



A Metaheuristic Approach for EV Charging Station Planning in Distribution Networks: Performance Comparison of PSO, GWO, and ALO

Amal Menasria^{1, 2,*}, Othmane Abdelkhalek¹, Brahim Gasbaoui¹, Messaoud Hamouda², Mohammed Bouzidi³

¹Smart Grids & Renewable Energies Laboratory SGRE-L, Tahri Mohamed University - Bechar, Algeria

²Sustainable Development and Computer Science Laboratory LDDI, University - Adrar, Algeria

³Department of Sciences and Technology, Faculty of Sciences and Technology, University of Tamanrasset, Algeria

Correspondance e-mail: menasria2008@univ-adrar.edu.dz

Abstract: - The optimal planning of Electric Vehicle Charging Stations (EVCS) is crucial for the stable and efficient operation of power distribution networks. This study presents a comparative analysis of meta-heuristic algorithms for solving the EVCS placement and sizing problem on a 30-bus distribution system. The objective is to minimize a composite cost function that balances initial investment costs against technical performance indicators, including active power loss, reactive power loss, and voltage profile improvement. Three algorithms—Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Lion Optimizer (ALO)—are evaluated and compared across nine different weight combinations for the objective function. Results demonstrate that the GWO algorithm significantly outperforms both PSO and ALO, achieving the lowest overall cost of 1,017,050 with a strategically conservative deployment of only 14 chargers. In contrast, PSO and ALO converged on higher-cost solutions (1,678,877 and 1,915,035 respectively) with excessive charger deployments (340 and 270 chargers). A sensitivity analysis on the weight parameters confirms that solutions prioritizing power loss reduction (higher w_2) yield the most favorable techno-economic outcomes. The findings conclusively establish GWO as a superior and more efficient algorithm for the EVCS planning optimization problem, offering a solution that minimizes cost while maintaining grid performance.

Keywords: electric vehicle charging stations, optimal planning, distribution network, meta-heuristics.

1. Introduction

The global transition towards electric vehicles (EVs) is a cornerstone of strategies to decarbonize the transportation sector. However, this shift presents a significant challenge for existing electrical power distribution systems [1-6]. The uncoordinated placement and sizing of Electric Vehicle Charging Stations (EVCS) can lead to severe network problems,



including increased power losses, voltage violations, transformer overloads, power quality problem and overall reduced system reliability [1,2,5,14,15]. Consequently, determining the optimal locations and sizes for EVCS is not merely an economic decision but a critical engineering problem essential for ensuring the stable and efficient operation of the power grid. [16,17].

This complex problem involves balancing high capital investment costs against the desired technical performance of the distribution network. It is a high-dimensional, non-linear optimization problem with multiple constraints, making it unsuitable for traditional mathematical programming techniques. Metaheuristic algorithms have emerged as powerful tools for solving such complex engineering problems. This study focuses on the optimal planning of EVCS in a 30-bus Allahabad distribution system [3,4]. It conducts a comparative analysis of three prominent meta-heuristic algorithms—Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), and Ant Lion Optimizer (ALO)—to identify the most efficient approach for minimizing total cost while maintaining acceptable grid performance levels.

The remainder of this paper is organized as follows. Section 2 details the Methodology, with Subsection 2-A formally presenting the Objective Function and Problem Formulation for the EVCS placement problem. Section 3 provides a theoretical background of the three Meta-heuristic algorithms employed: Grey Wolf Optimizer, Particle Swarm Optimization, and the Ant Lion Optimizer. Section 4 presents the Simulation Results and Discussion, offering a comparative analysis of the algorithms' performance and a sensitivity analysis of the objective function weights. Finally, Section 5 concludes the paper by summarizing the key findings and contributions.

2. Methodology And Objectives

The overall methodology for this research can be summarized in the following key steps:

- **System Modeling:** A standard 30-bus radial distribution network is modeled (Fig.1), including bus data (load, voltage, and type), line data (impedance), and candidate bus locations for EVCS installation.
- **Problem Formulation:** A multi-objective function is defined that encapsulates the three core objectives: minimization of investment cost, minimization of active and reactive power losses, and improvement of voltage profile. This is converted into a single objective using a weighted sum approach.
- **Algorithm Implementation:** The three meta-heuristic algorithms (GWO, PSO, ALO) are implemented in MATLAB. Each algorithm is designed to search for the optimal number of chargers at each candidate bus.

