

Optimal Siting and Sizing of EV Charging Stations in Distribution Networks: A Comparative Study of PSO, GWO, and HPSOGWO

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Abstract:

The rapid proliferation of Electric Vehicles (EVs) presents a critical challenge for existing power infrastructure, specifically concerning the integration of EV Charging Stations (EVCSs) into radial distribution networks. Uncoordinated EVCS placement significantly degrades network stability, exacerbating active power losses and inducing severe voltage deviations. This study addresses the optimal siting and sizing of EVCSs in a 30-bus radial distribution network by proposing a hybrid metaheuristic approach: the Hybrid Particle Swarm Optimization-Grey Wolf Optimizer (HPSOGWO). The optimization problem is formulated as a multi-objective task that simultaneously minimizes the total infrastructure investment cost, reduces active and reactive power losses, and ensures strict adherence to voltage profile limits. Unlike previous static models, this research introduces a mandatory 100-charger target demand constraint, forcing the algorithm to distribute load dynamically across candidate buses. The inclusion of quadratic penalty multipliers ($\lambda = 10^8$) ensures that all configurations strictly adhere to the $0.95 \leq V_i \leq 1.05$ p.u. nodal voltage operational limits. Simulation results across nine distinct weighting configurations (w_1, w_2, w_3) demonstrate that HPSOGWO effectively overcomes the premature convergence limitations of standard PSO and the late-stage stagnation observed in GWO. The hybrid approach achieves superior convergence performance, maintaining stable active power losses (18.075–18.079 MW) across all test cases. These findings establish HPSOGWO as a highly reliable and computationally efficient planning tool for modern distribution system operators, successfully balancing economic investment with the imperative requirements of grid technical stability and power system reliability in increasingly complex charging environments.

1. Introduction

The global transition toward sustainable transportation has accelerated significantly over the past decade, driven by increasing environmental concerns, rapid urbanization, and

the urgent need to reduce greenhouse gas emissions [1], [2]. Among the available clean transportation technologies, electric vehicles (EVs) have emerged as one of the most promising solutions for decreasing dependence on fossil fuels and mitigating the environmental impact of

conventional internal combustion engine vehicles [3], [4]. Supported by governmental policies, technological advancements, and continuous improvements in battery performance, the worldwide adoption of EVs is growing at an unprecedented rate. Consequently, the development of an efficient and reliable charging infrastructure has become an essential prerequisite for supporting this transition and ensuring the large-scale deployment of electric mobility [5], [6], [7]. Despite their environmental and economic benefits, the increasing penetration of EVs introduces new operational challenges for electrical distribution networks. Large-scale and uncoordinated charging demand can significantly affect network performance by increasing active and reactive power losses, causing unacceptable voltage deviations, overloading distribution equipment, and reducing the overall reliability and efficiency of the power system [8]. Therefore, the planning of Electric Vehicle Charging Stations has become a critical issue for distribution system operators and urban planners. Appropriate planning strategies are required not only to satisfy the charging demand of EV users but also to preserve the operational security and stability of the electrical grid [9].

The optimal allocation of EVCSs is inherently a complex multi-objective optimization problem involving several conflicting technical and economic criteria. On one hand, utility companies aim to minimize the investment cost associated with installing charging stations, while on the other hand they seek to reduce power losses and maintain an acceptable voltage profile throughout the network. Achieving an appropriate balance among these objectives requires advanced optimization techniques capable of efficiently exploring large and highly nonlinear search spaces while satisfying the operational constraints of the distribution system [10], [11], [12].

To address this, researchers have heavily utilized metaheuristic algorithms. Particle Swarm Optimization (PSO) and the Grey Wolf Optimizer (GWO) are widely applied due to their mathematical simplicity and effectiveness in power flow analyses. However, standard PSO frequently suffers from premature convergence in highly constrained multimodal spaces, losing swarm diversity and trapping solutions in local optima. Conversely, GWO exhibits exceptional localized exploitation but often experiences late-stage stagnation when its leadership hierarchy converges too closely. [13], [14].

