) \odot Y_i \quad (26)$$

$$w_{he} = e^{-\left| \frac{f(Y_{i-k})}{f(Y_{i+k}) + \varepsilon} \right|} \quad (27)$$

$$Rand = [rand_1, rand_2, \dots, rand_{dim}] \quad (28)$$

In this case, " $\pm$ " denotes the possibility that Y_{near} may be facing different directions from the i^{th} protozoan, and (Y_{near}) signifies a nearby location. With a rank index of $(i-k)$, Y_{i-k} represents the $(i-k)^{th}$ protozoan chosen from the k^{th} matching neighbor. In particular, (Y_{i-k}) is also set to (Y_1) if $Y_i = Y_1$. With a rank index of $(i+k)$, Y_{i+k} represents the $(i+k)^{th}$ protozoan chosen from the k^{th} paired neighbor. Specifically, (Y_{i+k}) is also set to Y_N if $Y_i = Y_{ps}$. The weight factor in the heterotrophic mode is denoted by (w_{he}) . A random number containing entries in the $[0,1]$ interval is called *Rand*.

Stage 2: Dormancy

To survive unfavorable circumstances, protozoa may be dormant when exposed to environmental stress. A dormant protozoan is replaced by a freshly created one to keep the population steady. The following is the mathematical model of dormancy.

$$Y_i^{new} = Y_{min} + Rand \odot (Y_{max} - Y_{min}) \quad (29)$$

The lower and upper bound vectors are denoted by Y_{min} and Y_{max} , respectively.

$$Y_{min} = [lo_1, lo_2, \dots, lo_{dim}] \quad (30)$$

$$Y_{max} = [up_1, up_2, \dots, up_{dim}] \quad (31)$$

lo_{di} and up_{di} represent the lower and upper limits of di^{th} variable

Stage 3: Reproduction

Protozoa divide asexually into two identical daughter cells by binary fission when they are of suitable age and health. This process is simulated by creating a duplicate protozoan and adding a disturbance. The following is the mathematical model of reproduction.

$$Y_i^{new} = Y_i \pm rand \cdot (Y_{min} + Rand \odot (Y_{max} - Y_{min})) \odot MV_r \quad (32)$$

$$MV_r[di] = \begin{cases} 1, & \text{if } di \text{ is in } randperm(dim, [dim \cdot rand]) \\ 0, & \text{otherwise} \end{cases} \quad (33)$$

where " $\pm$ " denotes the possibility of a forward or reverse perturbation. In the reproduction process, the mapping vector (MV_r) has a dimension of $(1 \times dim)$, with 0 or 1 for each member. To incorporate all mathematical models, the following parameters need to be considered:

$$pf = pf_{max} \cdot rand \quad (34)$$

$$\xi_{ah} = \frac{1}{2} \cdot \left(1 + \cos \left(\frac{it}{it_{max}} \cdot \pi \right) \right) \quad (35)$$

$$\xi_{dr} = \frac{1}{2} \cdot \left(1 + \cos \left(\left(1 - \frac{i}{N} \right) \cdot \pi \right) \right) \quad (36)$$

where pf_{max} is the greatest value, and pf is dormancy proportion fraction and protozoa population reproduction. The autotrophic probabilities and heterotrophic behaviors are represented by ξ_{ah} , while the dormancy probabilities and reproduction are represented by ξ_{dr} . It should be noted that the maximum percentage fraction (pf_{max}) and the number of neighbor pairs (NP) are the only two unique parameters in the suggested APO. Figure 1 illustrates the flow chart detailing the implementation of APO for the current problem.

4.2. Implementation of Artificial Protozoa Optimizer on the Present Problem

This paper suggests an APO solver for the optimal combined allocation of wind-based DGs and CBs with network reconfiguration. The APO algorithm is utilized to establish the appropriate size and placement of wind-based DGs and CBs, as well as the status of switches. The decision variables in this problem include the location of wind-based DGs and CBs and the status of remotely controlled switches. Equation (37) depicts the solution vector for the present optimization.

$$Y_i = [loc_{DG}, loc_{CB}, size_{DG}, size_{CB}, st_{sw}] \quad (37)$$

In Eq. (37), the locations of DGs and CBs are represented as a range of distribution network buses, the sizes of DGs and CBs are specified, and st_{sw} represents the status of remotely controlled switches in the distribution system. The pseudo-code of the present optimization is depicted in Table 1.

