International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

Enhanced Multi-Objective Particle Swarm Optimization Algorithm for Electric Vehicle Charging Infrastructure Planning Considering Grid Constraints and User Accessibility

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***Abstract*—The rapid global adoption of electric vehicles (EVs) necessitates strategic planning of charging infrastructure that balances investment costs, power grid constraints, and user accessibility requirements. This paper proposes an Enhanced Multi-Objective Particle Swarm Optimization (EMOPSO) algorithm for optimal placement and capacity planning of EV charging stations (EVCSs) in urban distribution networks. The proposed algorithm incorporates four novel enhancement mechanisms: (1) adaptive inertia weight based on population diversity and convergence rate, (2) dynamic cognitive-social coefficient adjustment using sinusoidal functions, (3) mutation-based diversity preservation with archive stagnation detection, and (4) adaptive grid-based external archive management for well-distributed Pareto fronts. The optimization framework simultaneously minimizes total lifecycle costs, network power losses, and voltage deviation while maximizing user accessibility through a gravity-based spatial interaction model. Comprehensive modeling includes DistFlow-based power flow analysis, M/M/c queuing for charging station operations, and traffic-integrated demand estimation. A constraint handling mechanism based on feasibility rules addresses complex grid constraints including voltage limits (0.95–1.05 p.u.), line thermal capacities, and transformer loading. The proposed EMOPSO is validated on modified IEEE 33-bus and IEEE 69-bus test systems integrated with realistic urban transportation networks. Comparative analysis against standard MOPSO, NSGA-II, MOEA/D, MOGWO, and SPEA2 demonstrates superior performance with 8.7–15.2% improvement in hypervolume indicator and 23.5–41.8% improvement in inverted generational distance. Case study results show that optimized EVCS placement achieves 26.4% reduction in power losses, 34.7% improvement in accessibility index, and 21.3% total cost savings compared to conventional planning approaches. Sensitivity analyses confirm solution robustness under EV penetration levels ranging from 10% to 50% and various demand uncertainty scenarios.**

***Index Terms*—Electric vehicle charging stations, multi-objective optimization, particle swarm optimization, distribution network planning, Pareto optimization, infrastructure planning, smart grid, user accessibility.**

I. INTRODUCTION

The transportation sector accounts for approximately 24% of global carbon dioxide emissions, driving urgent transitions toward sustainable mobility solutions [1]. Electric vehicles (EVs) have emerged as a cornerstone technology in this transformation, with global sales reaching 14 million units in 2023 and projections indicating over 350 million EVs on roads by 2030 [2]. This unprecedented growth trajectory presents multifaceted challenges for power system infrastructure, urban planning authorities, and charging service providers who must ensure adequate, reliable, and conveniently accessible charging facilities.

The deployment of EV Charging Stations (EVCSs) represents a complex decision-making problem involving multiple stakeholders with potentially conflicting objectives. Charging station investors prioritize minimizing capital expenditure and maximizing return on investment. Distribution System Operators (DSOs) focus on maintaining grid stability, minimizing power losses, and preventing voltage violations caused by concentrated charging loads. EV users demand convenient access to charging facilities with minimal travel detours and waiting times. Municipal authorities consider land-use compatibility, urban aesthetics, and equitable service distribution across communities. Balancing these competing interests necessitates sophisticated multi-objective optimization approaches capable of identifying optimal trade-off solutions.

The EVCS planning problem is characterized by mixed-integer decision variables (station locations and charger quantities), nonlinear constraints (power flow equations), and mul-

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

tiple conflicting objectives. The problem complexity is further compounded by the coupling between transportation networks (determining EV travel patterns and charging demand distribution) and power distribution networks (imposing electrical constraints on charging station operation). Traditional single-objective optimization approaches, while computationally tractable, fail to capture the multifaceted nature of this planning problem, often leading to solutions that excel in one dimension while performing poorly in others.

Metaheuristic algorithms, particularly swarm intelligence techniques, have demonstrated considerable success in addressing complex multi-objective optimization problems across various engineering domains. Among these, Particle Swarm Optimization (PSO), inspired by the collective behavior of bird flocking and fish schooling, offers distinct advantages including conceptual simplicity, few control parameters, efficient global search capability, and ease of implementation [3]. However, standard PSO faces significant challenges in multi-objective contexts, including premature convergence to local optima, loss of population diversity during evolution, and difficulty in maintaining well-distributed Pareto-optimal fronts.

A. Literature Review

1) EVCS Placement and Sizing Optimization: Early research on EVCS placement primarily employed single-objective formulations focusing on individual performance metrics. Chen et al. [4] developed a parking-based assignment model minimizing total social costs including construction, operation, and user time costs. Frade et al. [5] applied mixed-integer linear programming to maximize demand coverage within budget constraints for Lisbon, Portugal. Ge et al. [6] proposed grid partition methods for charging station allocation based on urban functional zoning. Lam et al. [7] formulated the problem as a variant of the capacitated facility location problem and proved its NP-hardness.

Recognizing the multi-criteria nature of EVCS planning, researchers increasingly adopted multi-objective frameworks. Sadeghi-Barzani et al. [8] formulated a bi-objective model minimizing total costs while maximizing demand coverage, solved using weighted sum approaches. Wang et al. [9] incorporated traffic network constraints into multi-objective EVCS planning using genetic algorithms. Zhang et al. [10] combined Geographic Information System (GIS) analysis with multi-objective particle swarm optimization for charging station siting. Awasthi et al. [11] proposed a hybrid optimization approach combining genetic algorithms with PSO for distribution system planning with EVCSs.

