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# Multi-Objective Optimal Placement of EVCS and DGs in Distribution Systems Using Flower Pollination Algorithm under Varying Load Scenarios

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***Abstract*—The increasing adoption of electric vehicles (EVs) and the shift towards decentralized power generation have driven significant changes in power distribution networks, necessitating optimized infrastructure planning for stability and efficiency. This paper presents a methodology for the optimal placement of Electric Vehicle Charging Stations (EVCS) and Distributed Generators (DGs) in distribution networks, using the Flower Pollination Algorithm (FPA) to minimize power losses and improve voltage stability across varied load conditions (100%, 125%, and 150%). The proposed multi-objective optimization approach combines biotic and abiotic pollination mechanisms to balance exploration and exploitation within the solution space, adapting to different load profiles by minimizing active and reactive power losses and maintaining voltage limits. Experimental results demonstrate the combined EVCS-DG configuration achieved active power loss reductions of 58.59%, 71.05%, and 79.80%, and reactive power loss reductions of 46.38%, 61.40%, and 71.92% for 100%, 125%, and 150% loads, respectively. Voltage stability was improved, with minimum bus voltages reaching 0.9661 p.u., 0.9616 p.u., and 0.9646 p.u., while convergence times ranged from 102.64 to 123.75 seconds. This study offers a comparative analysis with existing EVCS and DG placement methods, demonstrating enhanced efficiency and network stability across all scenarios.**

***Index Terms*—Optimal EVCS and DG placement, Flower Pollination Algorithm, distribution network stability, power loss reduction, voltage stability, load variation analysis, multi-objective optimization.**

## I. INTRODUCTION

THE increasing demand for electric vehicle (EV) infrastructure and distributed generation (DG) integration is transforming modern electrical distribution systems. This shift is primarily driven by the need for flexible, distributed energy solutions that can efficiently manage local demand and reduce reliance on centralized power sources. However, the introduction of Electric Vehicle Charging Stations (EVCS) and Distributed Generators (DGs) presents unique challenges, including increased power losses and potential voltage instability, especially as demand fluctuates.

The integration of Electric Vehicle Charging Stations (EVCS) and Distributed Generators (DGs) in distribution systems has been a topic of interest in recent research. Studies have shown that integrating EVCS with DGs can have significant impacts on the distribution system's load profiles and power flow [1] [2]. To address the challenges posed by EVCS integration, researchers have proposed optimizing the allocation of Renewable DGs, DSTATCOM, and Battery Energy Storage Systems (BESS) [3-5]. This optimization not only mitigates the impact of EVCS but also improves overall power system stability. In regions like developing country, where power outages are frequent [6], novel hybrid renewable energy systems that combine solar and biogas resources with technologies like Superconducting Magnetic Energy Storage (SMES) and Pumped Hydro Energy Storage (PHES) have been suggested to enhance power distribution networks for sustainable reliability and cost efficiency [7].

Additionally, research has highlighted the importance of integrating DGs with EVCS planning in Vehicle-to-Grid (V2G) mode to enhance clean energy utilization, reduce network loss, and lower unit costs [8-10]. Efforts have also been made to optimize EVCS integration using artificial intelligence-based strategies to ensure efficient energy utilization [11]. Furthermore, studies have focused on the allocation of sustainable DGs to mitigate the adverse effects of EVCS on distribution networks [12]. By incorporating DGs to minimize the impact of EV load on distribution units, researchers aim to improve system self-sufficiency and dependability [13]. Overall, research on the integration impacts of EVCS and DGs in distribution systems emphasizes the importance of optimizing allocation strategies, incorporating renewable energy sources, and utilizing advanced technologies to enhance system stability, reliability, and efficiency [14-17].

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The optimal placement of distributed generation in distribution systems is a critical aspect of modern power system planning. Various studies have been conducted to address this issue using different optimization algorithms and approaches. Ponnam et al. proposed a multi-objective optimization approach for simultaneously determining the optimal allocation of EVCS and DGs in radial distribution systems [18]. Their study aimed to optimize real power losses, Average Voltage Deviation Index (AVDI), and Voltage Stability Index (VSI). They found that their method effectively reduced power losses and improved voltage stability. However, the study was limited to the radial distribution system model, which may not be applicable to more complex network topologies. Selim et al. introduced an improved Harris Hawks Optimization (HHO) algorithm to optimally place DGs in radial distribution systems, enhancing both single- and multi-objective optimization scenarios [19]. By incorporating rabbit location in the IHHO algorithm, the study achieved high accuracy in voltage profile improvement and power loss reduction. However, this approach may encounter limitations in convergence speed when dealing with large-scale systems. Almabsout et al. developed a hybrid algorithm that combines genetic algorithms and local search techniques to determine the optimal placement and capacity of DGs and Shunt Capacitors (SCs) in radial distribution systems [20]. The inclusion of a local search scheme allowed for a wider exploration of the solution space and improved convergence. However, the study's findings were restricted to SCs and DGs without exploring potential synergies with EVCS placement. Dehghani et. al. applied the Spring Search Algorithm (SSA) for the optimal sizing and placement of Capacitor Banks (CBs) and DGs in distribution systems [21]. The method was tested on the IEEE 33-bus system, showing notable improvements in reactive power compensation and voltage stability. However, the SSA's computational complexity may pose a challenge when applied to real-time scenarios or larger systems. Bilal et al. in a hybrid AI-based approach combining grey wolf optimization and particle swarm optimization (HGWOPSO) for EVCS and DG placement [22]. Their findings demonstrated significant improvements in node reliability and system stability, encouraging wider adoption of EVs. A limitation of this study was the lack of scalability testing on more extensive distribution systems, which may impact its practicality. Haider et al. explored the placement and sizing of DGs in a reconfigured radial distribution network to enhance voltage profiles and minimize power losses [23]. Their algorithm, implemented in MATLAB, proved effective; however, its application was confined to static network configurations, which may reduce its adaptability to dynamic or real-time system changes. Venkatesan et al. propose an Enhanced Grey Wolf Optimizer and Particle Swarm Optimization (EGWO-PSO) algorithm for DG and CB placement in radial distribution systems [24]. Their hybrid approach achieved a high convergence speed and avoided local optima effectively. Nevertheless, the study did not account for variations in load scenarios, which could affect its robustness in practical applications. Kumar et al. conducted a comprehensive review on multi-objective DG planning in power networks [25]. They evaluated various optimization techniques, DG types, and performance parameters, providing a valuable overview of current research. However, this study focused on reviewing existing techniques rather than proposing a new solution, limiting its direct applicability. Mohanty et al. presented a fuzzy-based approach to the RAO-3 algorithm for optimally placing EVCS, DGs, and DSTATCOMs in radial distribution systems [26]. This method effectively reduced power losses, improved voltage profiles, and enhanced substation power factors. However, the algorithm's reliance on fuzzy logic may introduce challenges in handling precise real-time data. Pratap et al. proposed a novel hybrid optimization combining African Vulture Optimization and Pattern Search (HAVOPS) for the optimal placement of EVCS, DGs, and DSTATCOMs with network reconfiguration [27]. Their study achieved notable reductions in voltage deviation and real power losses while lowering investment costs. However, the limitations in investment cost analysis under different load scenarios were noted, potentially impacting financial feasibility assessments [28] [29]. From the literature, the strategic placement of EVCS and DGs within the distribution system is, therefore, a critical factor in minimizing power losses, maintaining voltage stability, and ensuring efficient energy management. Achieving optimal placement becomes even more complex under varying load scenarios, where the dynamic nature of load demands requires adaptable and robust optimization methods.