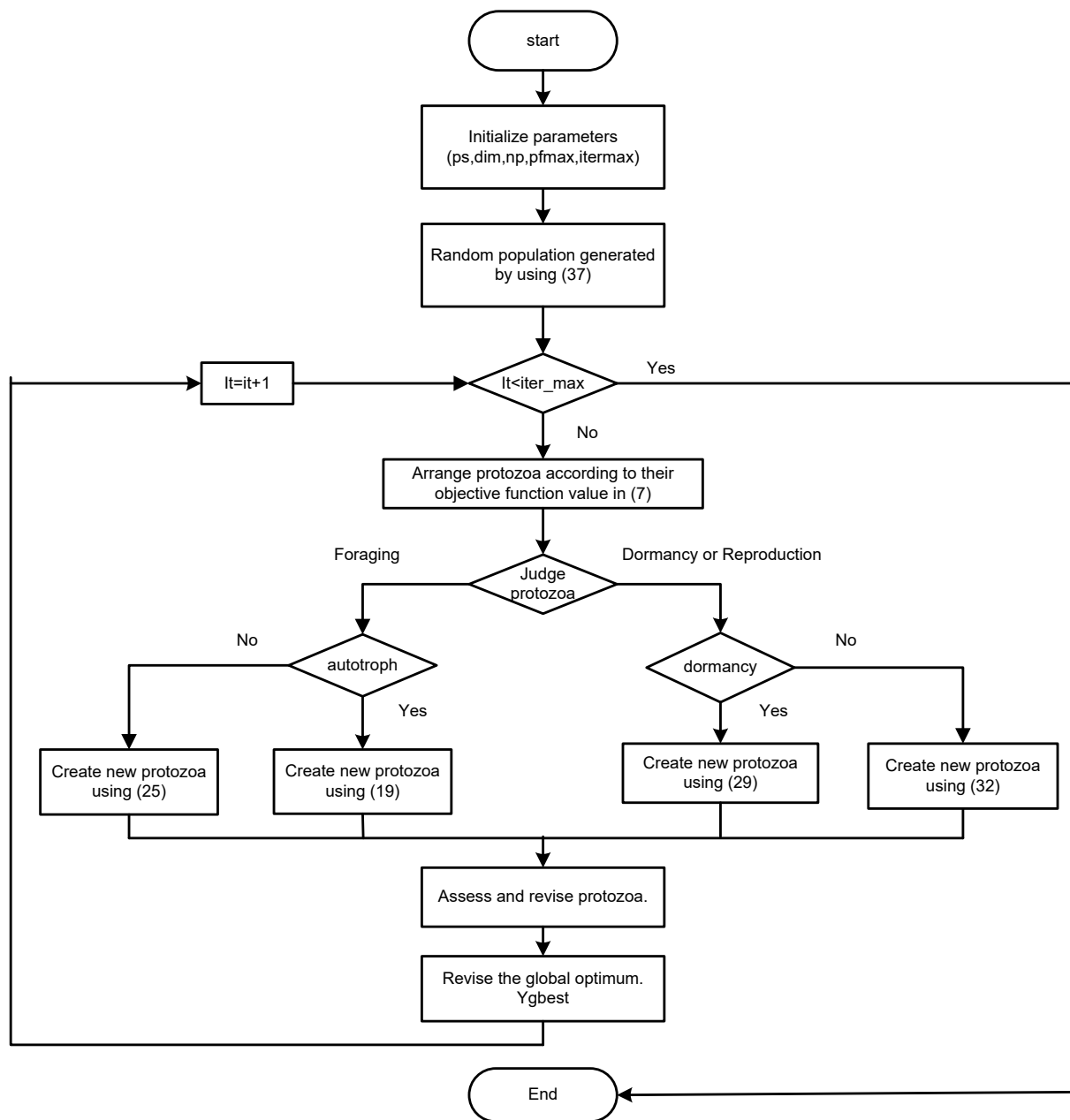


Figure 1. Flowchart of the Implementation of APO for the Current Problem

5. Simulation Results and Discussions

The optimization model proposed in this research was implemented in the MATLAB environment. The computations were done on a computer with an i3 processor, 2.5 GHz Core, and 4 GB RAM. The proposed methodology was assessed using the traditional IEEE 33-bus distribution system, with detailed line and load data sourced from [18]. The nominal active and nominal reactive power demands are 3715 kW and 2300 kVAR. Figure 2 shows the 33-bus distribution system single-line diagram. Figure 3 depicts the typical load profile and the output of wind generation over 24 hours [19].