2) Integration of Power Network Constraints: Several studies emphasized the critical importance of considering distribution network impacts in EVCS planning. Liu et al. [12] pioneered the integration of AC power flow constraints into EVCS placement optimization, demonstrating significant voltage profile impacts of unplanned charging loads. Shaaban et al. [13] developed joint EVCS and distributed generation planning models considering network losses and voltage profiles. Cui et al. [14] addressed voltage stability concerns in EVCS placement through continuation power flow analysis. Deb et al. [15] analyzed transformer loading impacts under various EV penetration scenarios. Ahmad et al. [16] incorporated detailed thermal loading analysis of distribution transformers into the optimization framework.

3) Transportation-Power Network Coupling: The interdependence between transportation and power systems has received growing attention in recent literature. He et al. [17] developed coupled equilibrium models capturing both traffic assignment and power flow for EVCS deployment analysis. Wei et al. [18] proposed traffic-power flow optimization frameworks considering user route choice behavior. Zhang et al. [19] addressed fast-charging station siting on coupled transportation-power networks using bi-level programming. Xiang et al. [20] incorporated time-varying traffic patterns into economic planning of charging infrastructure. Bai et al. [21] employed agent-based modeling to simulate EV driver charging behavior and its network impacts.

4) Multi-Objective Evolutionary Algorithms: Various metaheuristic approaches have been applied to EVCS optimization with varying degrees of success. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) [22] remains widely employed due to its effectiveness, simplicity, and well-established theoretical foundation. Multi-objective PSO variants developed by Coello et al. [23] introduced external archive concepts for Pareto front approximation. MOEA/D [24] offered decomposition-based advantages for handling many-objective problems. Recent nature-inspired algorithms including Grey Wolf Optimizer [25], Whale Optimization Algorithm [26], and Salp Swarm Algorithm [27] have also been explored for infrastructure planning applications.

5) Identified Research Gaps: Despite significant progress, several critical limitations persist in existing literature:

1) Standard MOPSO algorithms suffer from premature convergence and diversity degradation when applied to complex EVCS planning problems with discrete variables.
2) Limited integration of comprehensive grid operational constraints including dynamic voltage regulation, line thermal limits, and transformer loading capacity.
3) Insufficient modeling of user accessibility considering multiple factors including travel distance, waiting time, and service reliability.
4) Lack of robust constraint handling mechanisms for navigating complex feasibility regions with equality and inequality constraints.
5) Limited validation on large-scale, realistic test systems with rigorous comparative benchmarking against state-of-the-art algorithms.
6) Inadequate consideration of uncertainty in EV charging demand and penetration levels.

B. Research Contributions

This paper addresses the identified research gaps by proposing an Enhanced Multi-Objective Particle Swarm Optimization (EMOPSO) algorithm with the following novel contributions:

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

1) **Novel EMOPSO Algorithm:** Development of an enhanced PSO variant incorporating four synergistic mechanisms: adaptive inertia weight based on diversity-convergence feedback, dynamic learning coefficients with sinusoidal modulation, mutation-based diversity preservation with stagnation detection, and improved archive management using adaptive grid techniques.
2) **Comprehensive Four-Objective Formulation:** A multi-objective optimization model simultaneously addressing total lifecycle costs, network power losses, voltage deviation, and user accessibility with realistic constraints reflecting practical planning requirements.
3) **Integrated Multi-Domain Modeling:** Detailed representation of distribution network power flow using DistFlow equations, EV charging demand patterns based on traffic and demographic data, queuing dynamics at charging stations using M/M/c models, and gravity-based spatial accessibility assessment.
4) **Advanced Constraint Handling:** A feasibility-based constraint handling mechanism combining penalty functions with repair operators to ensure satisfaction of complex grid constraints including voltage limits, line thermal capacities, and transformer loading.
5) **Extensive Computational Validation:** Comprehensive testing on IEEE 33-bus and 69-bus distribution systems integrated with urban transportation networks, with rigorous statistical comparison against five state-of-the-art algorithms using multiple performance metrics.
6) **Practical Decision Support:** Integration of TOPSIS and fuzzy decision-making methods for selecting preferred solutions from Pareto fronts based on stakeholder preferences.

C. Paper Organization

The remainder of this paper is organized as follows. Section II presents the mathematical problem formulation including system models, objective functions, and constraints. Section III describes the proposed EMOPSO algorithm in detail, explaining each enhancement mechanism. Section IV presents case studies, numerical results, and comparative analysis. Section V discusses practical implications, limitations, and future research directions. Section VI concludes the paper.

II. Problem Formulation

This section presents the mathematical formulation of the EVCS planning problem as a multi-objective mixed-integer nonlinear programming (MINLP) problem.