To address these challenges, multi-objective optimization approaches have gained considerable attention. Unlike single-objective optimization, which may focus solely on minimizing power losses or enhancing voltage stability, multi-objective optimization considers a balanced trade-off between competing objectives, aligning well with the multifaceted needs of distribution networks. The primary contributions of this work are as follows:

1. The Flower Pollination Algorithm's dual pollination mechanism is introduced, utilizing both biotic (cross-pollination) and abiotic (self-pollination) processes to enhance solution convergence and optimize exploration-exploitation balance within complex distribution networks.
2. An optimized placement strategy for EVCS, DGs, and the combined EVCS-DG configuration is proposed, specifically designed to improve network efficiency through optimal resource allocation in distribution systems.
3. The methodology focuses on minimizing active and reactive power losses and enhancing voltage stability in the distribution network.
4. Adaptability across varied load conditions (100%, 125%, and 150%) is demonstrated, underscoring its feasibility in real-world applications with fluctuating demand profiles.

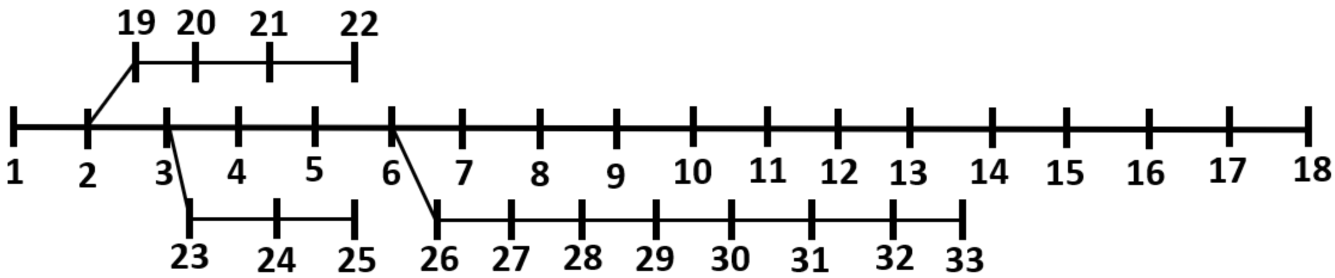


Fig. 1. Single-line diagram of IEEE-33 bus distribution networks.

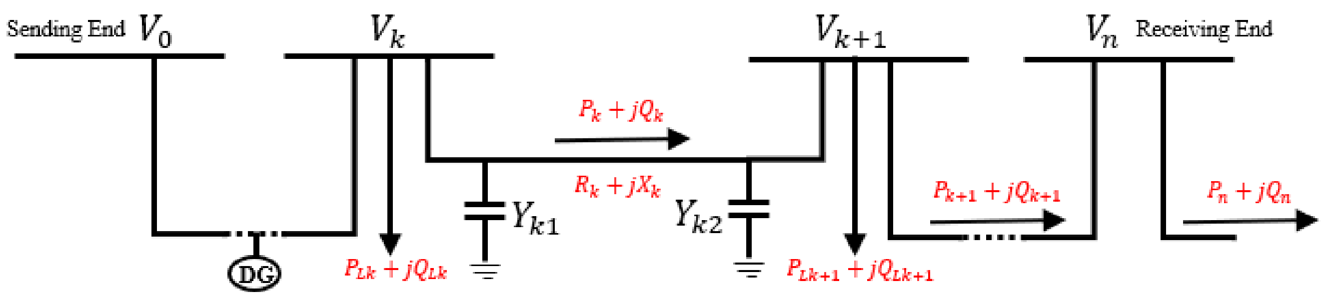


Fig. 2. Schematic diagram of distribution feeder.

The structure of this paper is organized as follows: Section II outlines the problem formulation and constraints, detailing the framework of the proposed Flower Pollination Algorithm (FPA) to address the problem under different load scenarios. Section III covers the simulation results along with a detailed discussion. Lastly, Section IV provides a summary of the conclusions and suggestions for future research directions.

## II. Methodology

This section details the experimental setup, parameter settings, and optimization methods, outlining objective functions, constraints, and algorithms to optimize EVCS and DGs placement under varying load scenarios for improved system performance.

### A. *Objective Function*

The goal is to minimize the total active and reactive power losses, and voltage deviation in the distribution system, as shown in Fig. 1. The objective function can be mathematically expressed as:

$$F_{obj} = \sum_{k=1}^{N_{branch}} \{R_k|I_k|^2 + X_k|I_k|^2 + (V_k + V_k^*)^2\} \quad (1)$$

$$minimize\ F_{active\ loss} = \sum_{k=1}^{N_{branch}} R_k|I_k|^2 \quad (2)$$

$$minimize\ F_{reactive\ loss} = \sum_{k=1}^{N_{branch}} X_k|I_k|^2 \quad (3)$$

$$minimize\ F_{voltage\ deviation} = \sum_{k=1}^{N_{branch}} (V_k + V_k^*)^2 \quad (4)$$

Where, $R_k$ and $X_k$ are the resistance and reactance of branch $k$, respectively. $I_k$ is the current magnitude flowing through branch $k$. $N_{branch}$ is the total number of branches.