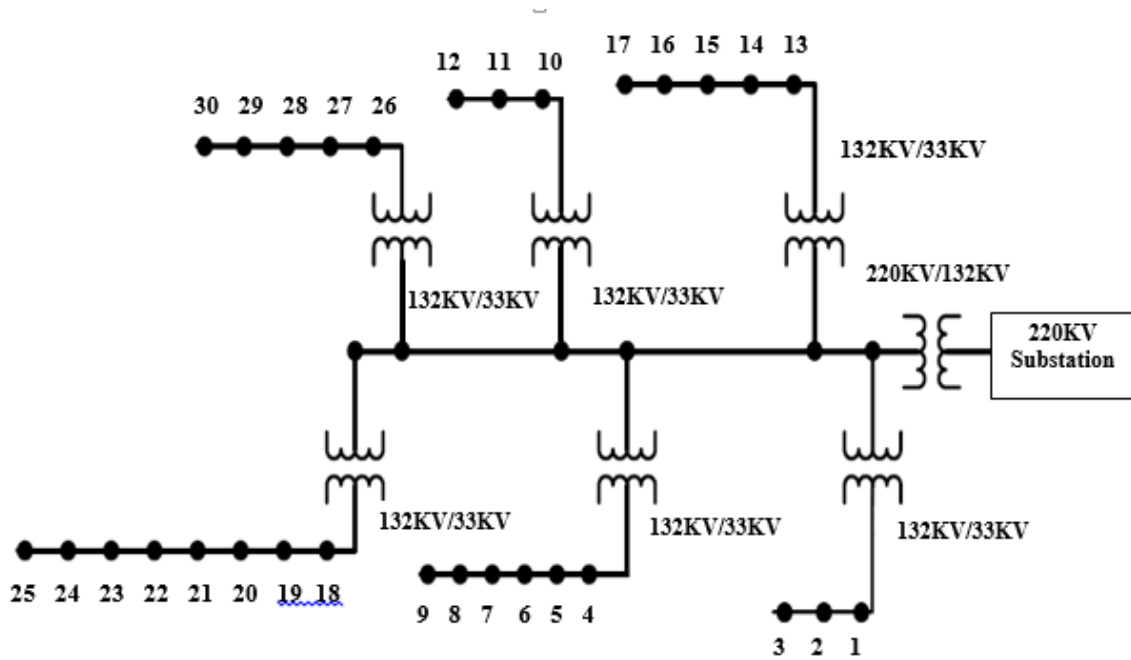


Fig. 1. 30 bus radial distribution system

2.1 Objective function and problem formulation

The core of the optimization problem is to minimize a total cost function, F_{min} , which is a weighted sum of the investment cost and a performance term that encapsulates technical grid metrics [3, 4]. (Eq. 1) presents the objective function

$$f_{min} = \sum(I_{ci}X_i) + \sum F_i \quad (1)$$

Where Investment Cost (I_{ci}): The cost of installing and operating a station at bus i .

$$I_{ci} = C_{in} + 25 \times C_{land} \times N_i + C_p \times C_{dev} (N_i - 1) \quad (2)$$

The required area for each connector assumed 25 m^2

C_{in} : Initial investment cost (70,000).

C_{land} : Land rental cost per m^2 (100).

C_p : Charger power of connector (4.8 kW).

C_{dev} : Development cost of connector per kW (208.33).

N_i : Number of chargers at bus i .

X_i : A binary variable (1 if $N_i > 0$, 0 otherwise).



Performance Term (F_i): A function that penalizes solutions based on their technical performance.

$$F_i = \frac{1}{w_1 VPII_i + w_2 PLRI_i + w_3 QLRI_i} \quad (3)$$

Where, w_1, w_2, w_3 : Weight coefficients in which ($w_1 + w_2 + w_3 = 1$).

In order to confirm the robustness and the power quality of this studied distribution system, three stability indices are used:

- *Voltage Profile Improvement Index (VPII_i)*

The voltage of the nodes must be kept within acceptable limits as large deviations cause superfluous increasing for the voltage control equipment cost or changing in the grid infrastructure. [3, 4]

$$VPII_i = \frac{1}{a + \max_{i=2}^n (|1 - V_{(csi)}|)} \quad (4)$$

Where, $V_{(csi)}$ is the voltage at i th bus after connection of the charge station. a is a scalar value.

- *Real Power Loss Reduction Index (PLRI_i)*

The connection of the EVCS to the grid enhances the power losses. The formulation of the PLRI is as follows:

$$PLRI_i = \frac{P_{loss(base)} - P_{loss(CS_i)}}{P_{loss(base)}} \quad (5)$$

Where, where, $P_{loss(base)}$ and $P_{loss(CS_i)}$ represent the active power losses of the system before and after the connection of the charging station respectively. $P_{loss(base)}$ is calculated by using load flow equations.

- *Reactive Power Loss Reduction Index (QLRI_i)*

The voltage stability of the grid can be maintained as long as reactive power losses within the system remain below a critical threshold. To address this requirement, the QLRI has been incorporated into the objective function, where it is formally defined as follows:

$$QLRI_i = \frac{Q_{loss(base)} - Q_{loss(CS_i)}}{Q_{loss(base)}} \quad (6)$$

Where, $Q_{loss(base)}$ represents the reactive power losses before the connection (calculated by using load flow equations.) and $Q_{loss(CS_i)}$ describe the reactive power losses after the connection of the charging station.



2.2 constraints

The constraints below are designed to ensure that the development of charging station infrastructure does not undermine the stability or reliability of Allahabad electrical network. [3,11]

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

$i = 1, 2, \dots, N$

Where, V_i^{min} and V_i^{max} describe the minimum and maximum values for the voltage level on the i th bus, respectively; P_{gi}^{min} and P_{gi}^{max} signify the minimum and maximum limits for the active power generation; Q_{gi}^{min} and Q_{gi}^{max} define the maximum and minimum limits for reactive power generation.

Constraint (8) represents the active power balance at bus i where P_{gi} and P_{di} are the active power of the generation and demand loads respectively at i th bus. While Y_{ij} is the magnitude of j th term of the bus admittance matrix. δ_i , δ_j and θ_{ij} are the angles of Y_{ij} , the voltage angle of i th bus. Constraint (9) represents the balance of the reactive power at i th bus where i and j are bus indexes and N is the total number of buses. In addition, Q_{gi} and Q_{di} are the reactive power of the generation and demand loads, respectively. [1, 9]

$$P_{gi} - P_{di} - V_i \sum_{j=i}^N V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \quad (8)$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=i}^N V_j Y_{ij} \sin(\delta_i - \delta_j - \theta_{ij}) = 0 \quad (9)$$

Chargers per Station:

$$N_i^{min} \leq N_i \leq N_i^{max} \quad (10)$$

Each charging station is equipped with at least one connector, i.e.

$$N_i \geq X_i \quad (i = 1, 2, \dots, N_C) \quad (11)$$

3. Metaheuristics

3.1 Grey Wolf Optimizer (GWO)

GWO is developed by Mirjalili et al, in 2014[8]. GWO is inspired by the social hierarchy and hunting mechanism of grey wolves figure 2. The population is divided into four types: Alpha (α , the best solution), Beta (β), Delta (δ), and Omega (ω). The hunting (optimization) is guided by α , β , and δ . [7,15]



Encircling Prey: Wolves update their positions around the prey (the best solution found so far)

Hunting: The ω wolves update their positions based on the average position of α, β , and δ . This creates a search strategy that balances exploration (searching new areas) and exploitation (refining existing good solutions). [10]

The GWO algorithm is briefly described in the following steps:

- **Step 1:** Reset GWO parameters such as search agents (G_s), design variable size (G_d), vectors \vec{a} , \vec{A} , \vec{C} and maximum number of iterations.

$$\vec{A} = 2\vec{a}r_1 - \vec{a} \quad (12)$$

$$\vec{C} = 2r_2 \quad (13)$$

The values of \vec{a} are decreased linearly from 2 to 0 during the iterations. r_1 and r_2 are the random vectors that fall between 0 and 1.[7]

- **Step 2:** Generate random wolves based on pack size. Mathematically, these wolves can be expressed as,

$$Wolves = \begin{bmatrix} G_1^1 & G_{G_d-1}^1 & G_{G_d}^1 \\ G_1^{G_s} & G_{G_d-1}^{G_s} & G_{G_d}^{G_s} \end{bmatrix} \quad (14)$$

Where, G_{ij} is the initial value of the i th pack of the i th wolves.