Table 1. Pseudo code of APO for proposed optimization problem

```

Input: Initialize parameters  $N$ ,  $np$ ,  $dim$ ,  $pf_{max}$ , and  $it_{max}$  (maximum iterations).
Output: The global optimal  $Y_{gbest}$  and  $f(Y_{gbest})$ .

1: while  $it < it_{max}$  do
2:     Compute  $f(Y_i)$  using Eq. (7) and sort it,  $i = 1, 2, \dots, N$ ;
3:      $pf = pf_{max} \cdot rand$ ; // proportion fraction
4:      $DR_{index} = randperm(N, [N \cdot pf])$ ;
5:     for  $i = 1 : ps$  do
6:         if  $i$  is in  $DR_{index}$  then
7:             if  $pdr > rand$  then
8:                 Compute  $Y_i^{new}$  employing Eq. (29)
9:             else
10:                 $MV_r = zeros(1, dim)$ ;
11:                 $MV_r[1, randperm(dim, [dim \cdot rand])] = 1$ ;
12:                Compute  $Y_i^{new}$  employing Eq. (32)
13:            end if
14:        else
15:             $MV_f = zeros(1, dim)$ 
16:             $MV_f[1, randperm(dim, [dim \cdot i/N])] = 1$ 
17:            if  $p_{ah} > rand$  then
18:                Compute  $Y_i^{new}$  employing Eq. (19)
19:            else
20:                Compute  $Y_i^{new}$  employing Eq. (25)
21:            end if
22:        end if
23:        if  $f(Y_i^{new}) < f(Y_i)$  then
24:             $Y_i = Y_i^{new}$  ;
25:        else
26:             $Y_i = Y_i$ ;
27:        end if
28:    end for
29:     $Y_{gbest} = opt\{Y_i\}$ ;
30:     $it = it + 1$ ;
31: end while

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The distribution network was assumed to accommodate a maximum of three units each for installed capacitors and wind-based distributed generation units. The population size is assumed to be 30, with a maximum of 100 iterations.

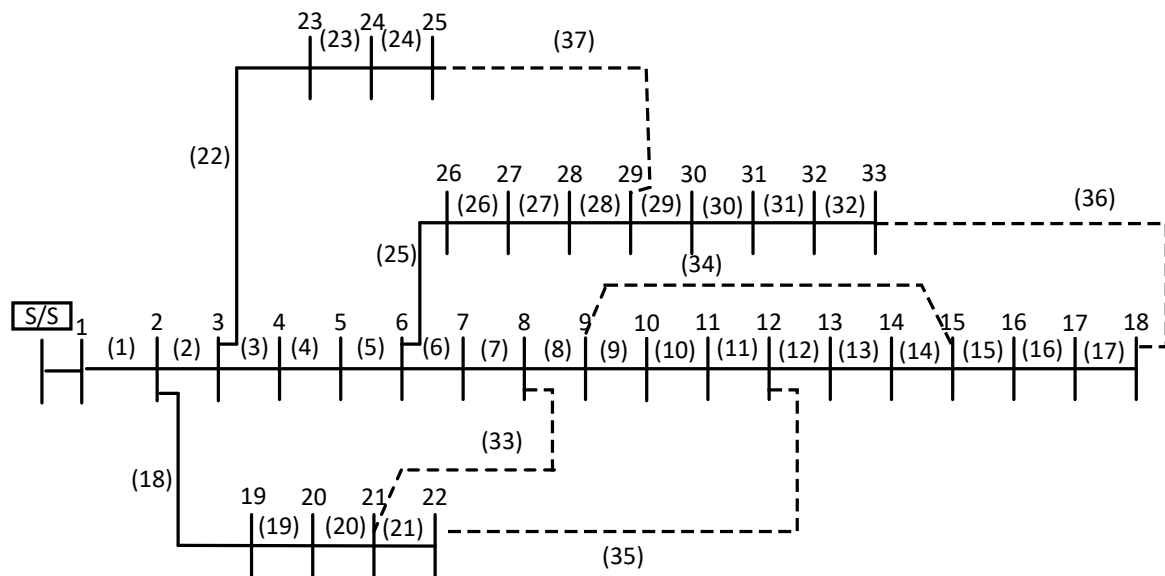


Figure 2. Single-line diagram of the 33-bus distribution system

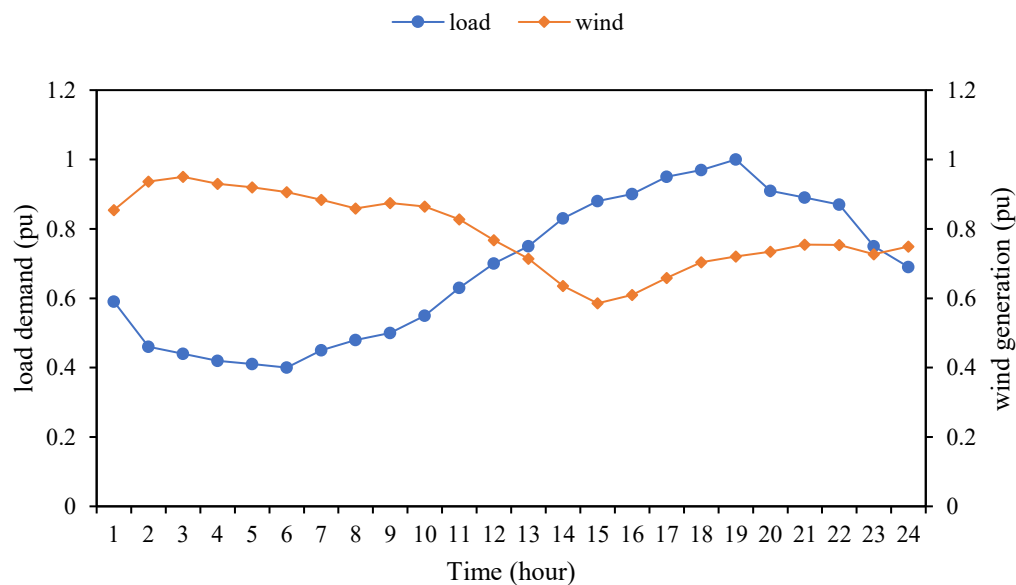


Figure 3. Typical load profile and the output of wind generation over 24 hours

5.1. Analysis of the Numerical Findings and Subsequent Discussions

The optimization difficulty was explained for five distinct cases, denoted as Case 1 through Case 5, as outlined in Table 2. Case 1 represents the base case with no additional devices installed in the distribution system. Case 2 involves the installation of shunt capacitor banks (CBs) only. Case 3 focuses on the allocation of wind-based DGs only. Case 4 considers the allocation of both wind-based DGs and shunt capacitor banks. Finally, Case 5 combines the allocation of wind-based DGs and shunt capacitor banks with network reconfiguration (NR).

Table 2. Different cases studies

Cases	CBs	Wind DGs	NR
Case 1	No	No	No
Case 2	Yes	No	No
Case 3	No	Yes	No