### B. *Voltage Constraints*

The voltage at each bus must remain within a specified range to ensure network stability, as shown in Fig. 2. This can be formulated as:

$$V_{min} \le V_i \le V_{max}, \qquad \forall i = 1,2, \dots \dots \dots, N_{bus} \quad (5)$$

Where, $V_i$ is the voltage magnitude at bus $i$. $V_{min}$ and $V_{max}$ are the minimum and maximum voltage limits, typically set to 0.90pu and 1.05p.u., respectively. $N_{bus}$ is the total number of buses.

### C. *Power Balance Constraints*

The active and reactive power injected or consumed at each bus must be balanced to maintain network stability.

*1) Active Power Balance:* For each bus $i$, the active power injected should balance the power consumed, including losses:

$$P_{inj,i} = P_{DG,i} + P_{sub} - \sum_{j=1}^{N_{branch}} P_{loss,j} - P_{D,i} - P_{EVCS,i} \quad (6)$$

$$P_{DG,i} = V_i I_{DG,i} \cos(\theta_{DG,i} - \delta_i) \quad (7)$$

$$P_{EVCS,i} = V_i I_{EVCS,i} \cos(\theta_{EVCS,i} - \delta_i) \quad (8)$$

Where, $P_{inj,i}$ is the net active power injected at bus $i$. $P_{DG,i}$ is the active power generated by the DG at bus $i$. $P_{substation}$ is the active power supplied by the substation. $P_{loss,j}$ is the active power loss in branch $j$. $P_{D,i}$ is the active power demand at bus $i$. $P_{EVCS,i}$ is the active power consumed by the EVCS at bus $i$. $V_i$ is the voltage magnitude at bus $i$. $I_{DG,i}$ is the current injected by the DG at bus $i$. $\theta_{DG,i}$ is the phase angle of the current injected by the DG at bus $i$. $I_{EVCS,i}$ is the current drawn by the EVCS at bus $i$. $\theta_{EVCS,i}$ is the phase angle of the current drawn by the EVCS at bus $i$. $\delta_i$ is the voltage angle at bus $i$.

*2) Reactive Power Balance:* Similarly, for reactive power, the balance equation is:

$$Q_{inj,i} = Q_{DG,i} + Q_{sub} - \sum_{j=1}^{N_{branch}} Q_{loss,j} - Q_{D,i} - Q_{EVCS,i} \quad (9)$$

$$Q_{DG,i} = V_i I_{DG,i} \sin(\theta_{DG,i} - \delta_i) \quad (10)$$

$$Q_{EVCS,i} = V_i I_{EVCS,i} \sin(\theta_{EVCS,i} - \delta_i) \quad (11)$$

Where, $Q_{inj,i}$ is the net reactive power injected at bus $i$. $Q_{DG,i}$ is the active power generated by the DG at bus $i$. $Q_{substation}$ is the active power supplied by the substation. $Q_{loss,j}$ is the active power loss in branch $j$. $Q_{D,i}$ is the active power demand at bus $i$. $Q_{EVCS,i}$ is the active power consumed by the EVCS at bus $i$. $V_i$ is the voltage magnitude at bus $i$. $I_{DG,i}$ is the current injected by the DG at bus $i$. $\theta_{DG,i}$ is the phase angle of the current injected by the DG at bus $i$. $I_{EVCS,i}$ is the current drawn by the EVCS at bus $i$. $\theta_{EVCS,i}$ is the phase angle of the current drawn by the EVCS at bus $i$. $\delta_i$ is the voltage angle at bus $i$.

### D. Power Generation Constraints for DGs and EVCS

The output from Distributed Generators (DGs) by [30] and Electric Vehicle Charging Stations (EVCS) is constrained within upper and lower bounds [31][32].

$$P_{DG,i}^{min} \le P_{DG,i} \le P_{DG,i}^{max} \quad (12)$$

$$P_{EVCS,i}^{min} \le P_{EVCS,i} \le P_{EVCS,i}^{max} \quad (13)$$

Where, $P_{DG,i}^{min}$ and $P_{DG,i}^{max}$ for DGs, $P_{EVCS,i}^{min}$ and $P_{EVCS,i}^{max}$ for EVCS, are the minimum and maximum active power limits at bus $i$.

$$Q_{DG,i}^{min} \le Q_{DG,i} \le Q_{DG,i}^{max} \quad (14)$$

$$Q_{EVCS,i}^{min} \le Q_{EVCS,i} \le Q_{EVCS,i}^{max} \quad (15)$$

Where, $Q_{DG,i}^{min}$ and $Q_{DG,i}^{max}$ for DGs, $Q_{EVCS,i}^{min}$ and $Q_{EVCS,i}^{max}$ for EVCS, are the minimum and maximum reactive power limits at bus $i$.

### E. Flower Pollination Algorithm (FPA) in Distribution System

The algorithm employs both biotic (cross-pollination) and abiotic (self-pollination) mechanisms, controlled by a probability switch, to maintain diversity among solutions and prevent premature convergence. The steps of the algorithm involve updating solutions based on the best-known solution and incorporating randomness via Lévy flights, which mimic long-distance pollen movement.

*1) Biotic Pollination Update (Cross-Pollination):* The biotic pollination update rule represents how pollinators (e.g., bees or birds) carry pollen over long distances, which helps explore the search space more globally. In this equation (16), the position of the $i$th solution $x_i^{t+1}$ at generation $t+1$ is updated by moving it closer to the best-known solution $g_{best}$. The movement step is scaled by a factor $\gamma_L$ and adjusted by a randomly sampled step length $L(\lambda)$ from a Lévy distribution. This approach allows for occasional long-distance moves, helping the algorithm avoid local optima and explore new areas in the solution space:

$$x_i^{t+1} = x_i^t + \gamma_L L(\lambda)(g_{best} - x_i^t) \quad (16)$$

*2) Lévy Distribution for Step Length:* The Lévy distribution is used to define the step length $L(\lambda)$ in the biotic pollination process. It's a probability distribution with heavy tails, which means it occasionally produces large values, resulting in substantial moves in the search space. The equation (17) provides the probability density function for Lévy flights, using a parameter $\lambda$ (often set to 1.5) that controls the distribution shape. This distribution gives the FPA its ability to make significant jumps, which improves exploration:

$$L(\lambda) \sim \frac{\lambda \Gamma(\lambda) \sin\left(\frac{\pi\lambda}{2}\right)}{\pi s^{\lambda+1}} \quad (17)$$