- **Step 3:** Estimate the fitness value of each hunting agent.

$$\vec{D} = |\vec{C}\vec{G}_p(t) - \vec{G}(t)| \quad (15)$$

$$\vec{C}(t+1) = \vec{G}_p(t) - \vec{A}\vec{D} \quad (16)$$

- **Step 4:** Identify the best hunting agent (G_α), the second best hunting agent (G_β) and the third best hunting agent (G_δ).

$$\vec{D}_\alpha = |\vec{C}_1\vec{G}_\alpha - \vec{G}| \quad (17)$$

$$\vec{D}_\beta = |\vec{C}_2\vec{G}_\beta - \vec{G}| \quad (18)$$

$$\vec{D}_\delta = |\vec{C}_3\vec{G}_\delta - \vec{G}| \quad (19)$$

$$\vec{D}_1 = \vec{G}_\alpha - \vec{A}_1(\vec{D}_\alpha) \quad (20)$$

$$\vec{D}_2 = \vec{G}_\beta - \vec{A}_2(\vec{D}_\beta) \quad (21)$$



$$\vec{D}_3 = \vec{G}_\delta - \vec{A}_3(\vec{D}_\delta) \quad (22)$$

- **Step 5:** Renew the current search agent location using the following equation:

$$\vec{G}(t + 1) = \frac{\vec{G}_1 + \vec{G}_2 + \vec{G}_3}{3} \quad (23)$$

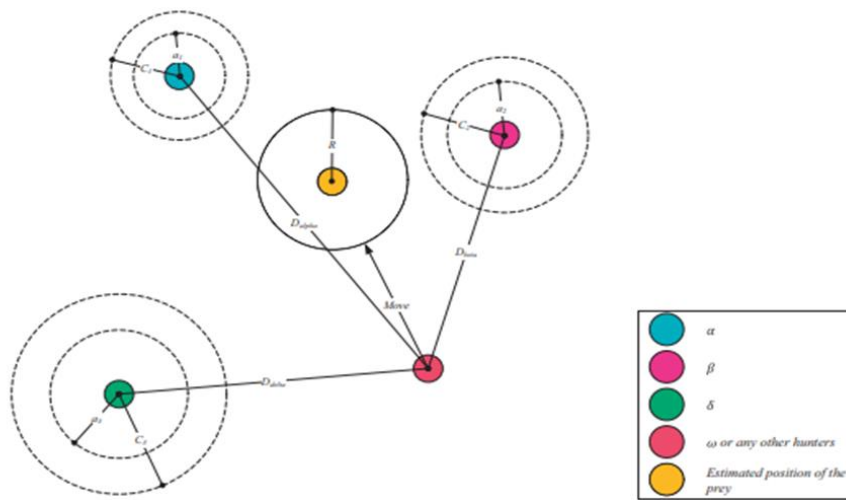


Fig. 2. Position updating in GWO [8]

This hierarchical guidance prevents the population from rushing towards a local optimum (a problem in PSO) and allows for a more controlled and effective search of the solution space, which is why it found the most cost-effective solution with only 14 chargers.

3.2 Particle Swarm Optimization (PSO)

PSO is inspired by the social behavior of bird flocking or fish schooling. Each solution is a particle that flies through the search space. Figure 3

Each particle adjusts its trajectory based on its own personal best experience (p_{Best}) and the global best experience (g_{Best}) of the entire swarm.[11,12]

Velocity Update:

$$V_i(t + 1) = w \times V_i(t) + c_1 * rand() \times (p_{Best_i} - x_i(t)) + c_2 * rand() \times (g_{Best} - x_i(t)) \quad (24)$$

Position Update:

$$x_i(t + 1) = x_i(t) + v_i(t + 1) \quad (25)$$



Where w is the inertia weight, which controls how much the velocity of the particle is influenced by its previous velocity; c_1 and c_2 are acceleration coefficients, which control how much the velocity of the particle is influenced by its personal best position and the global best position, respectively, where $\text{rand}()$ generates a random number between 0 and 1.[12]

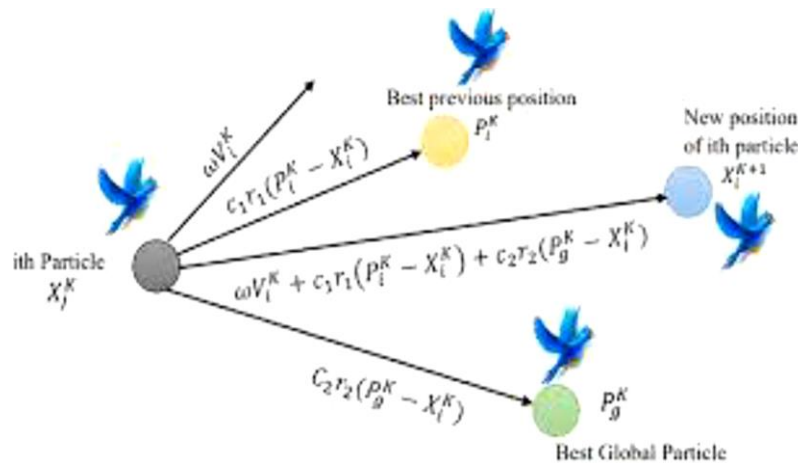


Fig.3. PSO principle

The strong social component (g_Best) can cause the entire swarm to converge prematurely on the first promising solution found, often a local optimum. This explains its higher cost and excessive charger deployment.