Motivated by these challenges, this paper proposes a Hybrid PSO-GWO (HPSOGWO) algorithm to

optimize EVCS placement in a 30-bus distribution system. By embedding the dynamic velocity vectors of PSO into the position updates of the GWO hierarchy, the proposed method sustains kinetic search energy, bypasses local minima, and effectively resolves the optimal load distribution for a mandatory 100-charger grid quota [15], [16]. The objective function is formulated using a weighted-sum approach, and nine different weight configurations are examined to evaluate the influence of the objective priorities on the optimization results and to identify the most suitable weighting combination.

The simulation results demonstrate that the proposed HPSOGWO-based optimization framework efficiently determines the optimal locations and capacities of EV charging stations while maintaining satisfactory technical performance of the distribution network. The obtained solutions achieve an effective compromise between economic and operational objectives, confirming the suitability of HPSOGWO as a reliable optimization tool for modern EVCS planning.

The remainder of this paper is organized as follows. Section 2 presents the problem formulation of the optimization problem together with the system constraints. Section 3 describes the three algorithms selected and their implementation for EVCS planning. Section 4 presents and discusses the simulation results obtained under different weighting configurations. Finally, Section 5 summarizes the main findings of the study and highlights possible directions for future research.

2. Optimization framework

This work presents an optimization framework for the optimal siting and sizing of Electric Vehicle Charging Stations (EVCS) in a 30-bus radial distribution network (Figure 1). [17] The framework consists of three core components: a system model incorporating bus data (load, voltage, and type), line impedance parameters, and candidate installation buses; a multi-objective function that targets investment cost minimization, power loss reduction, and voltage profile improvement using a weighted-sum approach; and a comparative analysis of PSO, GWO, and the hybrid HPSOGWO algorithm, implemented in MATLAB to determine the optimal placement of 100 chargers while balancing economic and technical performance.

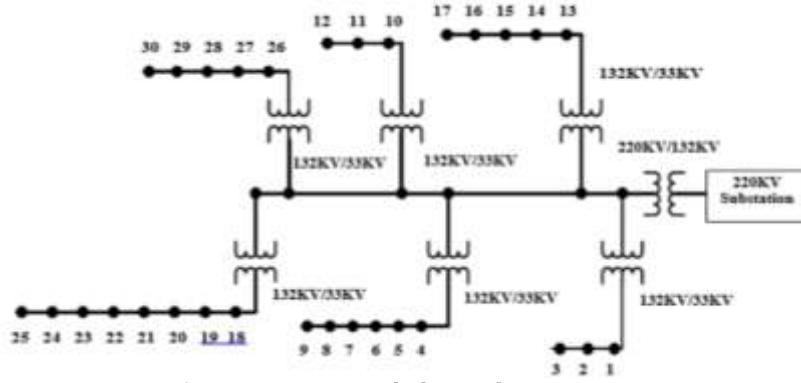


Figure 1. 30-Bus Radial Distribution System

2.1 Problem Formulation

The optimization problem is formulated to minimize a multi-objective cost function F_{min} that encompasses investment expenditures, grid performance indices, and rigid stability penalties.

A. Investment Cost Model

The investment cost for installing and operating charging stations at bus i comprises the base installation cost C_{in} , land rental C_{land} for the footprint of N_i chargers (based on 25 m² per charger), and individual charger development costs C_{dev} , given the charger power capacity C_p . This is represented as:

$$IC_i = C_{in} + 25 \cdot C_{land} \cdot N_i + C_p \cdot C_{dev} \cdot (N_i - 1) \quad (1)$$

where N_i represents the total number of chargers deployed at bus i .

B. Grid Performance Penalty

The electrical impact of EVCS integration is normalized against the base case using three weighted metrics: the Voltage Profile Improvement Index (VP_{II}), the Active Power Loss Ratio (PLR), and the Reactive Power Loss Ratio (QLR). These metrics are defined as follows:

VP_{II} : Measures the cumulative absolute deviation of bus voltages from the nominal value (1.0 p.u.):

$$VP_{II} = \sum_{i=1}^{N_b} |1.0 - V_i| \quad (2)$$

Where N_b is the total number of buses.