*3) Mantegna's Algorithm for Lévy Step Sampling:* Mantegna's algorithm is a practical way to generate step sizes that follow the Lévy distribution, as directly sampling from the Lévy distribution can be challenging. In this approach, the step size $M(\omega)$ is calculated by dividing a normally distributed variable $X$ by another normally distributed variable $Y$ raised to a power. This combination of two Gaussian variables produces the desired Lévy-like heavy-tailed step size distribution:

$$M(\omega) = \frac{X}{|Y|^{1/\omega}} \quad (18)$$

*4) Variance Calculation for Mantegna's Algorithm:* The variance $\sigma^2$ for the normal distribution of $X$ in Mantegna's algorithm is calculated here, ensuring that $X$ has a suitable spread. The formula uses the gamma function $\Gamma$ and a trigonometric term based on $\omega$, which influences how spread out the steps are. This setup allows Mantegna's algorithm to produce Lévy-distributed steps effectively for the FPA:

$$\sigma^2 = \left[\frac{\Gamma(1+\omega)\sin\left(\frac{\pi\omega}{2}\right)}{\Gamma\left(\frac{1+\omega}{2}\right)\omega 2^{(\omega-1)/2}}\right]^{1/\omega} \quad (19)$$

*5) Alternative Biotic Pollination Update Using Mantegna's Algorithm:* The FPA can also update solutions during biotic pollination by applying Mantegna's algorithm instead of the Lévy distribution directly. In this case, the new position $x_i^{t+1}$ for each solution moves toward the best-known solution $g_{best}$ with a step size $M(\omega)$ that follows the Lévy distribution properties, thanks to Mantegna's algorithm. This update

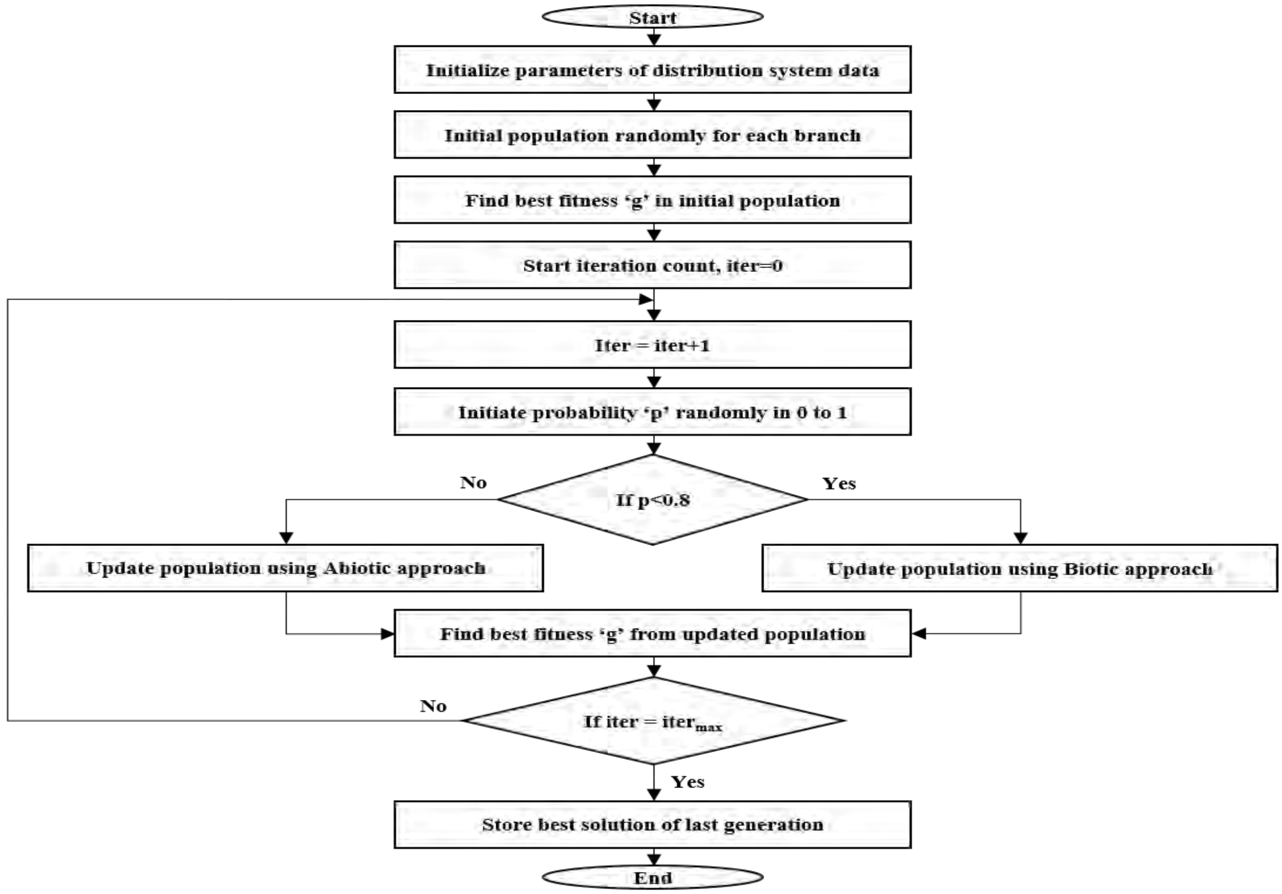


Fig. 3. Flowchart of FPA in the distribution system.

provides an alternate way to apply biotic pollination while maintaining global search characteristics:

$$x_i^{t+1} = x_i^t + \gamma_M M(\omega)(g_{best} - x_i^t) \tag{20}$$

*6) Abiotic Pollination Update (Self-Pollination):* In abiotic pollination, pollen transfer occurs within the same or nearby flowers, enabling a more localized search. The new solution $x_i^{t+1}$ is updated by combining two randomly selected solutions $x_j^t$ and $x_k^t$, which represent nearby flowers. The scaling factor $\epsilon$ is a random number between 0 and 1, ensuring that the update is modest. This localized search helps the FPA fine-tune solutions around promising areas, providing a balance between exploration and exploitation:

$$x_i^{t+1} = x_i^t + \varepsilon\left(x_j^t - x_k^t\right) \tag{21}$$

The parameters used in this study are outlined in Table I, offering essential details for setting up the process. A comprehensive step-by-step summary, based on the flowchart in Fig. 3 and the pseudocode in Fig. 4, describes the application of the Flower Pollination Algorithm (FPA) for optimization as follows:

**Step 01. Start**: Initialize by reading the distribution system data and FPA parameters.

**Step 02. Generate Initial Population**: Create an initial population with random conductor types for each branch.

**Step 03. Evaluate Fitness**: Run load flow analysis and calculate the fitness for each member of the population.

**Step 04. Identify Best Solution**: Find the best fitness value $g$ in the initial population.

**Step 05. Initialize Iterations**: Set the iteration counter to zero.

**Step 06. Increment Iteration**: Increase the iteration count by 1.

**Step 07. Probability Switch**: Randomly set the probability $p$ between 0 and 1.

**Step 08. Pollination Choice**: If p<0.8,

- Use the **Biotic Pollination Approach** to update the population.
- Otherwise, use the **Abiotic Pollination Approach**.