Case 4	Yes	Yes	No
Case 5	Yes	Yes	Yes

Table 3 concisely overviews important factors across various scenarios, such as active and reactive energy losses and voltage deviation values. The results demonstrate substantial percentage decreases with the deliberate deployment of wind-based distributed generation (DG) and capacitor banks (CBs). For Case 2, installing capacitor banks results in a decrease of approximately 25.53% in active energy losses and a reduction of approximately 24.27% in reactive energy losses. There is a 26.04% decrease in voltage deviations compared to Case 1. Case 3 demonstrates that the distribution of wind-based Distributed Generation (DG) leads to a decrease of approximately 50.48% and 49.88% in active and reactive energy losses, respectively.

Additionally, voltage variations are decreased by 50.09% compared to Case 1. In Case 4, the combined use of wind-based distributed generation (DG) and capacitors results in significant reductions of roughly 73.59% and 71.76% in active and reactive energy losses, respectively. The reduction in voltage deviations compared to Case 1 is 68.87%. This highlights the benefits of integrating renewable energy sources (RES) and capacitors, rather than using them separately. Case 5 demonstrates that by efficiently distributing renewable energy sources (RES) and capacitors, along with implementing Network Reconfiguration (NR) by opening switches {5, 13, 11, 15, 26} and closing switches {33, 34, 35, 36, 37} to maintain radiality, significant advantages can be achieved. Specifically, this approach results in a remarkable reduction of 80.53% in active energy losses and 76.88% in reactive energy losses. Additionally, there is a 69.96% reduction in voltage deviations compared to Case 1. These findings highlight the importance of synchronizing the distribution of RES, capacitors, and NR in distribution networks.

Table 3. Outcomes in various scenarios

Parameters	Case 1	Case 2	Case 3	Case 4	Case 5
Active energy losses (kWh)	2403.54	1789.92	1190.30	634.72	467.88
Active energy losses (% reduction)	-----	25.53	50.48	73.59	80.53
Reactive energy losses (kVARh)	1601.89	1213.17	802.84	452.45	370.36
Reactive energy losses (% reduction)	-----	24.27	49.88	71.76	76.88
Voltage deviations	27.39	20.26	13.67	8.53	8.23
Voltage deviations (% reduction)	-----	26.04	50.09	68.87	69.96

Table 4 displays the most advantageous positions and sizes for wind-based distributed generation (DG) and capacitors in different scenarios. In Case 2, the best size of the capacitor bank (CB) is approximately 2220 kvar, while in Case 3, the optimal size of the distributed generation (DG) is around 1670 kilowatts (kW). In the scenario where the allocation is combined (referred to as Case 4), the best sizes for CB and DG are 2180 kvar and 1660 kW, respectively. These numbers are slightly less than those in Cases 2 and 3. This demonstrates the advantages of integrated allocation.