PLR : Quantifies the efficiency impact on active power transmission:

$$PLR = P_{loss,EV} / P_{loss,base} \quad (3)$$

QLR : Quantifies the efficiency impact on reactive power transmission:

$$QLR = Q_{loss,EV} / Q_{loss,base} \quad (4)$$

The grid performance penalty function, F_{perf} , is then formulated as:

$$F_{perf} = K \cdot \sum_{i=1}^{N_c} (w_1 \cdot |1.0 - V_{CS,i}| + w_2 \cdot PLR + w_3 \cdot QLR) \quad (5)$$

Where K is a scaling factor used to align the magnitude of the performance penalty with capital investment costs; N_c is the number of candidate buses; w_1, w_2 , and w_3 are weighting factors assigned by the grid operator ($w_1 + w_2 + w_3 = 1$); and $V_{CS,i}$ represents the nodal voltage after EVCS integration.

The comprehensive objective function minimized by the metaheuristic is defined as:

$$F_{min} = \sum_{i=1}^{N_c} IC_i + F_{perf} + \lambda (\sum_{i=1}^{N_b} \Delta V_i^2 + \sum_{i=1}^{N_c} \Delta N_i^2) \quad (6)$$

Where λ is a quadratic penalty multiplier ($\lambda = 10^8$) used to strictly enforce operational constraints; $\sum \Delta V_i^2$ represents the summation of squared voltage violation penalties across all buses in the network (N_b); and $\sum \Delta N_i^2$ represents the summation of squared target demand violation penalties for the charger deployment quota across all candidate buses (N_c). This quadratic penalty approach ensures that any deviation from the operational limits ($0.95 \leq V_i \leq 1.05$ p.u.) or the mandatory deployment quota ($N = 100$) is heavily penalized, forcing the algorithm to prioritize feasible solutions.

2.2 Constraints

To ensure grid stability and reliability, EVCS deployment is subject to the following operational constraints. At each bus i , nodal voltage V_i , active generation P_{gi} , and reactive generation Q_{gi} must remain within their defined limits[18]:

$$\begin{cases} V_i^{min} \leq V_i \leq V_i^{max} \\ P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \\ Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \end{cases} \quad (7)$$

Additionally, the algorithm must satisfy a mandatory total charger deployment quota of $N_{target} = 100$ across a designated set of 14

candidate buses (7, 10, 15, 17, 18–25, 26, and 30). Constraint violations are handled via a quadratic penalty approach within the objective function (Equation 6). The violation magnitudes are defined as:

Voltage Deviation (ΔV_i): If the voltage falls outside the acceptable range [0.95,1.05] p.u., ΔV_i quantifies the magnitude of the breach; otherwise, $\Delta V_i = 0$.

Demand Violation (ΔN): Defined as $\Delta N = \max(N_{target} - \sum_{i=1}^{N_c} N_i, 0)$. If the total installed capacity meets or exceeds 100, $\Delta N = 0$; otherwise, it represents the deficit. Severe quadratic penalties ($\lambda = 10^8$) are applied to these violations, strictly enforcing physical network stability and operator requirements.

3. Optimization algorithms

The techniques utilized to solve the multi-objective optimization problem are discussed in the following sections.

A. Particle Swarm Optimization (PSO)

PSO is a population-based metaheuristic inspired by the social behavior of bird flocking or fish schooling. Each candidate solution is represented as a particle that traverses the search space. Particles adjust their trajectories based on their own personal best experience (p_{Best_i}) and the global best experience (g_{Best}) of the entire swarm.[13],[14],[15]

Velocity Update:

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 (p_{Best_i} - X_i^t) + c_2 r_2 (g_{Best} - X_i^t) \quad (8)$$

Position Update:

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (9)$$

Where ω is the inertia weight, which regulates the influence of the previous velocity; c_1 and c_2 are the acceleration coefficients, representing the cognitive and social components, respectively; and r_1, r_2 are random numbers generated within the range [0,1].