**Step 09. Update Best Solution**: Find the best fitness value $g$ in the updated population.

**Step 10. Check Termination**: If iter =$iter_{max}$

- Go to the next, Step 11.
- Otherwise, return to Step 6.

**Step 11. Store Final Solution**: Save the best solution from the last generation.

**Step 12. End**: Complete the process.

```
# Generate Initial Population
Initialize N solutions with random conductor types for branches
Calculate initial fitness (power losses) for each solution
Set Best_Solution as the one with minimum fitness

 # Optimization Loop
 FOR iteration = 1 to Max_Iter:
    FOR each solution i in the population:
       p_val = random number between 0 and 1

       IF p_val < 0.8 THEN
          # Biotic Pollination
          Lévy step L ~ Lévy(lambda)
          Solution_i = Solution_i + L * (Best_Solution - Solution_i)

       ELSE
          # Abiotic Pollination
          Select two random solutions Sol_j, Sol_k
          Solution_i = Solution_i + epsilon * (Sol_j - Sol_k)

       Calculate new fitness for Solution_i

       IF fitness of Solution_i < fitness of Best_Solution
          THEN
          Best_Solution = Solution_i
    END FOR
 END FOR

 Output Best_Solution with minimum power loss
END
```

Fig. 4. Pseudocode for FPA in the distribution system.

TABLE I
PARAMETERS OF EVCS AND DGS FOR OPTIMIZATION PROCESS

| Parameter | Value |
|---|---|
| Bus Type | 33-bus |
| Voltage Level | 12 kV |
| Power Rating | 100 MVA |
| Number of EVCS | 2 |
| Number of DGs | 2 |
| Power Factor | 0.9 |
| Population for Optimization | 20 |
| Number of Iterations | 60 |
| DG Capacity Minimum | 350 kW |
| DG Capacity Maximum | 350 kW |
| EVCS Rating | 50 kW per station |
| Number of EV | 30 |
| Base Load Percentage | 100% |

## III. RESULT AND DISCUSSION

This section presents the analysis of FPA's effectiveness in optimizing distribution network performance by optimally placing EVCS and DGs, reducing active and reactive power losses, and improving voltage profiles across 100%, 125%, and 150% load variations.

### A. *Convergent Iteration*

The convergence performance of the Flower Pollination Algorithm (FPA) across different load scenarios demonstrates its efficiency in reaching optimal solutions within a limited number of iterations. As shown in Fig. 5, the FPA achieved convergence by iteration 17 for the 100% load scenario, iteration 23 for the 125% load scenario, and iteration 25 for the 150% load scenario. These results highlight FPA's adaptability, with a relatively faster convergence under lighter load conditions and a controlled increase in iteration count as load levels intensify.

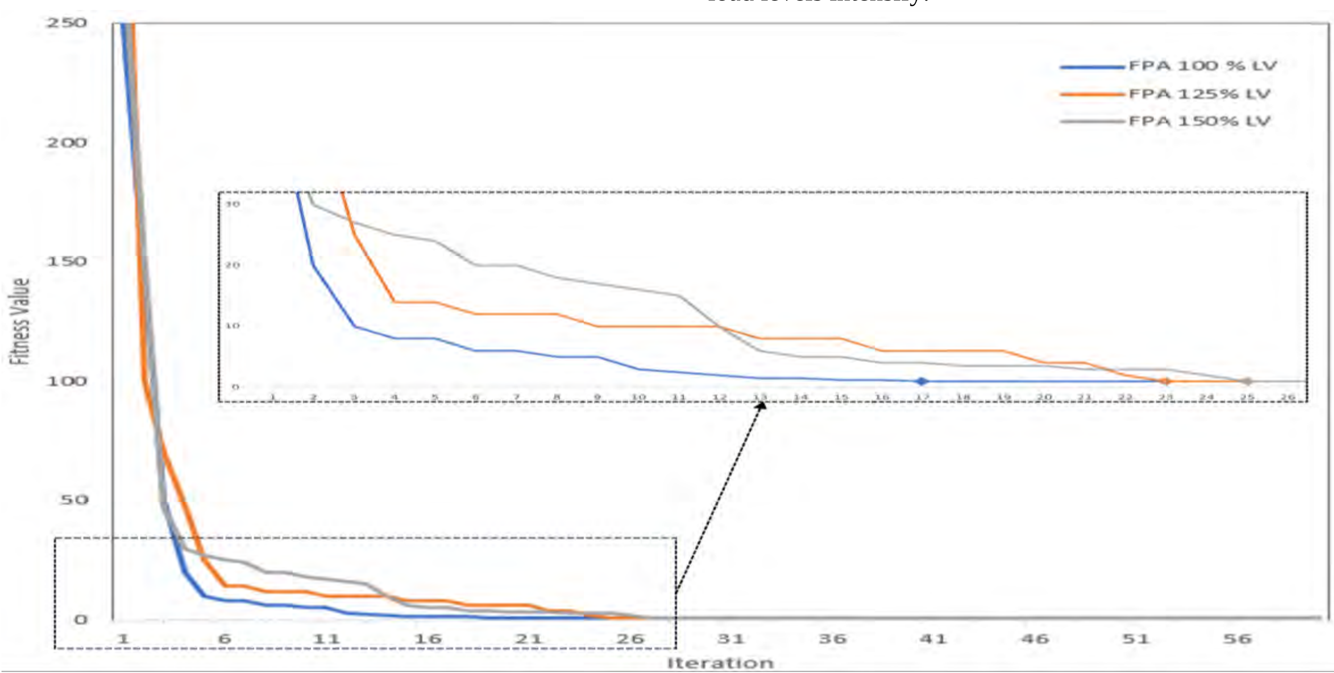


Fig. 5. Convergence curve for different load variations.