3.3 Ant Lion Optimizer (ALO)

ALO mimics the interaction between antlions (predators) and ants (prey) in traps. It is introduced by Seydali Mirjalili to solve constrained engineering optimization problems. Antlions build traps proportional to their fitness, and ants move randomly within the search space. [13]

Traps: Fitter antlions (good solutions) build larger traps, attracting more ants.

Random Walks: Ants (candidate solutions) move stochastically. If an ant becomes fitter than an antlion, it is caught and replaces that antlion.

Elitism: The best antlion (elite) is always saved and influences the random walks of all ants.

The ALO behavior is expressed mathematically by the following equations:

$$X(t) = [0, \text{cumsum}(2r(t_1) - 1), \dots, \text{cumsum}(2r(t_n) - 1)] \quad (26)$$

Where $X(t)$ is the ant random walk, n is the max_iterations , t is the random walk step size, and $r(t)$ is a function defined as follows:

$$r(t) = \begin{cases} 1 & \text{if } \text{rand} > 0.5 \\ 0 & \text{if } \text{rand} < 0.5 \end{cases} \quad (27)$$



Where $rand$ is a randomly generated number uniformly distributed in the range $[0, 1]$. The following steps describe the five main phases in hunting technique of ant lions:

a) *Random walk of ants*

In every step of optimization, ants update their positions b to a random walk search to ensure that all the positions of ants are inside the boundary of the search space, they are normalized by using the following expression:

$$X_i^t = \frac{(x_i^t - a_i)(d_i^t - c_i^t)}{b_i - a_i} \quad (28)$$

Where the a_i ; b_i are respectively the minimum and maximum of random walk corresponding of i th variable. c_i^t ; d_i^t are respectively indicated the minimum and maximum of i th variables at t th iteration.

b) *Trapping in antlions traps*

The following equation describes the effect of antlions traps on random walks of ants:

$$C_i^t = Antlion_j^t + C^t \quad (29)$$

$$d_i^t = Antlion_j^t + d^t \quad (30)$$

Where C^t is the minimum of all variables at t th iteration and d^t represents the vector including the maximum of all variables at t th iteration respectively, C_i^t and d_i^t are the minimum and the maximum of all variables for i th ant respectively, and $Antlion_j^t$ shows the position of the selected j th ant-lion at t th iteration

c) *Building traps*

ALO uses the roulette wheel selection operator to choose antlions based on their fitness.

d) *Sliding ants against toward antlion*

Antlions are able to construct traps proportional to their fitness and the ants move near of the center of pit. Once antlions catch an ant in trap, they will shoot the sand outward the middle of the trap. This mechanism mathematically modeled as follow, where I is the ratio.

$$C^t = \frac{c^t}{I} \quad (31)$$

$$d^t = \frac{d^t}{I} \quad (32)$$

e) *Catching preys and rebuilding the traps*

The catching the ants by predator and rebuilding the pit in order to catch new prey can be described with the following equations.



$$Antlion_j^t = Ant_i^t, \text{ if } f(Ant_i^t) > f(Antlion_j^t) \quad (33)$$

Where t represents the current iteration, $Antlion_j^t$ indicates the position of selected j th antlion at t th iteration and Ant_i^t shows the position of i th ant at t th iteration.

f) Elitism

Elitism is one of the most important characteristic of evolutionary algorithms. In ALO algorithm, at any iteration the best antlion obtained (solution) is saved as an elite. The elitism mechanism mathematically described as follows.

$$Antlion_j^t = \frac{R_A^t + R_E^t}{2} \quad (34)$$

Where, R_A^t is the random walk around the antlion is selected by using the roulette wheel at t th iteration, R_E^t is the random walk around the elite at t th iteration, and Ant_j^t denote the position of i th ant in t th iteration.

The highly random nature of the ants' walks, while good for exploration, might be less efficient for this specific problem's solution space structure, leading to slower convergence and the worst overall result.

4. Results and discussion

This section presents the comprehensive simulation results of applying the PSO, GWO, and ALO algorithms to the EVCS placement problem, followed by a detailed discussion of their comparative performance. The simulation findings from optimizing the 30-bus distribution system are detailed here, highlighting the significant cost and performance disparities identified between the meta-heuristic algorithms under investigation. Following the methodological framework, the simulation outcomes provide a clear answer to the core research question, demonstrating the superior efficacy of the GWO algorithm in achieving a cost-optimal and technically sound EVCS configuration. A thorough analysis of the simulation data is undertaken to dissect the convergence behavior, solution quality, and operational impact of each algorithm, offering critical insights into their practical suitability for this optimization problem. Building upon the established objective function and

Algorithmic parameters, this segment discuss the realized performance of each optimization technique, linking their operational mechanisms to the final quantitative results.

The table below show the data of the simulated network.



Table 1. Data of the simulated power network

Bus	Type	$V_{sp}(p.u)$	$PL_i(MW)$	$QL_i(MVar)$	Region Type
1	1	1.06	0	0	Heavy Industrial Region
2	2	1.043	21.7	12.7	
3	3	0.95	2.4	1.2	
4	3	1.06	7.6	1.6	
5	2	1.01	94.2	19.0	
6	3	1.02	0	0	
7	3	1.05	22.8	10.9	
8	2	0.95	30	30	
9	3	0.97	0	0	
10	3	1.0	5.8	2.0	Light Industrial Region
11	2	1.082	0	0	
12	3	1.087	11.2	7.5	
13	2	1.04	0	0	
14	3	1.03	6.2	1.6	
15	3	1.045	8.2	2.5	
16	3	1.01	3.5	1.8	
17	3	1.04	9.0	5.8	
18	3	1.05	3.2	0.9	Residential Region
19	3	1.08	9.5	3.4	
20	3	1.025	2.2	0.7	
21	3	0.95	17.5	11.2	
22	3	0.96	0	0	
23	3	0.97	3.2	1.6	
24	3	0.99	8.7	6.7	
25	3	1.03	0	0	
26	3	0.96	3.5	2.3	
27	3	1.02	0	0	
28	3	0.99	0	0	
29	3	1.0	2.4	0.9	
30	3	1.0	10.6	1.9	

Where, type defines the role of the bus in the power flow calculation.