While efficient, the strong social component (g_{Best}) can cause the swarm to converge prematurely on local optima. In the context of EVCS planning, this often manifests as suboptimal solutions characterized by excessive infrastructure costs.[14]

B. Grey Wolf Optimizer GWO

The Grey Wolf Optimizer (GWO), introduced by Mirjalili et al. in 2014 [19], is a gradient-free Swarm Intelligence (SI) algorithm inspired by the social hierarchy and cooperative hunting behavior of grey wolves. It is particularly effective for solving non-differentiable, multimodal, and high-dimensional optimization problems. [13], [19], [20].

Grey wolf packs operate under a strict four-tier leadership structure, which underpins their collective decision-making: the Alpha (α) as the dominant leader, the Beta (β) as the second-in-command, the Delta (δ) as the third-tier subordinate, and the Omega (ω) as the followers. This social structure serves as the conceptual backbone of GWO's search mechanism, where α , β , and δ collectively guide candidate solutions toward increasingly promising regions of the search space.

The hunting mechanism is formalized by the encircling behavior [15],[22]:

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \quad (10)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (11)$$

Where $\vec{X}_p(t)$ denotes the position of the prey (the best current solution), $\vec{X}(t)$ is the current wolf position, and $\vec{A}$ and $\vec{C}$ are coefficient vectors defined as:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (12)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (13)$$

Here, $\vec{a}$ is a control parameter that decreases linearly from 2 to 0 over the iterations, allowing for a transition from broad exploration to fine-grained exploitation, while $\vec{r}_1$ and $\vec{r}_2$ are random vectors uniformly distributed in the range [0,1].

Since the global optimum is unknown, the algorithm assumes the α , β , and δ wolves have superior knowledge. Each search agent updates its position based on the influence of these three leaders [21],[22]:

$$\begin{cases} \vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \\ \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \\ \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \end{cases} \quad (14)$$

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{cases} \quad (15)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (16)$$

Equation (16) computes the new position of each candidate solution as the centroid of the vectors derived from the three leaders. This process, proceeding through iterative fitness evaluation and position updating, preserves a balanced trade-off between exploration and exploitation until the optimal solution is obtained.

C. Hybrid PSO-GWO (HPSOGWO)

A. Hybrid PSO-GWO (HPSOGWO)

The hybrid PSO-GWO (HPSOGWO) methodology synthesizes the broad exploratory velocity of PSO with the targeted exploitation of the GWO. In standard GWO, subordinate wolves update their positions based on the arithmetic mean of the α , β , and δ leaders. In a highly constrained distribution network, this mean-averaging can lead to rapid search space collapse. HPSOGWO replaces this static update with a momentum-driven equation, injecting PSO-driven velocity vectors

into the position updates of the subordinate agents. This maintains search diversity, prevents premature convergence, and effectively resolves the optimal load distribution for the mandatory 100-charger grid quota.[14],[15],[22].

The hybrid velocity and position updates are represented as:

$$\vec{V}_i(t+1) = \omega \vec{V}_i(t) + c_1 r_1 (\vec{X}_\alpha - \vec{X}_i(t)) + c_2 r_2 (\vec{g}_{Best} - \vec{X}_i(t)) \quad (17)$$

$$\vec{X}_i(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} + \vec{V}_i(t+1) \quad (18)$$

Where $\vec{X}_1$, $\vec{X}_2$, and $\vec{X}_3$ are the positions derived from the three leaders (α, β, δ) as defined in the GWO methodology (Equations 14-16). The inclusion of $\vec{V}_i(t+1)$ in Equation (18) allows the swarm to retain the social momentum of PSO while being steered by the hierarchical guidance of the GWO leaders, ensuring a robust balance between exploration and exploitation.

The pseudo-code of HPSOGWO is presented in Algorithm 1.