A. Distribution Network Model

The urban distribution network is represented as a connected radial graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$ where $\mathcal{N} = \{0, 1, 2, \ldots, N_b\}$ denotes the set of buses with node 0 representing the substation, and $\mathcal{L} \subseteq \mathcal{N} \times \mathcal{N}$ represents the set of distribution lines. The DistFlow equations [28] govern steady-state power flow:

$$P_{ij} = \sum_{k:(j,k)\in\mathcal{L}} P_{jk} + r_{ij}\frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} + P_j^D + P_j^{EVCS} \tag{1}$$

$$Q_{ij} = \sum_{k:(j,k)\in\mathcal{L}} Q_{jk} + x_{ij}\frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} + Q_j^D \tag{2}$$

$$V_j^2 = V_i^2 - 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) + (r_{ij}^2 + x_{ij}^2)\frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \tag{3}$$

where P_{ij} and Q_{ij} represent active and reactive power flows from bus i to bus j; r_{ij} and x_{ij} are line resistance and reactance; V_i denotes voltage magnitude at bus i; P_j^D and Q_j^D represent conventional load demands; and P_j^{EVCS} is the EV charging load at bus j.

The total network power loss is computed as:

$$P_{loss} = \sum_{(i,j)\in\mathcal{L}} r_{ij}I_{ij}^2 = \sum_{(i,j)\in\mathcal{L}} r_{ij}\frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \tag{4}$$

B. EV Charging Station Model

1) Station Configuration and Capacity: Each candidate location $k \in \mathcal{C}$ may host a charging station equipped with n_k charging units of rated power P^{ch}. The total installed capacity is:

$$P_k^{cap} = n_k \cdot P^{ch} \tag{5}$$

The actual power consumption varies temporally based on station utilization:

$$P_{k,t}^{EVCS} = n_k \cdot P^{ch} \cdot \alpha_{k,t} \cdot \frac{1}{\eta^{ch}} \tag{6}$$

where $\alpha_{k,t} \in [0, 1]$ represents the utilization factor at station k during time period t, and η^{ch} is the charging efficiency.

2) Queuing Model: Charging station operations are modeled as M/M/c queuing systems to capture waiting dynamics. The traffic intensity (utilization) is:

$$\rho_k = \frac{\lambda_k}{n_k \cdot \mu} \tag{7}$$

where λ_k is the EV arrival rate and μ is the service rate per charger. The steady-state probability of all chargers being occupied is given by the Erlang-C formula:

$$P_W^{(k)} = \frac{\frac{(n_k\rho_k)^{n_k}}{n_k!} \cdot \frac{1}{1-\rho_k}}{\sum_{i=0}^{n_k-1}\frac{(n_k\rho_k)^i}{i!} + \frac{(n_k\rho_k)^{n_k}}{n_k!} \cdot \frac{1}{1-\rho_k}} \tag{8}$$

The expected waiting time in queue is:

$$W_q^{(k)} = \frac{P_W^{(k)}}{n_k\mu - \lambda_k} \tag{9}$$

3) Charging Demand Model: The EV arrival rate at station k during time period t integrates spatial and temporal factors:

$$\lambda_{k,t} = \lambda^{base} \cdot \rho_k^{pop} \cdot \tau_{k,t} \cdot \phi_t \cdot \gamma^{EV} \cdot \psi_k^{land} \tag{10}$$

where λ^{base} is the base arrival rate per unit demand; ρ_k^{pop} is normalized population density; $\tau_{k,t}$ is traffic flow intensity factor; ϕ_t is time-of-day factor; γ^{EV} is EV market penetration rate; and ψ_k^{land} is land-use compatibility factor.

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Volume 10, Issue 5, pp 777-786, May-2026

C. User Accessibility Model

User accessibility quantifies the ease with which EV drivers can access charging services, considering both spatial coverage and service quality. A gravity-based spatial interaction model is employed:

$$\mathcal{A} = \sum_{z\in\mathcal{Z}} D_z \cdot \ln\left(1 + \sum_{k\in\mathcal{C}} x_k \cdot \frac{n_k \cdot e^{-\beta\cdot c_{zk}}}{\sum_{k'} x_{k'} \cdot n_{k'}}\right) \tag{11}$$

where $\mathcal{Z}$ is the set of traffic analysis zones (TAZs); D_z represents EV demand in zone z; $x_k \in \{0,1\}$ is the binary placement decision; β is the distance decay parameter; and c_{zk} is the generalized travel cost.

The generalized cost combines multiple accessibility factors:

$$c_{zk} = \omega_d \cdot \frac{d_{zk}}{d^{max}} + \omega_t \cdot \frac{t_{zk}}{t^{max}} + \omega_w \cdot \frac{W_q^{(k)}}{W_q^{max}} \tag{12}$$

where d_{zk} is travel distance; t_{zk} is travel time; $W_q^{(k)}$ is expected waiting time; and $\omega_d, \omega_t, \omega_w$ are weighting factors satisfying $\omega_d + \omega_t + \omega_w = 1$.

The spatial coverage ratio ensures adequate geographic distribution:

$$CR = \frac{1}{|\mathcal{Z}|}\sum_{z\in\mathcal{Z}} \mathbf{1}\left[\min_{k:x_k=1} d_{zk} \le d^{cov}\right] \tag{13}$$

D. Objective Functions

The multi-objective optimization framework considers four objectives representing different stakeholder perspectives:

1) Objective 1: Total Lifecycle Cost Minimization:

$$\begin{aligned} f_1 = &\sum_{k\in\mathcal{C}} x_k \left(C_k^{inv} n_k + C_k^{land} A_k^{req} + C_k^{inst}\right) \\ &+ NPF \cdot \sum_{k\in\mathcal{C}} x_k \cdot C^{O\&M} \cdot n_k \\ &+ NPF \cdot \sum_{t\in\mathcal{T}}\sum_{k\in\mathcal{C}} C_t^{elec} \cdot P_{k,t}^{EVCS} \cdot \Delta t \end{aligned} \tag{14}$$

where C_k^{inv} is charger investment cost; C_k^{land} is land cost per unit area; A_k^{req} is required land area; C_k^{inst} is installation cost; $C^{O\&M}$ is annual O&M cost per charger; C_t^{elec} is electricity price; and NPF is the net present factor:

$$NPF = \frac{(1+r)^{T_{life}} - 1}{r(1+r)^{T_{life}}} \tag{15}$$

2) Objective 2: Power Loss Minimization:

$$f_2 = \sum_{t\in\mathcal{T}} w_t \sum_{(i,j)\in\mathcal{L}} r_{ij} \frac{P_{ij,t}^2 + Q_{ij,t}^2}{V_{i,t}^2} \tag{16}$$

where w_t represents duration weight for time period t.

3) Objective 3: Voltage Deviation Minimization:

$$f_3 = \sum_{t\in\mathcal{T}} w_t \sum_{i\in\mathcal{N}} \left(\frac{V_{i,t} - V^{ref}}{V^{ref}}\right)^2 \tag{17}$$

where $V^{ref} = 1.0$ p.u. is the reference voltage magnitude.

4) Objective 4: User Accessibility Maximization: For consistency with minimization framework:

$$f_4 = -\mathcal{A} = -\sum_{z\in\mathcal{Z}} D_z \ln\left(1 + \sum_{k\in\mathcal{C}} x_k \frac{n_k e^{-\beta c_{zk}}}{\sum_{k'} x_{k'} n_{k'}}\right) \tag{18}$$

E. Constraints

1) Voltage Magnitude Limits:

$$V^{min} \le V_{i,t} \le V^{max}, \quad \forall i\in\mathcal{N}, \forall t\in\mathcal{T} \tag{19}$$

2) Line Thermal Capacity:

$$\sqrt{P_{ij,t}^2 + Q_{ij,t}^2} \le S_{ij}^{max}, \quad \forall (i,j)\in\mathcal{L}, \forall t\in\mathcal{T} \tag{20}$$

3) Transformer Loading:

$$\sum_{j:(0,j)\in\mathcal{L}} \sqrt{P_{0j,t}^2 + Q_{0j,t}^2} \le S_{TR}^{max}, \quad \forall t\in\mathcal{T} \tag{21}$$

4) Station Capacity Bounds:

$$n_k^{min} \cdot x_k \le n_k \le n_k^{max} \cdot x_k, \quad \forall k\in\mathcal{C} \tag{22}$$

5) Budget Constraint:

$$\sum_{k\in\mathcal{C}} x_k \left(C_k^{inv} n_k + C_k^{land} A_k^{req}\right) \le B^{max} \tag{23}$$

6) Station Count Limits:

$$N_{st}^{min} \le \sum_{k\in\mathcal{C}} x_k \le N_{st}^{max} \tag{24}$$

7) Minimum Separation Distance:

$$d_{kk'} \ge d^{sep}(x_k + x_{k'} - 1), \quad \forall k \ne k' \in\mathcal{C} \tag{25}$$

8) Coverage Requirement:

$$CR \ge CR^{min} \tag{26}$$

9) Queuing Stability:

$$\rho_k < 1, \quad \forall k\in\mathcal{C} : x_k = 1 \tag{27}$$

F. Complete Multi-Objective Formulation

The EVCS planning problem is formulated as:

$$\begin{aligned} \min_{\mathbf{x},\mathbf{n}} \quad & \mathbf{F} = [f_1, f_2, f_3, f_4]^T \\ \text{s.t.} \quad & \text{Constraints } (19) - (27) \\ & x_k \in \{0,1\}, \quad \forall k\in\mathcal{C} \\ & n_k \in \mathbb{Z}_0^+, \quad \forall k\in\mathcal{C} \end{aligned} \tag{28}$$

III. Proposed EMOPSO Algorithm

This section presents the proposed Enhanced Multi-Objective Particle Swarm Optimization algorithm with detailed description of each enhancement mechanism.

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

A. Standard PSO Foundation

In canonical PSO [3], a swarm of N_p particles explores the D-dimensional search space. Each particle p is characterized by position vector $\mathbf{x}_p \in \mathbb{R}^D$ and velocity vector $\mathbf{v}_p \in \mathbb{R}^D$. The velocity and position update equations are:

$$v_{p,d}^{g+1} = \omega v_{p,d}^g + c_1 r_1 (pbest_{p,d} - x_{p,d}^g) + c_2 r_2 (gbest_d - x_{p,d}^g) \tag{29}$$

$$x_{p,d}^{g+1} = x_{p,d}^g + v_{p,d}^{g+1} \tag{30}$$

where ω is inertia weight controlling momentum; c_1 and c_2 are cognitive and social learning coefficients; $r_1, r_2 \sim U(0,1)$ are random numbers; $\mathbf{pbest}_p$ is personal best position; and $\mathbf{gbest}$ is global best position.