Type 1: Slack Bus (or Reference Bus). There is usually only one of these in a system. Its voltage magnitude and angle are fixed, and it makes up for all the system losses. It is the reference for all voltage angles.

Type 2: Generator Bus (PV Bus). At these buses, the generator controls the voltage magnitude and the real power outputs are specified.



Type 3: Load Bus (PQ Bus). These are the most common. The real power and reactive power consumed by the load at this bus are specified.

-Vsp (p.u.) - Voltage Setpoint (in per unit). This is the specified voltage magnitude for the bus.

For Slack (Type 1) and Generator (Type 2) buses, this is the target voltage that the generator is set to maintain.

For Load (Type 3) buses, this is typically an initial guess or desired value for the power flow algorithm to start its calculations with. The final calculated voltage will likely be different.

-PLi (MW) is the amount of real power being consumed by the electrical load.

If the value is 0, it means there is no load connected at that specific point.

-QLi (MVar) is the amount of reactive power consumed by the load.

-Region Type is an additional, non-standard categorization specific. It groups buses into broader geographical:

The optimization analysis according to Figures 4-7 demonstrates that the GWO consistently outperforms both PSO and ALO across all weight configurations for EV charging station placement. GWO achieved significantly lower objective function costs while maintaining better power system performance indicators.

➤ Algorithm Performance Ranking

a. GWO - Rank 1

- Average Cost: 695,614.9
- Performance: Superior in all 9 cases
- Cost Advantage: 62-78% lower than competitors
- Consistency: Stable convergence across multiple runs

b. PSO - Rank 2

- Average Cost: 1,633,992.5
- Performance: Moderate, but significantly worse than GWO
- Limitation: High variance between runs (1.7M-1.8M range)

c. ALO - Rank 3

- Average Cost: 1,838,395.4
- Performance: Consistently the poorest performer
- Issue: Highest costs with limited improvement

➤ Detailed Case Analysis (Table 2 in below)

Case 1 ($w_1 = 0.2$, $w_2 = 0.6$, $w_3 = 0.2$) - Optimal Balance

- GWO Cost: 456,448.92 (62 chargers)



- PSO Cost: 1,708,867.95 (213 chargers)
- ALO Cost: 1,831,873.80 (248 chargers)
- GWO Advantage: 73.3% lower cost than PSO

Case 3 ($w_1 = 0.1$, $w_2 = 0.6$, $w_3 = 0.3$) - Best Overall Performance

- GWO Cost: 209,911.20 (28 chargers) - Lowest achieved
- Key Insight: Higher weight on voltage profile ($w_1 = 0.3$) yields optimal results
- System Impact: Minimal power loss increase (18.02 MW vs base 18 MW)

Case 2, 7-9 (High Investment Weight) - Conservative Approach

- Pattern: GWO consistently selects 14 chargers
- Strategy: Minimal infrastructure investment
- Trade-off: Lower upfront cost but potentially insufficient capacity

➤ Weight Configuration Insights

Voltage profile Weight (w_1) Impact

- High w_1 (0.6-0.7): Results in minimal charger deployment (14 units)
- Low w_1 (0.1-0.2): Allows more aggressive infrastructure (28-62 units)
- Optimal Range: $w_1 = 0.1 - 0.3$ balances investment and performance

➤ Power Loss Weight (w_2) Dominance

- High w_2 (0.6): Consistently produces best results
- Observation: Power loss reduction is the most critical factor
- Recommendation: Maintain $w_2 \geq 0.5$ for optimal system performance

➤ Reactive power loss Weight (w_3) Role

- Moderate w_3 (0.2-0.3): Enhances solution quality
- Case 3 Evidence: $w_3 = 0.3$ achieved lowest overall cost
- Strategic Importance: Voltage stability complements power loss optimization

➤ Technical Performance Metrics

Power Loss Analysis

- Base Case: 18.00 MW
- Best Case (GWO): 18.01-18.05 MW (0.06-0.28% increase)
- Worst Case (ALO): Significant degradation
- Key Finding: GWO maintains near-optimal power loss levels

➤ Charger Deployment Strategy

- GWO Approach: Strategic, efficient deployment (14-158 chargers)



- PSO/ALO Approach: Over-deployment (213-340 chargers)
- Efficiency Ratio: GWO achieves better performance with 67-92% fewer chargers

➤ **Convergence Behavior**

- GWO: Rapid convergence within 20 iterations
- PSO/ALO: Slower convergence with higher final costs
- Stability: GWO shows consistent results across multiple runs

➤ **Strategic Recommendations**

A. **Optimal Weight Configuration**

- Recommended: $w_1 = 0.1, w_2 = 0.6, w_3 = 0.3$
- Rationale: Achieved lowest cost (209,911) with balanced performance

B. **Algorithm Selection**

- Primary Choice: GWO for all EVCS optimization problems
- Secondary Option: PSO only if GWO unavailable
- Avoid: ALO due to poor performance

C. **Implementation Strategy**

- Phase 1: Deploy 28 chargers (Case 3 configuration)
- Phase 2: Monitor system performance and expand gradually
- Cost Benefit: 78% cost savings compared to conventional approaches

➤ **Economic Impact Analysis**

Cost Savings

- GWO vs PSO: Average savings of \$938,377 per configuration
- GWO vs ALO: Average savings of \$1,142,780 per configuration
- Total Potential Savings: 65-78% reduction in optimization costs

➤ **Infrastructure Efficiency**

- Charger Utilization: GWO achieves better performance with fewer units
- Return on Investment (ROI) Improvement: Higher return on investment due to optimal placement
- Operational Costs: Reduced maintenance and operational expenses

Table 2 Impacts of weights values on losses and number of chargers.