Algorithm 1. The HPSOGWO Pseudo-Code

- **Step 1: System Initialization:** Load the 30-bus radial distribution network parameters, including line impedance matrices (Z_{ij}), bus load demands, the fourteen predefined candidate buses, and algorithm parameters (population size, max iterations).
- **Step 2: Population Generation:** Initialize a population of search agents. Each agent's position vector represents the charger allocation at candidate buses. Initialize PSO velocity vectors for all agents to zero.
- **Step 3: Fitness Evaluation:** Execute load flow analysis for each agent's configuration. Calculate the comprehensive objective function (F_{min}), applying quadratic penalty multipliers λ to agents violating voltage limits or falling below the N_{target} (100) charger quota.
- **Step 4: Hierarchical Assignment:** Rank the population by fitness; designate the three best agents as the α , β , and δ leaders.
- **Step 5: Hybrid Position Update:**
 - **GWO Guidance:** Calculate the directional influence vectors toward the α , β , and δ leaders.
 - **Velocity Injection:** Update the agent velocity ($\vec{V}_i$) using modified PSO coefficients directed toward the identified GWO leaders.
 - **Position Update:** Calculate the new agent position using the hybrid update rule (Equation 18).
- **Step 6: Constraint Clamping:** Apply boundary conditions to ensure all charger counts (N_i) adhere to defined feasibility limits.
- **Step 7: Termination:** If the maximum iteration limit (maxIter) is reached, output the optimal siting and sizing configuration (X_{best}); otherwise, return to Step 3.

4. Results and discussion

This section evaluates the performance of the HPSOGWO algorithm in determining the optimal siting and sizing of Electric Vehicle Charging Stations (EVCSs) within the 30-bus distribution network. The optimization process leverages the proposed objective function and operational constraints to minimize installation costs while ensuring network reliability. The results are analyzed to assess the algorithm's convergence behavior, solution quality, and overall

effectiveness. Figure 3 illustrates the electrical characteristics of the test system, including voltage set points magnitude V_{sp} , while PL_i and QL_i denote the active and reactive power demands, respectively, alongside the categorization of buses into residential, light industrial, and heavy industrial regions. The bus types indicate the function of each bus in the power flow analysis, where Type 1 is the slack bus, Type 2 is the generator (PV) bus, and Type 3 is the load (PQ) bus. The simulation demonstrates that HPSOGWO effectively identifies optimal EVCS placement,

achieving a balanced minimization of installation costs and operational penalties.

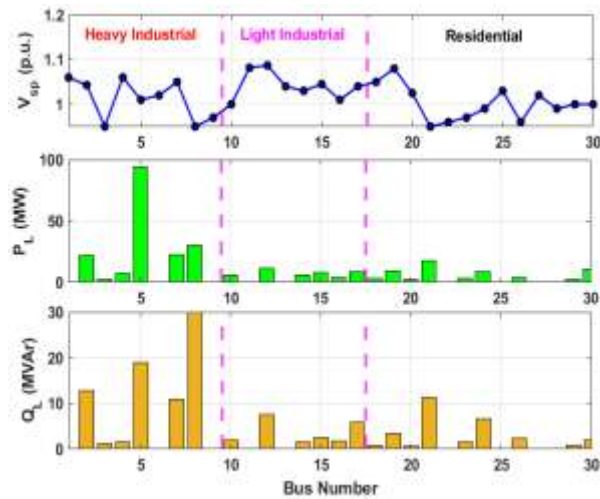


Figure 3. Electrical data of the simulated 30-bus distribution network

The algorithm exhibits stable convergence; however, sensitivity analysis reveals that the solution quality is highly dependent on the weighting coefficients (w_1, w_2, w_3), as illustrated in Figure 4. Analysis demonstrates that Case 4 ($w_1 = 0.4, w_2 = 0.5, w_3 = 0.1$) achieves technical performance nearly identical to Case 3 ($w_1 = 0.1, w_2 = 0.6, w_3 = 0.3$), with power losses of 18.076 MW and 18.075 MW, respectively—a variance of less than 0.006%. Notably, Case 4 provides a superior balance in investment expenditure (\$2.0 million vs. \$2.6 million in Case 3). This confirms that Case 4 represents a more

efficient use of resources, maximizing grid stability while maintaining fiscal responsibility.