*B. For 100% Load Variation:*

Under the 100% load scenario, optimal placements yielded substantial reductions in power losses and improved voltage profiles. Table II, shows that EVCS placement alone reduced active power losses by 22.90%, DGs alone by 44.01%, and the combined EVCS-DG setup achieved the highest reduction at 58.59%. Reactive power losses were similarly reduced, with EVCS alone at 2.05%, DGs at 35.15%, and the combined setup reaching 46.38%. Voltage stability also improved, as illustrated in Fig.6, with minimum voltage levels increasing from 0.9127p.u. to 0.9661p.u. for the combined setup, compared to 0.9489p.u. for EVCS and 0.9559p.u. for DG placements. The combined approach achieved a 5.85% reduction in voltage deviation, and the convergence time was 102.64 seconds, ensuring optimal performance for load management.

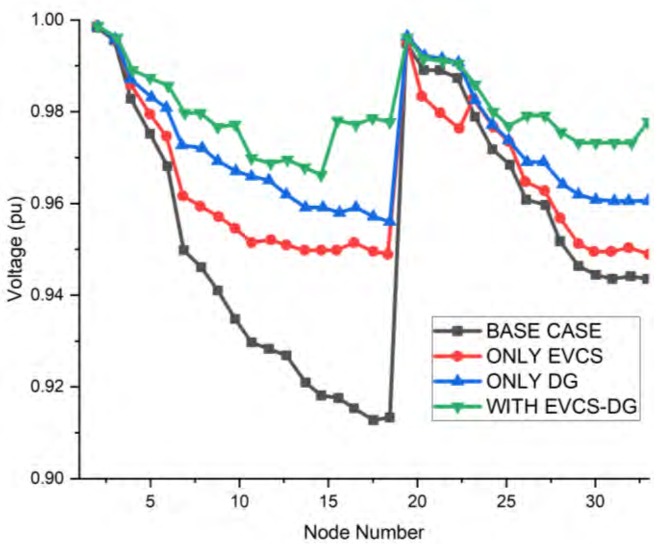


Fig. 6. Voltage profile for different cases under 100% load variation at IEEE 33-bus system using FPA.

TABLE II
COMPARISONS DIFFERENT PARAMETERS 100% LOAD VARIATION USING FPA

| Parameters | 100% Load Variation using FPA | | |
|---|---|---|---|
| | EVCS | DGs | EVCS-DG |
| Best Location | 19, 2 | 25, 16 | 2, 4 and 17, 32 |
| Existing Active $P_{Loss}$ (kW) | 202.677 | | |
| Existing Reactive $P_{Loss}$ (kVar) | 135.141 | | |
| Active Power Loss (kW) | 156.263 | 113.482 | 83.937 |
| Reactive Power Loss (kVar) | 132.375 | 87.633 | 72.462 |
| Active $P_{Loss}$ Reduction (%) | 22.90 | 44.01 | 58.59 |
| Reactive $P_{Loss}$ Reduction (%) | 2.05 | 35.15 | 46.38 |
| Execution Time (s) | 112.73 | 130.77 | 102.64 |
| Existing Minimum Voltage (p.u) | 0.9127 | | |
| Minimum Voltage (p.u) | 0.9489 | 0.9559 | 0.9661 |
| % Voltage deviation | 3.97 | 4.73 | 5.85 |

*C. For 125% Load Variation*

Under the 125% load scenario, optimal placements further reduced power losses and improved voltage stability. As detailed in Table III, placing EVCS alone reduced active power losses by 47.90%, DGs alone by 63.04%, while the combined EVCS-DG placement achieved the highest reduction at 71.05%. Reactive power losses were reduced by 28.58% with EVCS, 54.66% with DGs, and 61.40% with the combined setup. Voltage profiles also saw improvements, with minimum voltage increasing from 0.9112p.u. to 0.9616p.u. for the combined configuration, compared to 0.9346p.u. with EVCS and 0.9495p.u. with DG placements, as shown in Fig. 7. The combined approach minimized voltage deviation by 5.53%, with a convergence time of 110.53 seconds, supporting efficient load handling under increased demand.

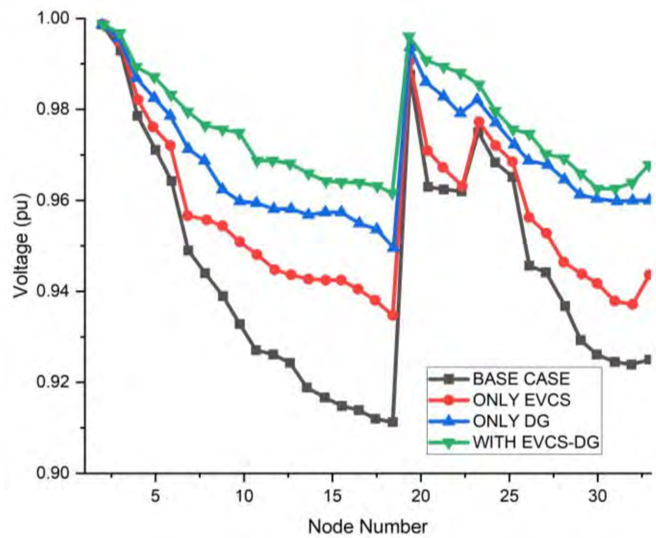


Fig. 7. Voltage profile for different cases under 125% load variation at IEEE 33-bus system using FPA.

TABLE III
COMPARISONS DIFFERENT PARAMETERS 125% LOAD VARIATION USING FPA

| Parameters | 125% Load Variation using FPA | | |
|---|---|---|---|
| | EVCS | DGs | EVCS-DG |
| Best Location | 19, 4 | 16, 11 | 2, 3 and 17, 31 |
| Existing Active $P_{Loss}$ (kW) | 330.705 | | |
| Existing Reactive $P_{Loss}$ (kVar) | 219.273 | | |
| Active Power Loss (kW) | 172.310 | 122.235 | 95.726 |
| Reactive Power Loss (kVar) | 156.603 | 99.428 | 84.638 |
| Active $P_{Loss}$ Reduction (%) | 47.90 | 63.04 | 71.05 |
| Reactive $P_{Loss}$ Reduction (%) | 28.58 | 54.66 | 61.40 |
| Execution Time (s) | 123.42 | 136.31 | 110.53 |
| Existing Minimum Voltage (p.u) | 0.9112 | | |
| Minimum Voltage (p.u) | 0.9346 | 0.9495 | 0.9616 |
| % Voltage deviation | 2.57 | 4.20 | 5.53 |

*D. For 150% Load Variation*

Under the 150% load scenario, optimal placement configurations led to notable reductions in power losses and improved voltage stability. According to Table IV, placing only EVCS reduced active power losses by 58.67%, DGs alone by 63.61%, and the combined EVCS-DG placement achieved the highest reduction at 79.80%. Reactive power losses were minimized by 50.23% with EVCS, 53.98% with DGs, and 71.92% with the combined setup. Voltage stability also improved, with the minimum voltage increasing from 0.9094 p.u. to 0.9646 p.u. for the combined configuration, compared to 0.9283 p.u. for EVCS and 0.9538 p.u. for DGs, as illustrated in Fig. 8. The combined approach achieved a 6.07% reduction in voltage deviation, and the convergence time was 123.75 seconds, effectively supporting high-load conditions with optimal performance.