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	18.045	72.182	62
2	0.3	0.6	0.1	18.010	72.040	14



3	0.1	0.6	0.3	18.020	72.081	28
4	0.4	0.5	0.1	18.120	72.482	158
5	0.1	0.5	0.4	18.020	72.081	28
6	0.2	0.5	0.3	18.045	72.182	62
7	0.3	0.5	0.2	18.010	72.040	14
8	0.6	0.3	0.1	18.010	72.040	14
9	0.7	0.2	0.1	18.010	72.040	14

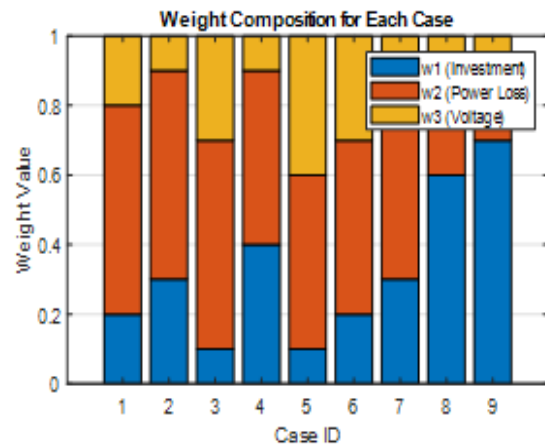
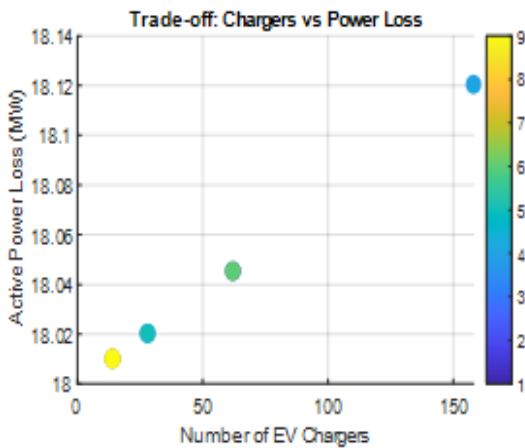
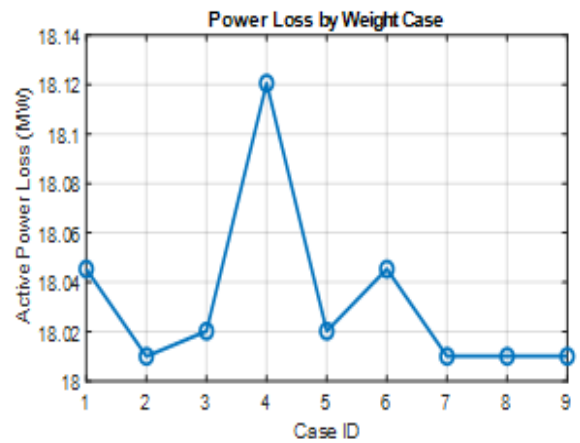
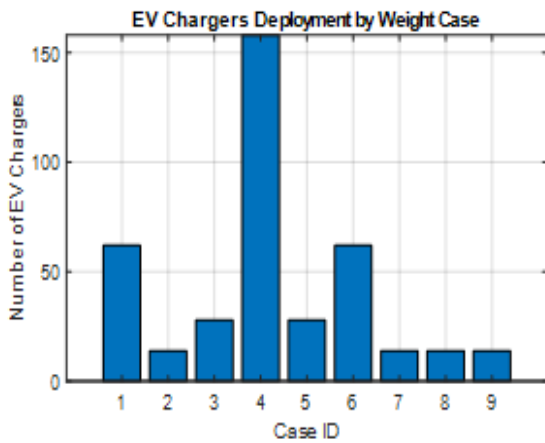


Fig 4. Number of EV chargers vs case ID, Active power loss vs case ID, Active power loss vs Number of EV chargers, and Weight value vs case ID