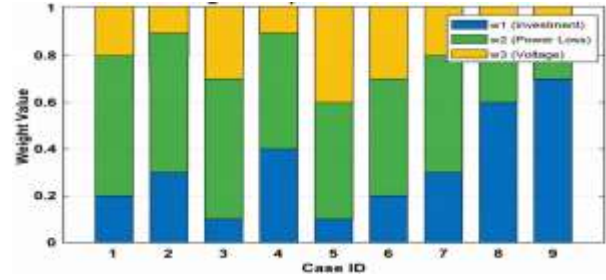


Figure 4. Objective Function Weight Coefficients for Different Cases.

Consequently, Case 4 serves as the optimal techno-economic compromise between infrastructure cost and grid efficiency. Table 1 summarizes the impact of weight configurations on power losses, assuming a mandatory 100-charger quota across all nine cases. Furthermore, Figure 5 validates the robustness of the HPSOGWO framework, demonstrating its ability to consistently satisfy the deployment quota while optimizing system stability across all weight configurations.

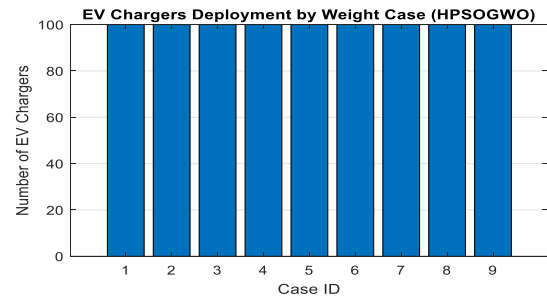


Figure 5. Optimal EV Charger Deployment for Different Weight Cases.

Table 1. Impact of Weight Values on EV Charger Deployment and Power Loss.

Case	w_1	w_2	w_3	Active power Loss (MW)	Reactive Power Loss (MVar)	No. Of EV chargers
1	0.2	0.6	0.2	18.078	72.310	100
2	0.3	0.6	0.1	18.076	72.305	100
3	0.1	0.6	0.3	18.075	72.301	100
4	0.4	0.5	0.1	18.076	72.303	100
5	0.1	0.5	0.4	18.075	72.299	100
6	0.2	0.5	0.3	18.075	72.300	100
7	0.3	0.5	0.2	18.077	72.307	100
8	0.6	0.3	0.1	18.079	72.316	100
9	0.7	0.2	0.1	18.078	72.313	100

Analysis demonstrates that a power loss weight of $w_2 \geq 0.5$ consistently produces the most favorable optimization results, confirming that active power loss reduction is the critical determinant of the objective function. The impact of these configurations on system efficiency is illustrated in Figure 6, which plots active power loss across all nine cases. It is observed that weight configurations prioritizing active power loss reduction ($w_2 \geq 0.5$)

generally yield lower loss profiles, as evidenced by the local minima achieved in Case 5 (18.0747 MW) and Case 3 (18.075 MW). Conversely, configurations that shift priority toward higher investment weights (w_1) demonstrate an upward trend in power dissipation, peaking in Case 8 (18.079 MW). This sensitivity analysis confirms that while all configurations successfully maintain operational stability, assigning a higher relative

weight to active power losses is essential to achieving superior system performance.

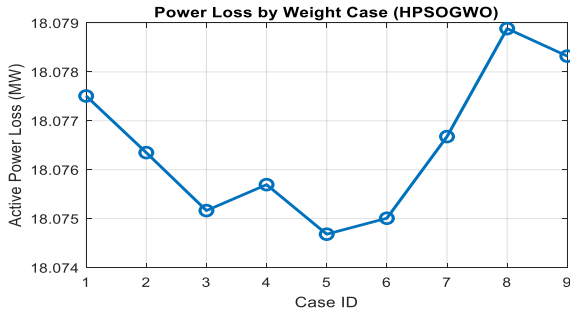


Figure 6. Active Power Loss Under Different Weight Cases.

The optimized power losses remain within 0.42% to 0.44% of the base case (18.00 MW), demonstrating that the integration of EV charging stations has a negligible impact on system performance when the proposed optimization strategy is adopted. Furthermore, the HPSOGWO algorithm demonstrates rapid convergence, consistently reaching optimal solutions within 20 iterations. The relationship between the mandatory 100-charger deployment across the 14 candidate buses and the resulting active power loss is further examined in Figure 7, which highlights the trade-

off between infrastructure investment and grid efficiency.