Additionally, when network reconfiguration (NR) is in operation, the recommended sizes for CB and DG are 2020 kvar and 1645 kW, respectively. The statistics unambiguously demonstrate that the necessary capabilities for DG and capacitors are significantly diminished in Cases 4 and 5 compared to Cases 2 and 3. The decrease in energy consumption is credited to the synchronized distribution of Renewable Energy Sources (RES), capacitors, and NR schemes, emphasizing the effectiveness of a comprehensive strategy.

Table 4. Location and capacity of Wind and CB under different cases

Cases	Installed devices	(bus#location, capacity#size kW/kVAR))	Total capacity (kW/kVAR)
Case 2	CBs	(6,1300); (11,360); (23,560)	2220
Case 3	Wind DGs	(7,600); (24,330); (33,740)	1670
Case 4	CBs	(6,1280); (11,350); (23,550)	2180
	Wind DGs	(7,590); (24,340); (33,730)	1660
Case 5	CBs	(3,600); (12,250); (30,430)	2020
	Wind DGs	(8,600); (25,415); (32,630)	1645

5.2. Impact on Energy Losses and Voltage Deviation

Figures 4 and 5 show that Case 1 has the highest active and reactive power losses, with incremental improvements observed in Cases 2 and 3 due to the installation of capacitor banks and wind-based distributed generation (DG), respectively. Case 4, which combines these elements, significantly reduces power losses. Case 5, which integrates wind-based DG, CBs, and Network Reconfiguration (NR), achieves the lowest power losses, emphasizing the effectiveness of a coordinated approach. Figure 6 demonstrates a similar trend for voltage deviations, with the highest deviations in Case 1. The reductions in voltage deviations follow the same pattern, with Case 5 showing the greatest improvement. Overall, the data highlight the substantial benefits of integrating RES, CBs, and NR for optimizing power losses and voltage stability in distribution networks.

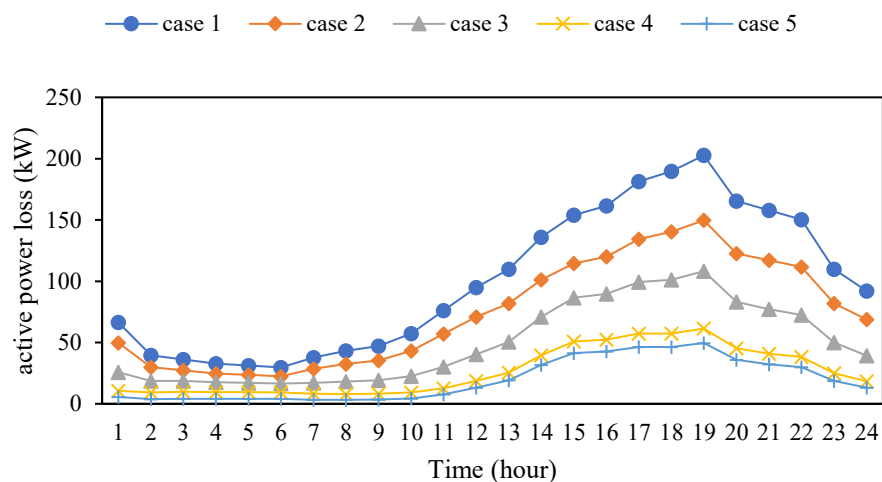


Figure 4. Active power losses throughout various scenarios

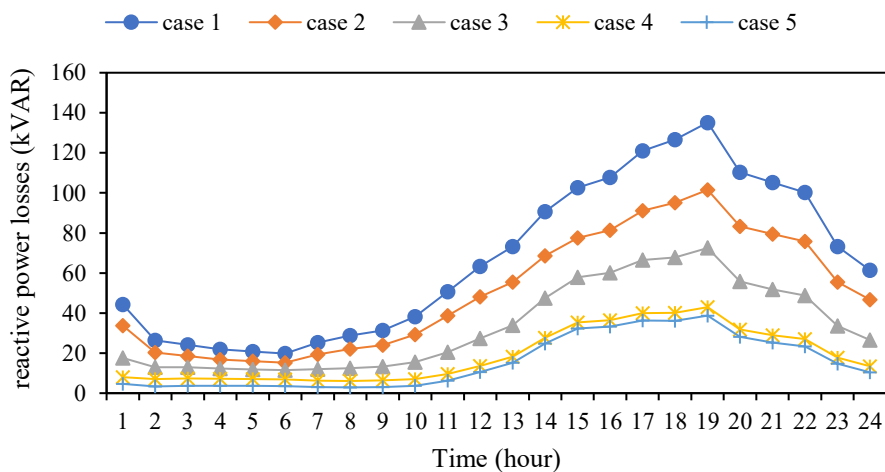


Figure 5. Reactive power losses throughout various scenarios

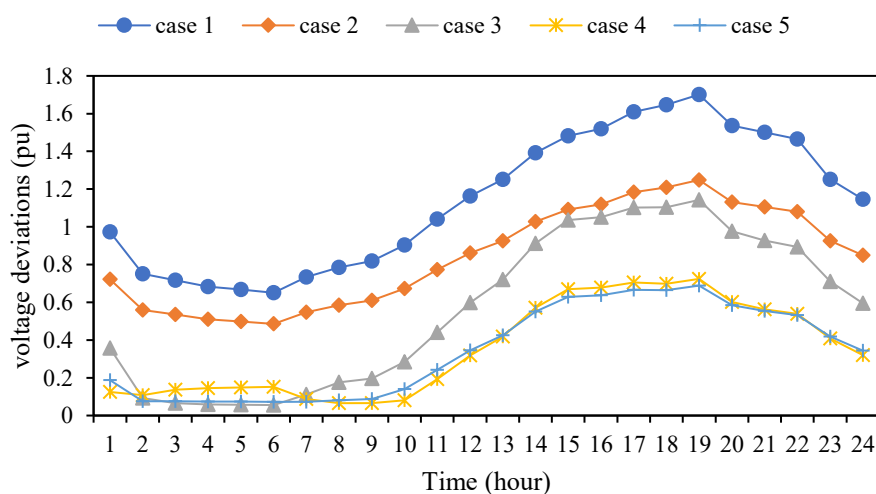


Figure 6. Voltage deviations across different cases

5.3. Impact on Voltage Profiles at Low Loading and High Loading Hours