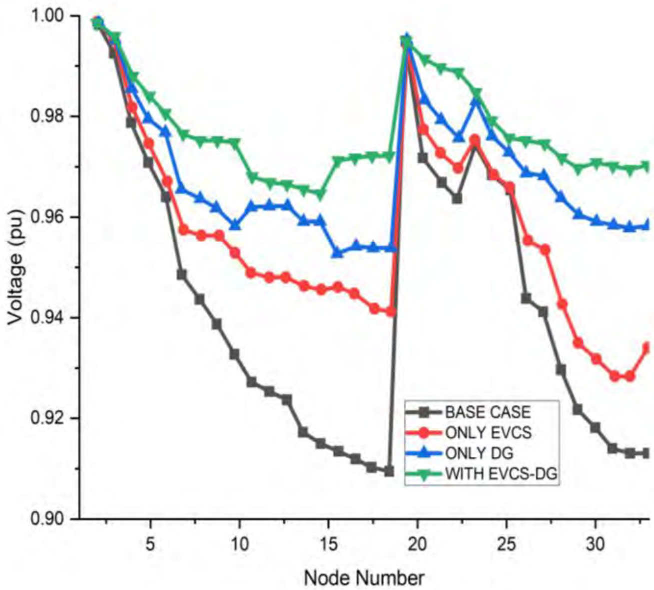


Fig. 8. Voltage profile for different cases under 150% load variation at IEEE 33-bus system using FPA.

TABLE IV
COMPARISONS DIFFERENT PARAMETERS 150% LOAD VARIATION USING FPA

| Parameters | 150% Load Variation using FPA | | |
|---|---|---|---|
| | EVCS | DGs | EVCS-DG |
| Best Location | 19, 3 | 11, 16 | 3, 4 and 31, 32 |
| Existing Active $P_{Loss}$ (kW) | | 501.117 | |
| Existing Reactive $P_{Loss}$ (kVar) | | 328.715 | |
| Active Power Loss (kW) | 207.110 | 182.342 | 101.204 |
| Reactive Power Loss (kVar) | 163.603 | 151.263 | 92.317 |
| Active $P_{Loss}$ Reduction (%) | 58.67 | 63.61 | 79.80 |
| Reactive $P_{Loss}$ Reduction (%) | 50.23 | 53.98 | 71.92 |
| Execution Time (s) | 134.53 | 148.62 | 123.75 |
| Existing Minimum Voltage (p.u) | | 0.9094 | |
| Minimum Voltage (p.u) | 0.9283 | 0.9538 | 0.9646 |
| % Voltage deviation | 2.08 | 4.88 | 6.07 |

### *E. Comparative Study*

The comparison of the performance of combined EVCS-DG placements across different load conditions focuses on power loss minimization and voltage stability to identify the most effective configuration for network efficiency.

*1) Power Loss Minimization*: The comparison of power loss minimization across load scenarios demonstrates that the combined EVCS-DG configuration consistently delivered the greatest reductions in both active and reactive power losses. At 100% load, the EVCS-DG setup achieved a 58.59% reduction in active power losses, increasing to 71.05% at 125% load, and reaching the highest reduction of 79.80% at 150% load. Reactive power losses also followed this trend, with reductions of 46.38% at 100%, 61.40% at 125%, and 71.92% at 150% loads. This pattern underscores the effectiveness of the EVCS-DG placement in maximizing power loss reduction as system load increases, providing an optimal solution for enhancing efficiency across varying demand conditions, as shown in Fig. 9.

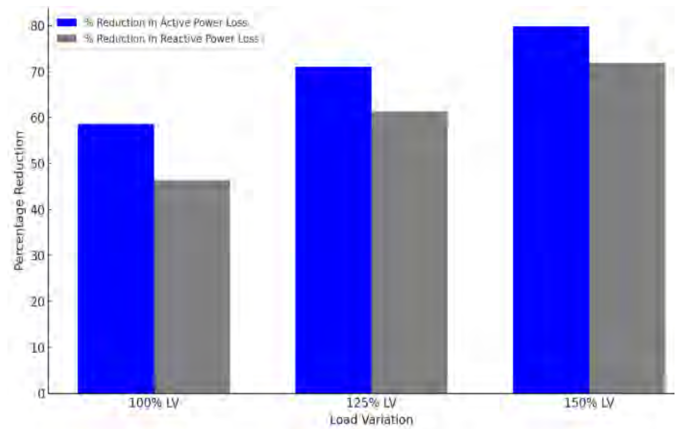


Fig. 9. Percentage Reduction in Power Losses for EVCS-DG placement under different load variations.

*2) Voltage Deviation Analysis:* The voltage deviation analysis for the combined EVCS-DG configuration, as shown in Fig. 10, demonstrates effective control of voltage stability across different load conditions. At 100% load, voltage deviations reach a maximum of 2.5618%, which is well within the commonly acceptable limit of ±5% as per ANSI C84.1 Standard (USA) and preferred by IEC Standards (Europe and International). When the load increases to 125%, deviations extend to 4.6226%, still falling within this ±5% threshold. At 150% load, the deviation peaks at 6.2623%, slightly exceeding the preferred ±5% limit but remaining within the broader ±10% tolerance permitted by IEC standards for certain conditions. This analysis highlights the capability of the EVCS-DG configuration to maintain voltage deviations within industry-accepted standards, achieving the objective of enhanced voltage stability.