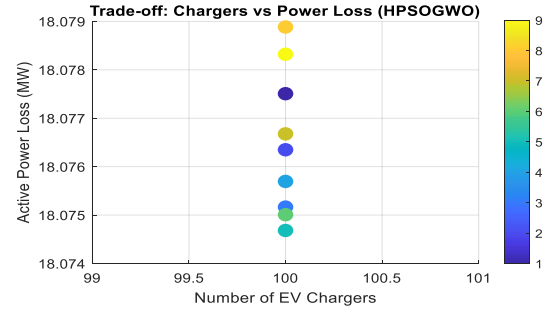


Figure 7. Trade-off Between EV Charger Deployment and Active Power Loss.

Figure 8 illustrates the convergence curves for the HPSOGWO algorithm across all nine weight configurations. The algorithm consistently achieves a rapid decline in the objective function value within the first 20 iterations before reaching a steady-state. This performance confirms the HPSOGWO's fast convergence and its ability to escape local optima during the initial search stages. While Case 9 ($w_1 = 0.7, w_2 = 0.2, w_3 = 0.1$) yielded the lowest final cost, Case 3 exhibited higher costs with a narrower improvement range. Overall, these profiles validate the numerical stability and reliability of the HPSOGWO across diverse objective function priorities.

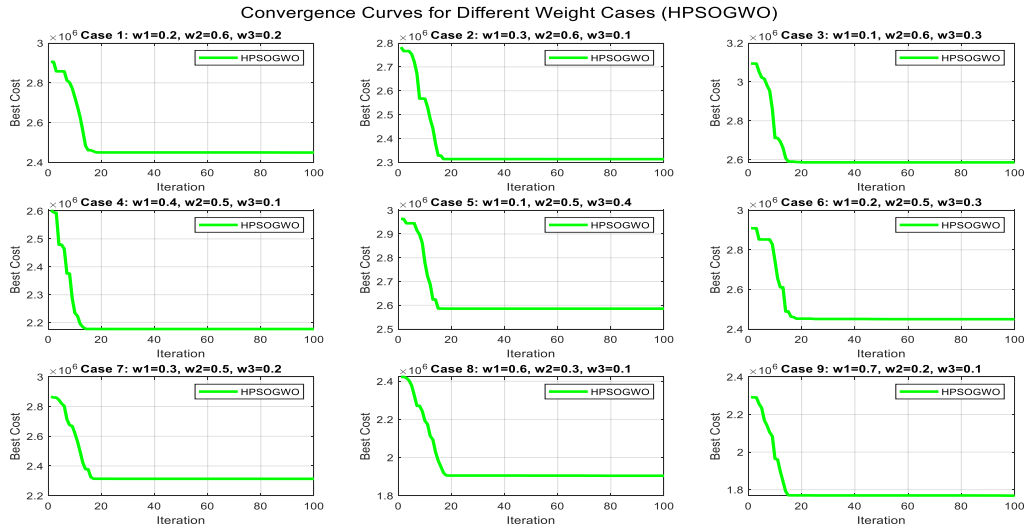


Figure 8. Convergence Curves of the HPSOGWO Algorithm for Different Weight Configurations.

Figure 9 provides a comprehensive performance evaluation of the implemented metaheuristic algorithms. The 'Final Cost Comparison' demonstrates that HPSOGWO consistently outperforms PSO and GWO across all weight configurations, achieving the lowest objective costs. Furthermore, the 'Convergence Comparison' illustrates the superior exploration-exploitation balance of HPSOGWO, effectively avoiding the

premature convergence observed in standard PSO and GWO. The 'Algorithm Ranking' confirms that HPSOGWO is the most effective approach for the EVCS placement problem, offering a robust solution that maximizes techno-economic efficiency.

As illustrated in Figure 10, voltage deviations from the nominal 1.0 p.u. are maintained at or below the 0.05 p.u. threshold across all buses. This ensures

that the voltage at every node remains within the secure operational limits, validating the robustness

of the HPSOGWO optimization in maintaining system power quality.