Figures 7 and 8 depict the voltage trends at various buses during periods of low loading (6:00) and high loading (19:00) hours. Case 5 exhibits the highest enhancement in voltage profile compared to other cases, regardless of whether it is during low or high loading hours. This highlights the effectiveness of integrating renewable energy sources (RES) and capacitor banks (CBs) with network reconfiguration (NR) operations.

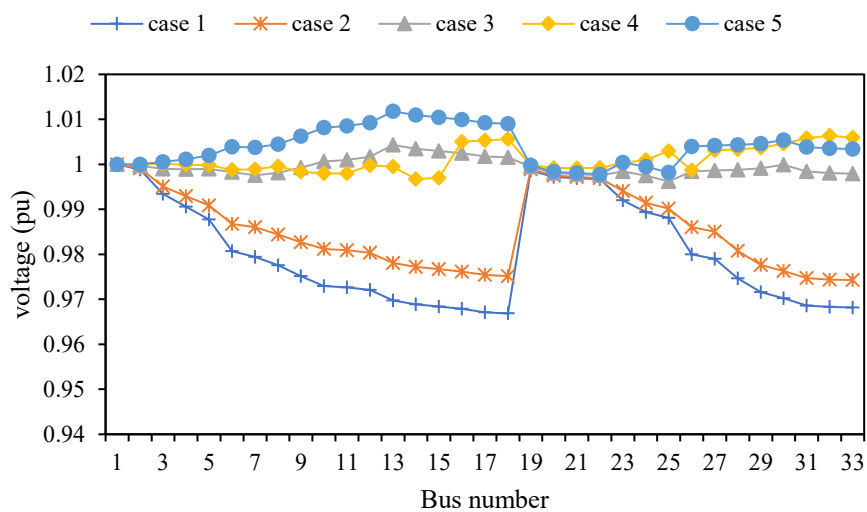


Figure 7. Voltage patterns at different buses at hour 6:00

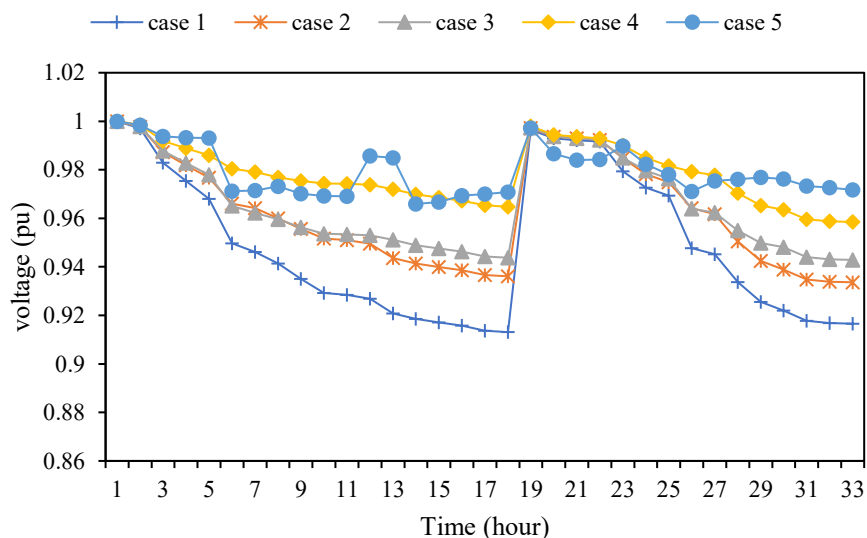


Figure 8. Voltage patterns at different buses at hour 19:00

5.4. Stochastic Analysis for Uncertainty of Load and Wind Generation

The stochastic analysis performed to account for forecasting errors in load demand and wind generation demonstrates significant insights into optimizing power losses and voltage stability by simulating 50

scenarios with $\pm 10\%$ and $\pm 15\%$ variations in load and wind generation, respectively. Figures 9, 10, and 11 illustrate the active and reactive power, as well as the voltage deviation, under various cases. The results highlight that Case 5 achieves the most notable performance improvements. It exhibits the lowest active energy losses (mean: 465.26, min: 248.92), reactive energy losses (mean: 371.24, min: 167.28), and voltage deviations (mean: 7.09, min: 1.43), along with reduced variations, as indicated by lower standard deviations. This superior performance is attributed to the appropriate allocation of distributed generators (DGs) and capacitor banks (CBs) combined with network reconfiguration (NR) using the proposed method. Compared to other cases, Case 5 demonstrates the most effective integration of these components, resulting in reduced power losses and enhanced voltage stability even under uncertain conditions. This analysis highlights the substantial benefits of integrating DGs, CBs, and NR to optimize distribution networks in real-world scenarios.

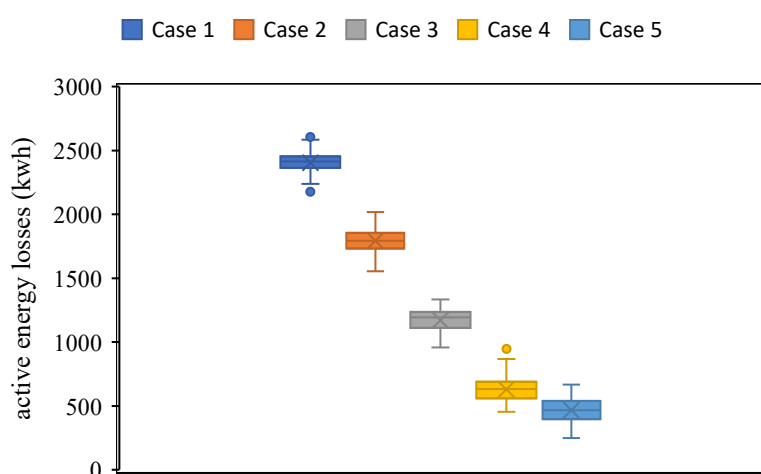


Figure 9. Stochastic analysis on active power losses under different cases

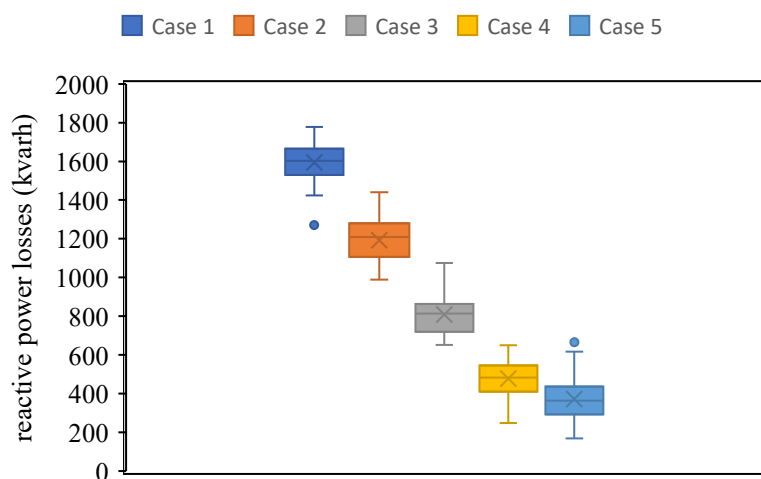


Figure 10. Stochastic analysis on reactive power losses under different cases

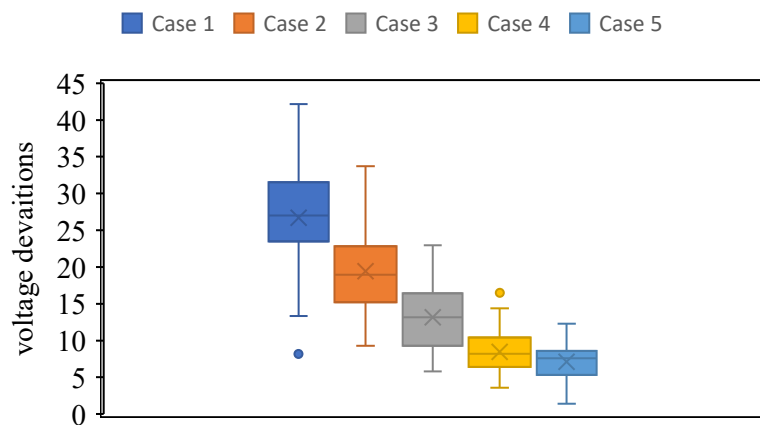


Figure 11. Stochastic analysis on voltage deviation under different cases

5.5. Evaluation of Proposed APO and Other Metaheuristic Approaches

To address the complex structure of Case 5, which involves integrating wind-based distributed generators (DGs) and shunt capacitor banks with network reconfiguration, various metaheuristic algorithms were assessed, including gorilla troops optimizer GTO [2], PSO [8], WHO [14], ACA [11], HBA [13], and the proposed Artificial Protozoa Optimizer (APO). The results in Table 5 and Figure 12 demonstrate the superior performance