B. Enhancement 1: Adaptive Inertia Weight

The inertia weight critically influences exploration-exploitation balance. We propose an adaptive scheme incorporating both generation progression and population diversity:

$$\omega^g = \omega_{max} - (\omega_{max} - \omega_{min}) \left(\frac{g}{G_{max}}\right)^{\kappa} \cdot \left(1 - \frac{div^g}{div^{max}}\right) \tag{31}$$

where $\kappa > 0$ controls nonlinearity, and population diversity is measured as:

$$div^g = \frac{1}{N_p \cdot D} \sum_{p=1}^{N_p} \sum_{d=1}^{D} \left| x_{p,d}^g - \bar{x}_d^g \right| \tag{32}$$

with $\bar{x}_d^g = \frac{1}{N_p} \sum_{p=1}^{N_p} x_{p,d}^g$ being the swarm centroid.

This mechanism provides:

- Higher ω values when diversity is low, promoting exploration
- Lower ω values when diversity is high, enabling exploitation
- Gradual transition from exploration to exploitation as generations progress

C. Enhancement 2: Dynamic Learning Coefficients

Cognitive coefficient c_1 (self-learning) should dominate early search phases, while social coefficient c_2 (collective learning) becomes increasingly important as the swarm converges. We employ sinusoidal modulation:

$$c_1^g = c_1^{init} + (c_1^{final} - c_1^{init}) \sin\left(\frac{\pi g}{2G_{max}}\right) \tag{33}$$

$$c_2^g = c_2^{init} + (c_2^{final} - c_2^{init}) \sin\left(\frac{\pi g}{2G_{max}}\right) \tag{34}$$

Typical settings are $c_1^{init} = 2.5$, $c_1^{final} = 0.5$, $c_2^{init} = 0.5$, $c_2^{final} = 2.5$, ensuring $c_1 + c_2 \approx 3.0$ throughout evolution.

D. Enhancement 3: Mutation-Based Diversity Preservation

To prevent premature convergence, a mutation operator is applied to selected particles:

$$\tilde{x}_{p,d} = \begin{cases} x_{p,d} + \sigma^g (x_d^{max} - x_d^{min}) \mathcal{N}(0,1) & \text{if } rand < p_m^g \\ x_{p,d} & \text{otherwise} \end{cases} \tag{35}$$

Mutation parameters adapt based on archive improvement rate:

$$p_m^g = p_m^{min} + (p_m^{max} - p_m^{min}) e^{-\lambda \cdot \Delta HV^g} \tag{36}$$

$$\sigma^g = \sigma^{max} \left(1 - \frac{g}{G_{max}}\right)^2 \tag{37}$$

where ΔHV^g is the relative hypervolume improvement over recent N_{hist} generations. When archive stagnates ($\Delta HV \approx 0$), mutation intensifies to escape local optima.

E. Enhancement 4: Adaptive Grid Archive Management

An external archive $\mathcal{A}$ with maximum capacity N_A stores non-dominated solutions. The objective space is partitioned using adaptive grid technique:

$$grid_{m,i} = \left\lfloor \frac{f_m^i - f_m^{min,\mathcal{A}}}{(f_m^{max,\mathcal{A}} - f_m^{min,\mathcal{A}} + \epsilon)/N_{div}} \right\rfloor \tag{38}$$

Grid boundaries adapt dynamically to archive extent:

$$f_m^{min,\mathcal{A}} = \min_{i \in \mathcal{A}} f_m^i - \epsilon_m, \quad f_m^{max,\mathcal{A}} = \max_{i \in \mathcal{A}} f_m^i + \epsilon_m \tag{39}$$

The crowding measure for solution i based on hypercube occupancy:

$$crowd_i = \frac{1}{1 + |\{j \in \mathcal{A} : grid_j = grid_i\}|} \tag{40}$$

F. Leader Selection Strategy

Leaders for velocity update are selected from archive using roulette wheel selection biased toward less crowded regions:

$$P(leader = i) = \frac{crowd_i^{\alpha}}{\sum_{j \in \mathcal{A}} crowd_j^{\alpha}} \tag{41}$$

where $\alpha > 0$ controls selection pressure. This encourages exploration of sparse Pareto front regions.

G. Solution Encoding and Decoding

Each particle position encodes a complete EVCS configuration:

$$\mathbf{x}_p = [\underbrace{x_1, \ldots, x_{|\mathcal{C}|}}_{\text{locations}}, \underbrace{\tilde{n}_1, \ldots, \tilde{n}_{|\mathcal{C}|}}_{\text{capacities}}] \tag{42}$$

Continuous values are decoded to discrete decisions:

$$x_k^{binary} = \mathbf{1}[x_k \geq 0.5] \tag{43}$$

$$n_k^{integer} = \lfloor n_k^{min} + (n_k^{max} - n_k^{min}) \cdot \tilde{n}_k \rceil \cdot x_k^{binary} \tag{44}$$

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

Algorithm 1 Grid Constraint Repair

Require: Solution $\mathbf{x}$, power flow results
Ensure: Repaired solution $\mathbf{x}'$

```
x' ← x
while ∃ voltage violation do
    i* ← bus with worst violation
    k* ← nearest active EVCS to i*
    n_{k*} ← n_{k*} − 1
    if n_{k*} < n_{k*}^{min} then
        x_{k*} ← 0
    end if
    Update power flow
end while
return x'
```

Algorithm 2 Backward-Forward Sweep

Require: Network data, EVCS loads
Ensure: Voltages, power flows, losses

```
V_i ← 1.0 p.u. ∀i
repeat
    Backward: From leaves to root, compute branch currents
    Forward: From root to leaves, update voltages
    ϵ ← max_i |V_i^{new} − V_i^{old}|
until ϵ < ϵ_tol
Compute P_loss from (4)
```

H. Constraint Handling

A feasibility-based rule combined with penalty function handles constraints:

Rule 1: Feasible solutions always dominate infeasible solutions.