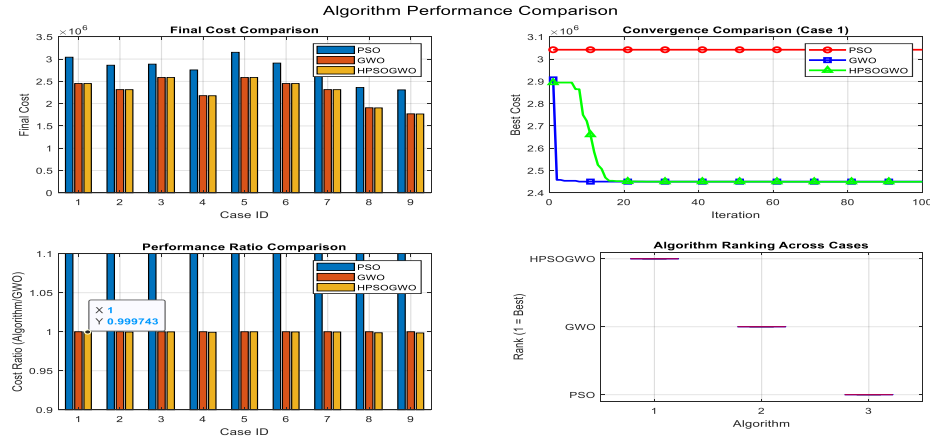


Figure 9. Algorithm performances and ranging

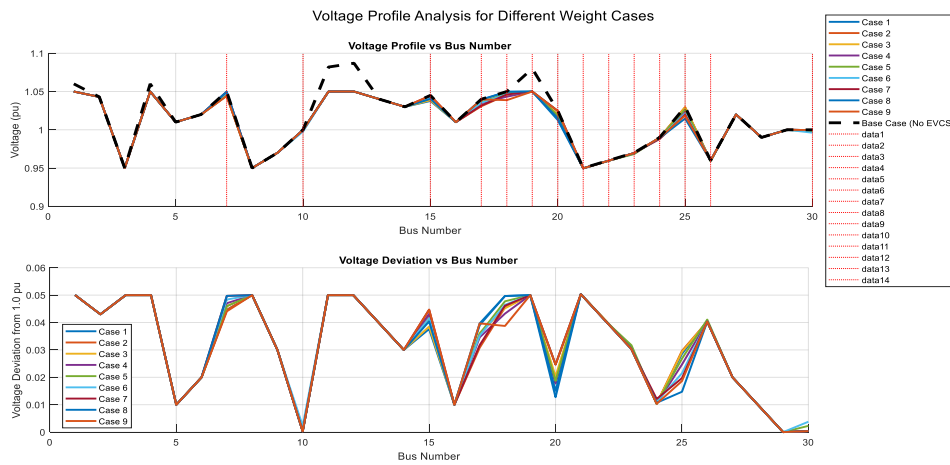


Figure 10. Voltage Profile and Voltage Deviation Versus Bus Number.

5. Conclusion

This study confirms that the HPSOGWO is a highly effective and reliable approach for EVCSs integration in radial distribution networks. Across all nine tested weighting configurations, the algorithm exhibited rapid convergence, numerical stability, and consistent solution quality, confirming its robustness for this class of complex, non-linear optimization problems.

The results establish that the hybrid methodology consistently reaches the global minimum cost and satisfies all technical constraints, including the mandatory 100-charger quota and voltage regulation limits, with higher efficiency than the parent metaheuristics. This performance confirms the algorithm's suitability as a robust decision-support tool for utility operators and sustainable distribution network expansion.

Future work should incorporate stochastic EV arrival models to further refine grid-responsive planning. Additionally, integrating real-time pricing mechanisms, predictive demand models for

charging load fluctuations, and environmental objectives will enhance the practical applicability of the framework. Comprehensive economic feasibility analyses should be conducted to support sustainable and scalable deployment of EV charging infrastructure in real distribution networks.

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