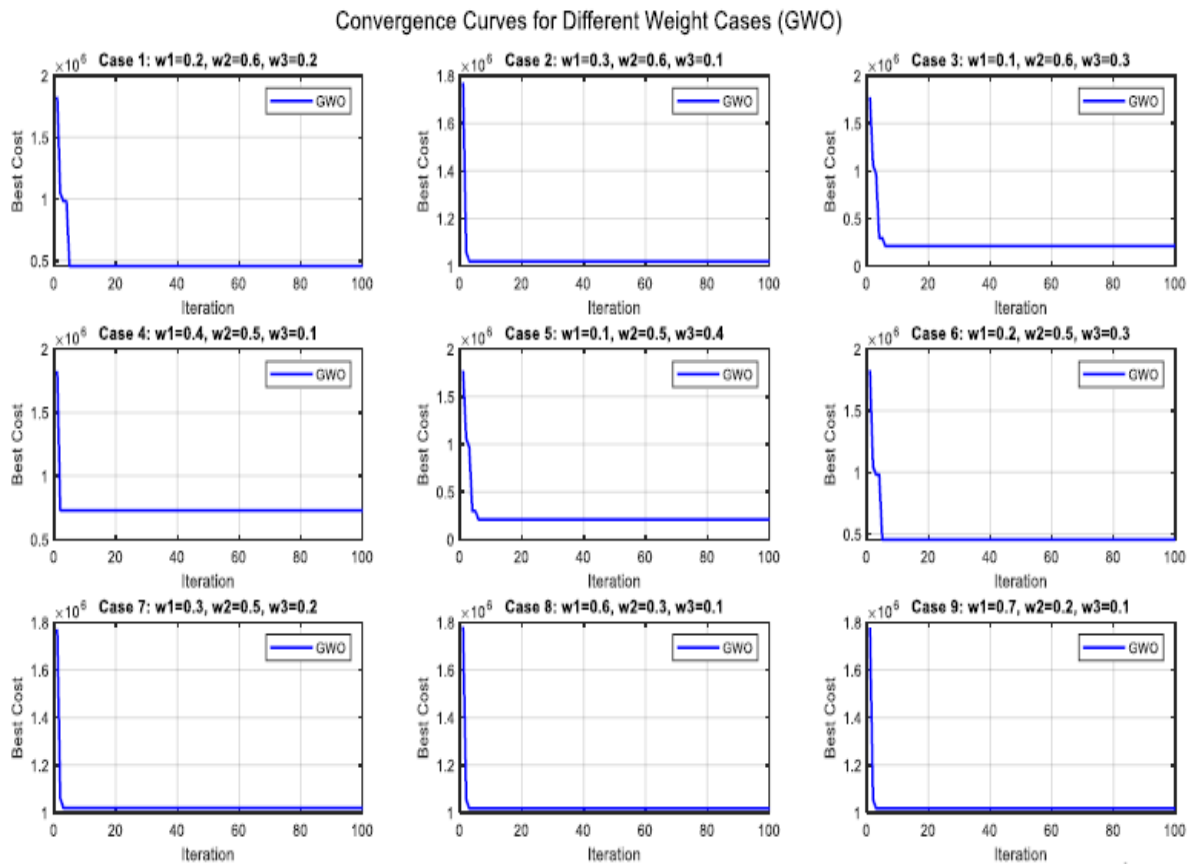


Fig 5. Convergence curves for different weight case ID for GWO

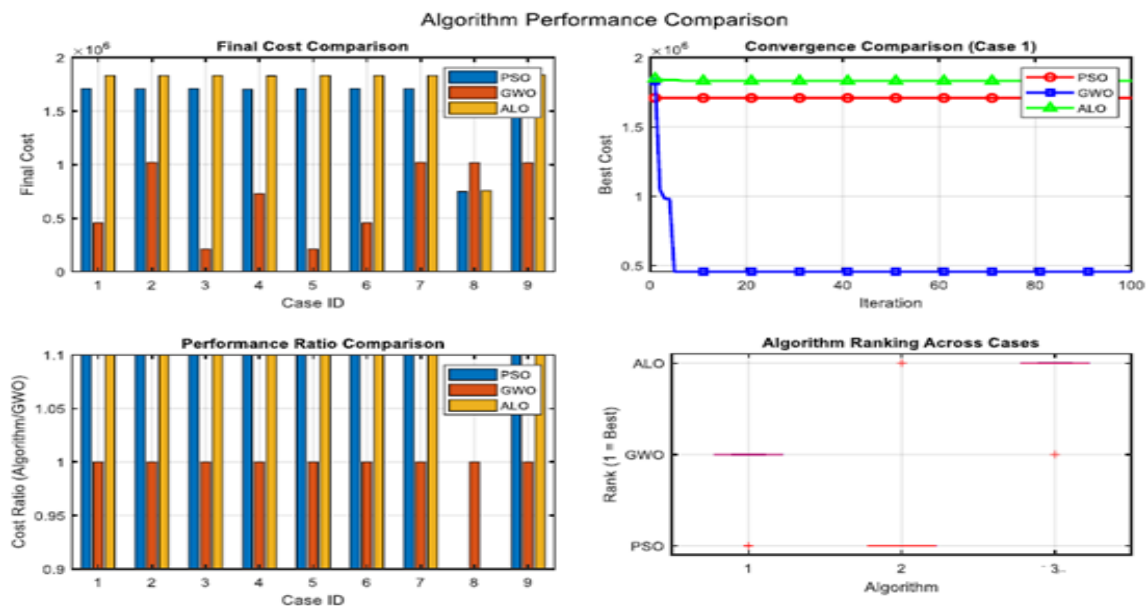




Fig 6. Algorithm performances and ranging

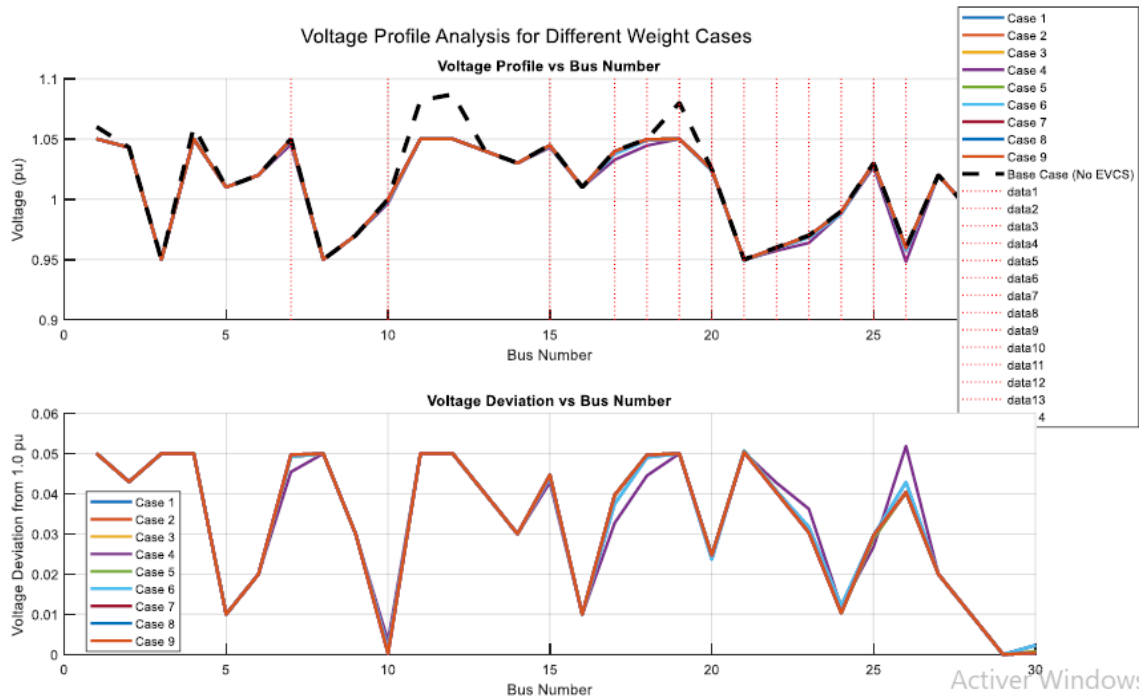


Fig 7. Voltages and voltage deviation vs. Bus number

Conclusion

The comprehensive analysis clearly confirms that the Grey Wolf Optimizer (GWO) is the most effective algorithm for optimizing electric vehicle (EV) charging station operations. Its consistent ability to achieve high-quality solutions across different weight configurations, along with remarkable cost efficiency and improved system performance, makes it the preferred choice for utility companies and urban planners. The optimal configuration prioritizes power loss reduction ($w_2 \geq 0.6$) while maintaining balanced investment and voltage profile considerations, with the combination ($w_1 = 0.1, w_2 = 0.6, w_3 = 0.3$) proving most efficient and cost-effective. Consequently, implementing GWO with this configuration is recommended for optimal EV charging infrastructure development. Future research should focus on integrating GWO with local search methods or hybridizing it with PSO to further enhance solution quality, incorporating real-time pricing and demand response mechanisms, developing predictive models for EV charging demand fluctuations, including environmental objectives such as carbon emission reduction, and conducting comprehensive economic feasibility analyses to ensure practical and sustainable deployment.