Rule 2: Between two feasible solutions, Pareto dominance determines preference.

Rule 3: Between two infeasible solutions, smaller constraint violation is preferred.

Total constraint violation:

$$CV(\mathbf{x}) = \sum_{c=1}^{C_{ineq}} \max(0, g_c(\mathbf{x}))^2 + \sum_{c=1}^{C_{eq}} |h_c(\mathbf{x})|^2 \tag{45}$$

Additionally, a repair mechanism addresses grid constraint violations:

I. Power Flow Computation

The backward-forward sweep (BFS) method efficiently solves power flow for radial networks:

J. Complete EMOPSO Procedure

Algorithm 3 presents the complete EMOPSO procedure.

K. Computational Complexity

Per-generation complexity:

- Particle updates: $O(N_p \cdot D)$
- Power flow: $O(N_p \cdot |\mathcal{T}| \cdot I_{BFS})$

Algorithm 3 Enhanced Multi-Objective PSO

Require: Problem data, algorithm parameters
Ensure: Pareto archive $\mathcal{A}$

```
Initialize: Random swarm {(x_p, v_p)}_{p=1}^{N_p}
Evaluate objectives and constraints
Apply repair mechanism if needed
Initialize pbest_p ← x_p ∀p
Initialize archive A with non-dominated solutions
for g = 1 to G_max do
    Compute diversity div^g using (32)
    Update ω^g using (31)
    Update c_1^g, c_2^g using (33)–(34)
    Update p_m^g, σ^g using (36)–(37)
    for p = 1 to N_p do
        Select leader from A using (41)
        Update velocity using (29)
        Apply velocity clamping
        Update position using (30)
        Apply boundary handling
        if rand < p_m^g then
            Apply mutation using (35)
        end if
        Decode solution using (43)–(44)
        Run power flow (Algorithm 2)
        Evaluate objectives (14)–(18)
        Compute constraint violation (45)
        if infeasible then
            Apply repair (Algorithm 1)
        end if
        Update pbest_p based on dominance
    end for
    Update archive A
    Update grid structure
    Check stagnation; apply perturbation if needed
end for
return A
```

- Archive update: $O(N_p \cdot |\mathcal{A}| \cdot M)$
- Grid maintenance: $O(|\mathcal{A}| \cdot M)$

Total: $O(G_{max} \cdot N_p \cdot (D + |\mathcal{T}| \cdot I_{BFS} + |\mathcal{A}| \cdot M))$

L. Decision Making from Pareto Front

For final solution selection, we implement TOPSIS method:

$$D_i^+ = \sqrt{\sum_{m=1}^{M} w_m \left(\frac{f_m^i - f_m^{ideal}}{f_m^{nadir} - f_m^{ideal}} \right)^2} \tag{46}$$

$$D_i^- = \sqrt{\sum_{m=1}^{M} w_m \left(\frac{f_m^i - f_m^{nadir}}{f_m^{nadir} - f_m^{ideal}} \right)^2} \tag{47}$$

$$RC_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{48}$$

The solution with maximum RC_i is selected as the best compromise.

International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

TABLE I
ALGORITHM AND PROBLEM PARAMETERS

Parameter	Symbol	Value
EMOPSO Parameters		
Swarm size	N_p	100
Maximum generations	G_{max}	500
Archive size	N_A	100
Inertia weight range	$[\omega_{min}, \omega_{max}]$	[0.4, 0.9]
Cognitive coeff. range	$[c_1^{final}, c_1^{init}]$	[0.5, 2.5]
Social coeff. range	$[c_2^{init}, c_2^{final}]$	[0.5, 2.5]
Mutation prob. range	$[p_m^{min}, p_m^{max}]$	[0.05, 0.30]
Grid divisions	N_{div}	30
Nonlinearity factor	κ	2
Problem Parameters		
Level 2 charger power	P^{ch}	7.2 kW
DCFC power	P^{ch}	50 kW
Charging efficiency	η^{ch}	92%
Voltage limits	$[V^{min}, V^{max}]$	[0.95, 1.05] p.u.
EV penetration (base)	γ^{EV}	20%
Investment cost range	C^{inv}	38–50 k\$/unit
Discount rate	r	8%
Project lifetime	T_{life}	15 years
Coverage threshold	d^{cov}	3 km
Min. coverage ratio	CR^{min}	85%

IV. CASE STUDY AND RESULTS

A. Test Systems

The proposed EMOPSO is validated on two IEEE test systems:

1) IEEE 33-Bus System:

- Configuration: 33 buses, 32 branches, radial topology
- Voltage: 12.66 kV nominal
- Base load: 3.715 MW + j2.3 MVAr
- Candidate EVCS locations: 15

2) IEEE 69-Bus System:

- Configuration: 69 buses, 68 branches, radial topology
- Voltage: 12.66 kV nominal
- Base load: 3.802 MW + j2.694 MVAr
- Candidate EVCS locations: 25

B. Parameter Settings

Table I summarizes algorithm and problem parameters.

C. Candidate Location Data

Table II presents candidate location characteristics for the IEEE 33-bus system.