of APO, which achieves the lowest minimum value (846.76) and exhibits the smallest standard deviation (144.24), indicating both effectiveness and stability. In comparison, other algorithms, such as ACA (859.13), WHO (867.89), HBA (870.48), PSO (873.98), and GTO (876.45), achieved higher minimum values with greater variability. The APO's strategic balance between exploration and exploitation, leveraging past successes while maintaining solution diversity, enables it to consistently converge toward values closer to the global optimum, as evidenced by its steady convergence trends in Figure 12. These results establish APO as a robust and reliable optimization technique, outperforming established metaheuristic methods in addressing this complex renewable energy-integrated network reconfiguration problem.

Table 5. Relative study of different metaheuristic approaches

Metaheuristic approach	Minimum value	Mean value	Standard deviation
GTO [2]	876.45	958.14	165.05
PSO [8]	873.98	945.50	159.03
WHO [14]	867.89	952.71	171.37
ACA [11]	859.13	934.43	165.46
HBA [13]	870.48	933.68	148.28
Proposed APO	846.76	908.23	144.24

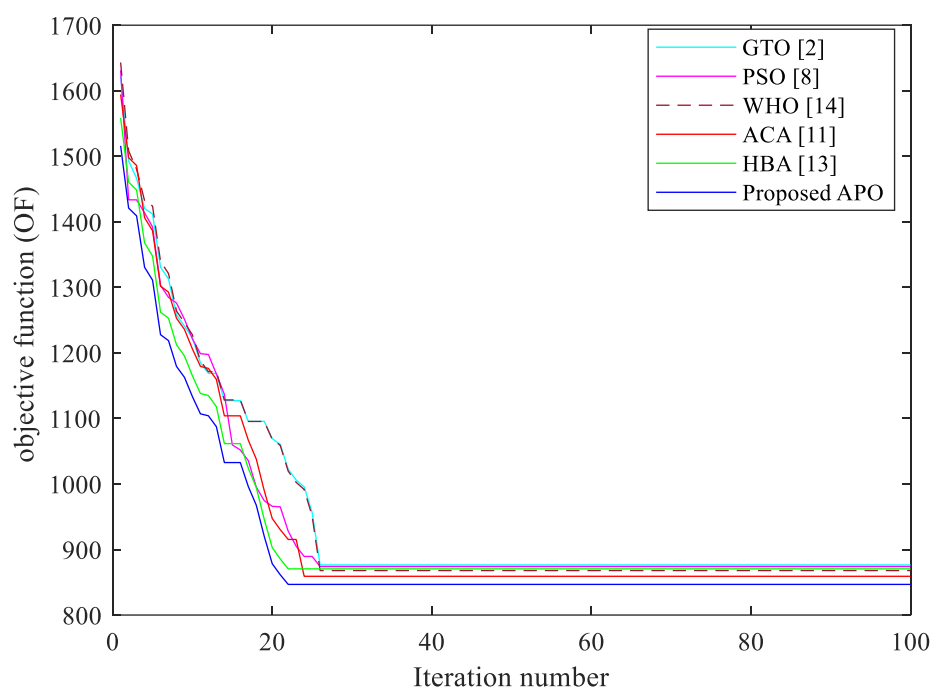


Figure 12. Convergence patterns for each algorithm

5.6. Effect of EV Load Penetration

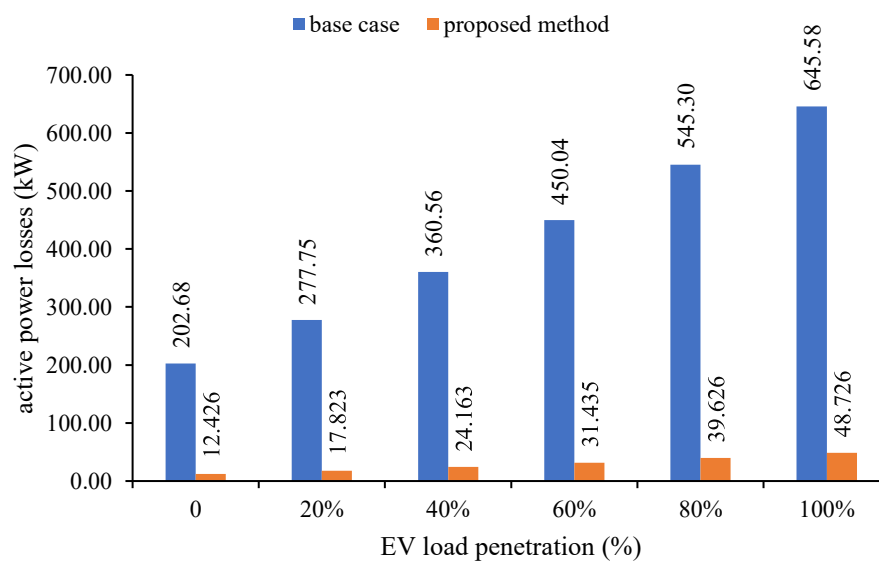
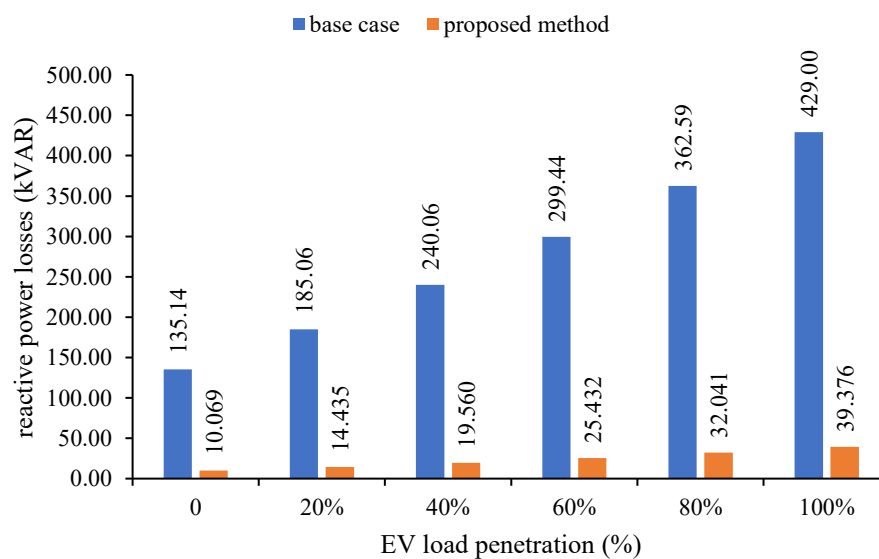
In this case, a 20% stepwise increase in EV penetration is considered in the distribution network, corresponding to their impact on total active power and reactive power losses, as well as voltage deviations, as shown in Table 6. As EV penetration increases stepwise, there is a corresponding increase in total active power, reactive power losses, and voltage deviations. However, with the proposed method (i.e., the combined placement of CBs and DGs) and the optimal location and rate of CBs and DGs in the distribution system, a significant reduction in total active power and reactive power losses, as well as voltage deviations, is observed, as depicted in Table 7. Furthermore, Figures 13, 14, and 15 show significant reductions in total active power and reactive power losses, as well as voltage deviations, compared to the base case method.

Table 6. Active and reactive power profiles with different EV penetration load

Penetration level (PL)	Active power load (kW)	Reactive power load (kVAR)	Active power losses (kW)	Reactive power losses (kVAR)	Voltage minimum (Vmin)	Voltage deviation (VD)
0%	3715.00	2300.00	202.68	135.14	0.9130905	0.0515438
20%	4353.07	2652.80	277.75	185.06	0.8983792	0.0603284
40%	4963.82	2979.92	360.56	240.06	0.8843597	0.0687179
60%	5549.64	3284.27	450.04	299.44	0.8709703	0.0767475