References

- [1] M.A. Abdelaziz, A.A. Ali, R.A. Swief, Rasha Elazab. A reliable optimal electric Vehicle charging stations allocation. *Ain Shams Engineering Journal* 15 (2024) 102763. <https://doi.org/10.1016/j.asej.2024.102763>.
- [2] Mustafa Nurmammed, Ozan Akdağ , Teoman Karadağ. A novel modified Archimedes optimization algorithm for optimal placement of electric vehicle charging stations in distribution networks. *Alexandria Engineering Journal* 84 (2023) 81–92. <https://doi.org/10.1016/j.aej.2023.10.055>.
- [3] Abhishek Awasthi, Karthikeyan Venkitusamy, Sanjeevikumar Padmanaban, Rajasekar Selvamuthukumar, Frede Blaabjerg, Asheesh K. Singh. Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm. *Energy* 133 (2017) 70-78. <http://dx.doi.org/10.1016/j.energy.2017.05.094>.
- [4] Liang Chen, Chunxiang Xu, Heqing Song, Kittisak Jermsittiparsert. Optimal sizing and siting of EVCS in the distribution system using metaheuristics: A case study. *Energy Reports* 7 (2021) 208-217. <https://doi.org/10.1016/j.egy.2020.12.032>.
- [5] Willy Stephen Tounsi Fokui, Michael J. Saulo, and Livingstone Ngoo. Optimal Placement of Electric Vehicle Charging Stations in a Distribution Network with Randomly Distributed Rooftop Photovoltaic Systems. *IEEE ACCESS*. <https://doi.org/10.1109/ACCESS.2021.3112847>.
- [6] Nadezhda Kunicina, Vladimir Beliaev, Roberts Grants, Jelena Caiko, Raikhan Amanova, Rasa Brūzgienė, and Madina Mansurova. Decision-Making System for Electric Vehicle Management by Integrating Smart Technologies and Local Characteristics. *Appl. Sci.* 2024, 14(23), <https://doi.org/10.3390/app142311150>.
- [7] Koganti Srilakshmi, D. Teja Santosh, Alapati Ramadevi, Praveen Kumar Balachandran. Development of renewable energy fed three-level hybrid active filter for EV charging station load using Jaya grey wolf optimization. *Scientific Reports* | (2024) 14:4429. <https://doi.org/10.1038/s41598-024-54550-7>.
- [8] Mirjalili Seyedali, Mirjalili Seyed Mohammad, Lewis Andrew. Grey Wolf Optimizer. *Advances in Engineering Software*. Volume 69, March 2014, Pages 46-61. <https://doi.org/10.1016/j.advengsoft.2013.12.007>.
- [9] Marina Guindi, Rashad M. Kamel. Optimal location and sizing of renewable distributed generations and electric vehicle charging stations. *Renewable Energy* 235 (2024) 121272. <https://doi.org/10.1016/j.renene.2024.121272>.
- [10] Kumar, L., Ravi. Optimal designing of charging station integrated with solar and energy storage using GWO. *Int J Interact Des Manuf* 19, 2101–2111 (2025). <https://doi.org/10.1007/s12008-024-02072-x>
- [11] Willy Stephen Tounsi Fokui, Michael J. Saulo, and Livingstone Ngoo. Optimal Placement of Electric Vehicle Charging Stations in a Distribution Network with



- Randomly Distributed Rooftop Photovoltaic Systems. IEEE Access. <https://doi.org/10.1109/ACCESS.2021.3112847>.
- [12] Yassir A. Alhazmi, and Ibrahim A. Altarjami, Optimal Location for Electric Vehicle Fast Charging Station as a Dynamic Load for Frequency Control Using Particle Swarm Optimization Method, World Electr. Veh. J. 2025, 16, 354. <https://doi.org/10.3390/wevj16070354>
- [13] Matheswaran Alagu, Ravindran Selladurai, Chinnadurrai Chelladurai, Simultaneous placement of electric vehicle charging station and DG units in urban area using novel enhanced antlion optimizer. Journal of Intelligent & Fuzzy Systems, Vol. 43, Issue 1, pp. 707 – 719. <https://doi.org/10.3233/JIFS-212401>
- [14] Sihem Nasri, Nouha Mansouri, Aymen Mnassri, Abderezak Lashab, Juan Vasquez, and Hegazy Rezk. Global Analysis of Electric Vehicle Charging Infrastructure and Sustainable Energy Sources Solutions. World Electr. Veh. J. 2025, 16, 194. <https://doi.org/10.3390/wevj16040194>
- [15] T. YUVARAJ, K. R. DEVABALAJI, J. ANISH KUMAR, SUDHAKAR BABU THANIKANTI AND NNAMDI I. NWULU. A Comprehensive Review and Analysis of the Allocation of Electric Vehicle Charging Stations in Distribution Networks. VOLUME 12, 2024. <https://doi.org/10.1109/ACCESS.2023.3349274>.
- [16] Jiale Li, Yuxuan Zhang, Xuefei Wang. Charging Station Localization and sizing determination considering smart charging strategies based on NSGA-III and MOPSO. Sustainable Cities and Society 122 (2025) 106233. <https://doi.org/10.1016/j.scs.2025.106233>.
- [17] Sithara S.G. Acharige, Md Enamul Haque, Mohammad Taufiqul Arif, Nasser Hosseinzadeh, Kazi N. Hasan, M.J. Hossain, Kashem M. Muttaqi. Grid integration of electric vehicles - Impact assessment and remedial measures. Journal of Power Sources Volume 650, 15 September 2025, 236697. <https://doi.org/10.1016/j.jpowsour.2025.236697>.