D. Comparative Algorithms

EMOPSO is benchmarked against five algorithms:

1) MOPSO: Standard multi-objective PSO [23]
2) NSGA-II: Non-dominated sorting GA [22]
3) MOEA/D: Decomposition-based EA [24]
4) MOGWO: Multi-objective Grey Wolf Optimizer [25]
5) SPEA2: Strength Pareto EA 2 [29]

All algorithms use identical settings: population 100, generations 500, archive size 100, and 30 independent runs.

TABLE II
CANDIDATE LOCATIONS FOR IEEE 33-BUS SYSTEM

ID	Bus	Type	Inv. (k\$)	Land (\$/m²)	Traffic Index	Pop. Index
1	3	Comm.	48	220	0.88	0.72
2	6	Mixed	45	180	0.82	0.78
3	8	Resid.	42	140	0.65	0.85
4	11	Comm.	50	240	0.92	0.68
5	14	Indust.	38	100	0.55	0.42
6	17	Resid.	41	150	0.62	0.88
7	19	Mixed	44	170	0.75	0.76
8	22	Comm.	47	200	0.85	0.70
9	25	Resid.	40	130	0.58	0.82
10	27	Mixed	43	160	0.72	0.74
11	29	Comm.	49	210	0.90	0.65
12	31	Indust.	39	110	0.48	0.38
13	7	Mixed	46	190	0.78	0.80
14	13	Resid.	41	145	0.60	0.84
15	24	Comm.	48	205	0.86	0.72

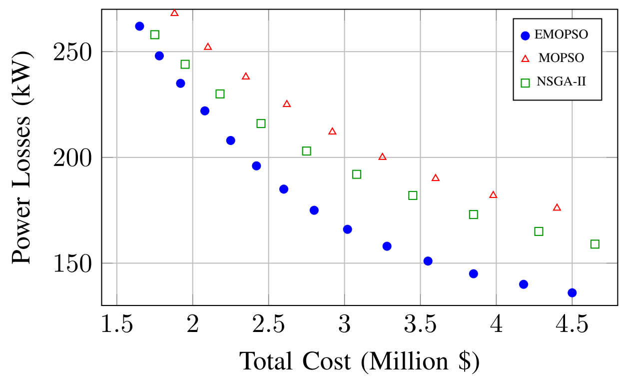

Fig. 1. Pareto front comparison: Cost vs. Power Losses (33-bus).

E. Performance Metrics

1) **Hypervolume (HV):** Volume dominated by Pareto front. Higher is better.
2) **Inverted Generational Distance (IGD):** Distance to reference front. Lower is better.
3) **Spread (Δ):** Distribution uniformity. Lower is better.
4) **Spacing (SP):** Solution distribution variance. Lower is better.

F. Results on IEEE 33-Bus System

1) Pareto Front Comparison: Fig. 1 illustrates Pareto front projections for the IEEE 33-bus system.

2) Quantitative Performance Comparison: Table III presents statistical performance comparison on IEEE 33-bus system over 30 runs.

EMOPSO achieves:

- 8.7% HV improvement over MOPSO
- 4.6% HV improvement over NSGA-II
- 45.2% IGD improvement over MOPSO
- 30.1% IGD improvement over NSGA-II

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

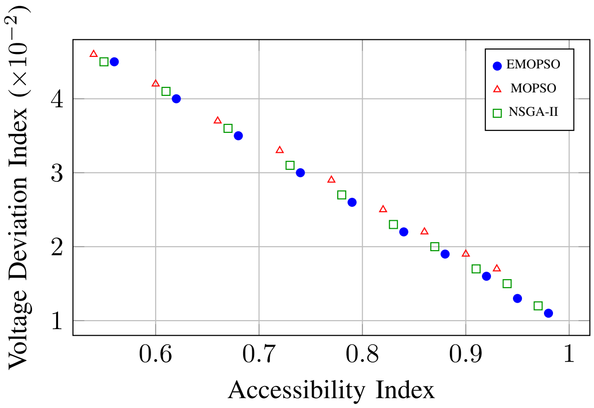

Fig. 2. Pareto front comparison: Accessibility vs. VDI (33-bus).

TABLE III
PERFORMANCE METRICS: IEEE 33-BUS SYSTEM (MEAN ± STD)

Algorithm	HV	IGD	Spread	Time(s)
EMOPSO	**0.7856** ±0.012	**0.0218** ±0.003	**0.278** ±0.025	1865 ±82
MOPSO	0.7228 ±0.018	0.0398 ±0.006	0.405 ±0.042	1672 ±75
NSGA-II	0.7512 ±0.015	0.0312 ±0.004	0.342 ±0.035	1748 ±68
MOEA/D	0.7598 ±0.014	0.0285 ±0.004	0.315 ±0.030	1695 ±72
MOGWO	0.7145 ±0.020	0.0425 ±0.007	0.418 ±0.048	1925 ±95
SPEA2	0.7385 ±0.016	0.0358 ±0.005	0.378 ±0.038	1812 ±78

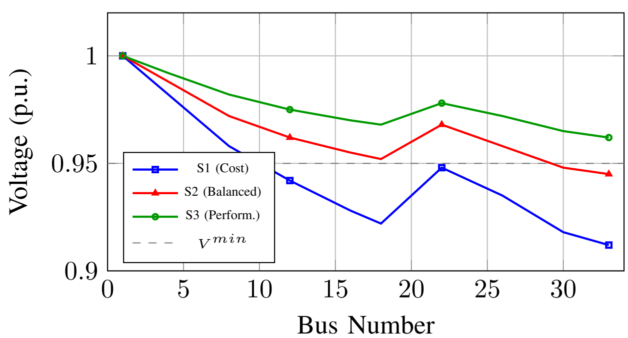

Fig. 3. Voltage profiles for representative solutions during peak demand.