80%	6112.59	3568.36	545.30	362.59	0.8581573	0.0844477
100%	6654.49	3834.30	645.58	429.00	0.8458739	0.0918452

Table 7. The proposed method with EV penetration load

PL	CBs (location, size in kVAR)			DGs (location, size in kW)			Active power losses (kW)	Reactive power losses	PL	CBs (location, size in kVAR)
0%	(14, 360)	(25, 420)	(30, 1030)	(14, 760)	(25, 860)	(30, 1070)	12.426	10.069	0.992	0.0039
20%	(14, 430)	(25, 500)	(30, 1230)	(14, 910)	(25, 1040)	(30, 1280)	17.823	14.435	0.990	0.0047
40%	(14, 500)	(25, 580)	(30, 1440)	(14, 1060)	(25, 1210)	(30, 1490)	24.163	19.560	0.988	0.0055
60%	(14, 570)	(25, 660)	(30, 1640)	(14, 1200)	(25, 1380)	(30, 1700)	31.435	25.432	0.987	0.0063
80%	(14, 630)	(25, 750)	(30, 1850)	(14, 1350)	(25, 1550)	(30, 1910)	39.626	32.041	0.985	0.0072
100%	(14, 700)	(25, 830)	(30, 2050)	(14, 1500)	(25, 1720)	(30, 2110)	48.726	39.376	0.983	0.0081

**Figure 13.** Active power losses under variations of different EV load penetration**Figure 14.** Reactive power losses under variations of different EV load penetration

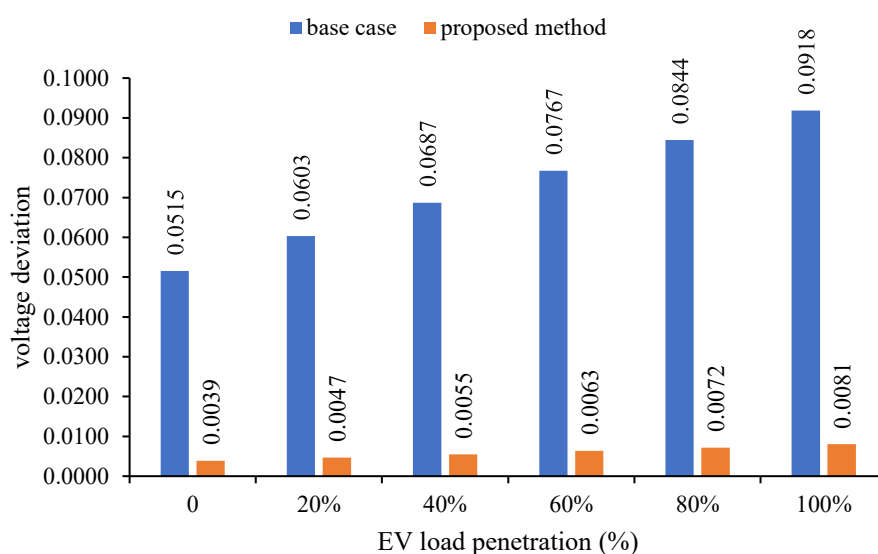


Figure 15. Voltage deviation under variation of different EV load penetration

6. Conclusion

This study examined the coordinated allocation of wind-based distributed generators and shunt capacitor banks within a distribution network with electric vehicle (EV) load penetration. Additionally, the impact of network reconfiguration (NR) was analyzed. The simulation results demonstrated the efficacy and practicality of the proposed planning model and the Artificial Protozoa Optimizer (APO) solver. The coordinated allocation of renewable energy sources (RES) and capacitors resulted in significant reductions in active energy losses, reactive energy losses, and voltage deviation by 73.59%, 71.76%, and 68.87%, respectively, as observed in case 4. This highlights the benefits of combining DGs and capacitors rather than deploying them individually. Incorporating NR further reduced active energy losses, reactive energy losses, and voltage deviation by 80.53%, 76.88%, and 69.96%, respectively, as seen in case 5, underscoring the importance of combined planning in distribution networks.

Additionally, the efficacy of the proposed method in response to varying levels of EV load penetration and in the context of uncertainty analysis was studied. The APO optimization solver outperformed existing metaheuristic algorithms for this optimization problem. In conclusion, implementing the NR scheme, along with the coordinated planning of DGs and capacitor banks, significantly enhances the performance of the distribution network.

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