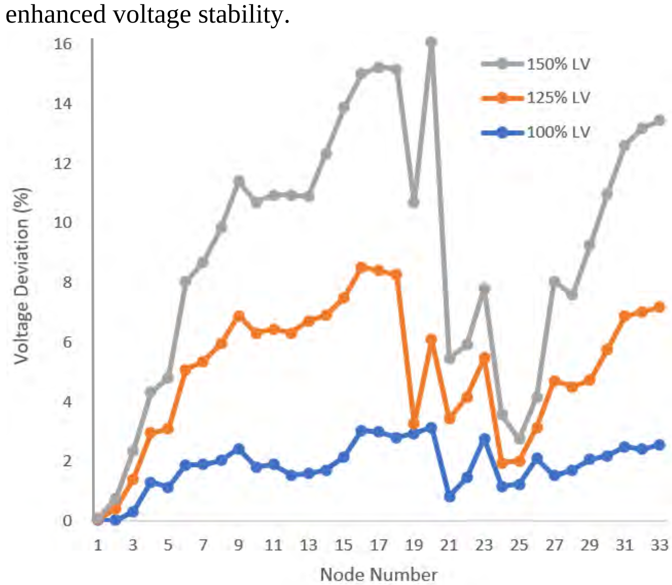


Fig. 10. Percentage of voltage deviation under different load variations.

**TABLE V**

**Comparative Analysis of Optimal Placement and Performance Metrics of EVCS and DGs across Different Optimization Methods**

| Ref. No. | Method | Optimal Placement | | | Active Power Loss (kw) | Minimum Voltage (pu) |
|---|---|---|---|---|---|---|
| | | EVCS | DG | EVCS-DG | | |
| **[18]** | HHO | - | 13, 24, 30 | - | 94.38(DG) | 0.9685 (DG) |
| **[19]** | IHHO | - | 14, 24, 30 | - | 72.79(DG) | 0.9673 (DG) |
| **[20]** | EGA | 6,2,11 | 11, 24, 31 | - | 112.32 (EVCS), 62.7 (DG) | 0.9324 (EVCS), 0.9464 (DG) |
| **[21]** | SSA | 3,4,18 | 31, 24, 11 | - | 119.32 (EVCS), 59.848 (DG) | 0.9493 (EVCS), 0.9635 (DG) |
| **[24]** | EGWO-PSO | - | 14, 24, 30 | - | 71.46 (DG) | 0.9687 (DG) |
| **[28]** | PSO | 2,3,4 | 6,32 | 3,13,2 and 30, 6 | 219 (EVCS), 71.85 (DG), 89.34 (EVCS-DG) | 0.9378 (EVCS), 0.9462 (DG), 0.9584 (EVCS-DG) |
| | COA | 3,19,2 | 25,30,13 | 2,3,8 and 25,31,14 | 137.00 (EVCS), 82.66(DG), 73.77 (EVCS-DG) | 0.9446 (EVCS), 0.9476 (DG), 0.9622 (EVCS-DG) |
| **[29]** | GA | 3,19,2 | 24,31,14 | 2,4,11 and 24,30,14 | 143.96 (EVCS), 88.32 (DG), 67.41 (EVCS-DG) | 0.9313 (EVCS), 0.9394 (DG), 0.9486 (EVCS-DG) |
| | GWO | 3,19,2 | 24,30,14 | 3,8,11 and 24,31,13 | 138.29 (EVCS), 91.28 (DG), 78.33 (EVCS-DG) | 0.9425 (EVCS), 0.9473 (DG), 0.9586 (EVCS-DG) |
| | FPA (100% LV) | 19, 2 | 25, 16 | 2, 4 and 17, 32 | 156.263 (EVCS), 113.482 (DG), 83.937 (EVCS-DG) | 0.9489 (EVCS), 0.9559 (DG), 0.9661 (EVCS-DG) |
| **This Work** | FPA (125% LV) | 19, 4 | 16, 11 | 2, 3 and 17, 31 | 172.310 (EVCS), 122.235 (DG), 95.726 (EVCS-DG) | 0.9346 (EVCS), 0.9495 (DG), 0.9616 (EVCS-DG) |
| | FPA (150% LV) | 19, 3 | 11, 16 | 3, 4 and 31, 32 | 207.110 (EVCS), 182.342 (DG), 101.204 (EVCS-DG) | 0.9283 (EVCS), 0.9538 (DG), 0.9646 (EVCS-DG) |

*3) Comparative Analysis of EVCS and DG Placement Methods:* In Table V, comparative analysis evaluates various optimization methods for the optimal placement of EVCS and DG in distribution systems, focusing on key metrics such as active power loss and minimum voltage. Methods like HHO, IHHO, EGA, SSA, EGWO-PSO, PSO, COA, GA, and GWO suggest specific placements for EVCS and DGs to improve distribution system performance. Among these methods, IHHO achieves a low active power loss of 72.79kW with a minimum voltage of 0.9673p.u. The proposed Flower Pollination Algorithm (FPA) demonstrates significant effectiveness, achieving active power losses of 83.937kW, 95.726kW, and 101.204kW for combined EVCS-DG placements under load variations of 100%, 125%, and 150%, respectively. Additionally, FPA maintains minimum voltage levels of 0.9661p.u., 0.9616p.u., and 0.9646p.u. across these load scenarios, highlighting its capability to provide reliable voltage stability and efficient power loss minimization under fluctuating demand conditions.

## IV. Conclusion

This research successfully applied the Flower Pollination Algorithm (FPA) to optimize the placement of Electric Vehicle Charging Stations (EVCS) and Distributed Generators (DGs) in distribution networks, achieving significant power loss reductions and voltage stability improvements under varied load conditions (100%, 125%, and 150%). Specifically, the combined EVCS-DG configuration demonstrated substantial active power loss reductions of 58.59%, 71.05%, and 79.80% across the 100%, 125%, and 150% load scenarios, respectively. Similarly, reactive power losses were minimized by 46.38% at 100% load, 61.40% at 125% load, and 71.92% at 150% load. This consistent reduction in power losses highlights the FPA's efficiency in optimizing power flow within distribution networks, adapting effectively to increased load demands. Voltage stability improvements were also significant, with the minimum bus voltages reaching 0.9661 p.u., 0.9616 p.u., and 0.9646 p.u. for the combined EVCS-DG placement across 100%, 125%, and 150% loads, respectively. Voltage deviation was controlled, reducing to 5.85% at 100% load, 5.53% at 125% load, and 6.07% at 150% load, well within acceptable limits and maintaining network stability. The FPA's rapid convergence further supports its applicability in real-time operations, achieving optimal placements within 102.64 seconds at 100% load, 110.53 seconds at 125% load, and 123.75 seconds at 150% load, thus balancing global and local search dynamics effectively.

Future work could integrate renewable sources like solar and wind and incorporate real-time load adjustments to enhance EVCS and DG adaptability in evolving grids. AI-driven optimization and storage solutions, such as BESS, could further stabilize voltage and reduce losses. Additionally, exploring hybrid EVCS-DG-renewable setups and assessing economic and regulatory impacts would support resilient, sustainable distribution networks.

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