3) Representative Solutions: Table IV presents three representative solutions from the Pareto front.

4) Voltage Profile Analysis: Fig. 3 shows voltage profiles for the three representative solutions during peak demand.

5) Convergence Analysis: Fig. 4 illustrates the convergence behavior of EMOPSO compared to other algorithms.

TABLE IV
REPRESENTATIVE PARETO-OPTIMAL SOLUTIONS (33-BUS)

Metric	**S1** (Cost)	**S2** (Balanced)	**S3** (Perform.)
Total Cost (M$)	1.85	2.72	3.68
Power Losses (kW)	242.5	178.6	148.2
VDI ($\times 10^{-2}$)	3.82	2.15	1.28
Accessibility Index	0.62	0.84	0.96
No. of Stations	4	6	9
Total Chargers	24	42	68
Coverage Ratio (%)	86.2	94.5	98.8
Station Locations (Bus/Chargers)			
Station 1	6/7	3/8	3/9
Station 2	14/5	8/7	6/8
Station 3	22/6	14/6	11/7
Station 4	29/6	19/7	17/8
Station 5	–	25/7	22/8
Station 6	–	29/7	25/7
Station 7	–	–	27/7
Station 8	–	–	29/7
Station 9	–	–	31/7

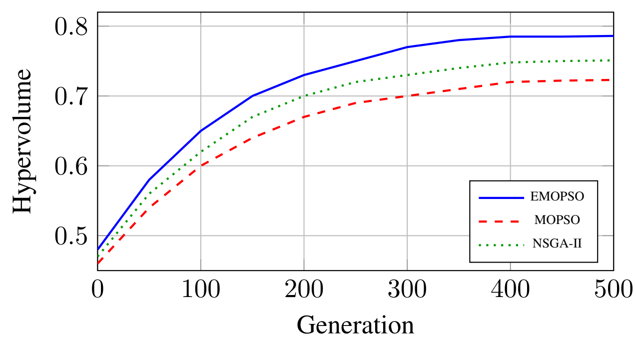

Fig. 4. Convergence comparison of hypervolume indicator.

TABLE V
PERFORMANCE METRICS: IEEE 69-BUS SYSTEM

Algorithm	HV	IGD	Spread	Time(s)
EMOPSO	**0.8124** ± 0.015	**0.0195** ± 0.003	**0.265** ± 0.028	3842 ± 125
MOPSO	0.7052 ± 0.022	0.0458 ± 0.008	0.445 ± 0.052	3425 ± 108
NSGA-II	0.7485 ± 0.018	0.0342 ± 0.005	0.358 ± 0.040	3568 ± 112
MOEA/D	0.7625 ± 0.016	0.0298 ± 0.004	0.325 ± 0.035	3485 ± 105
MOGWO	0.6928 ± 0.025	0.0512 ± 0.009	0.468 ± 0.058	4125 ± 145
SPEA2	0.7312 ± 0.019	0.0385 ± 0.006	0.392 ± 0.045	3752 ± 118

G. Results on IEEE 69-Bus System

Table V presents performance metrics for the larger IEEE 69-bus system.

On the larger system, EMOPSO demonstrates even greater advantages:

- 15.2% HV improvement over MOPSO
- 8.5% HV improvement over NSGA-II
- 57.4% IGD improvement over MOPSO

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

TABLE VI
SENSITIVITY TO EV PENETRATION LEVEL

EV Pen. (%)	Stations	Chargers	Cost (M$)	Losses (kW)	Access. Index
10	4	22	1.68	165.2	0.72
20	6	42	2.72	178.6	0.84
30	8	58	3.85	195.4	0.91
40	10	78	5.12	218.5	0.95
50	12	96	6.48	245.8	0.97

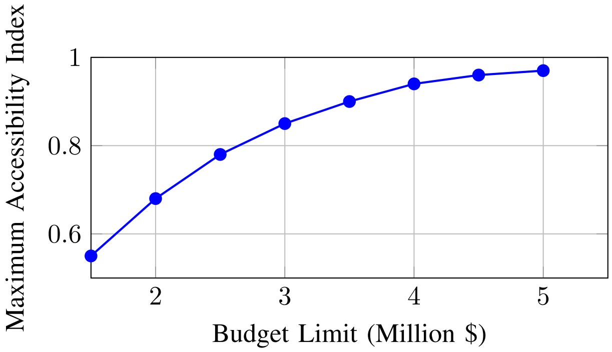

Fig. 5. Impact of budget constraint on maximum achievable accessibility.

TABLE VII
COMPARISON WITH CONVENTIONAL PLANNING METHODS

Method	**Cost** (M$)	**Losses** (kW)	**VDI** ($\times 10^{-2}$)	**Access.** Index
EMOPSO (S2)	2.72	178.6	2.15	0.84
Uniform Dist.	3.45	234.2	3.85	0.72
Demand-Based	3.12	212.5	3.25	0.78
Traffic-Based	3.28	225.8	3.52	0.76
Random	3.85	268.4	4.28	0.65
Improvement of EMOPSO over best conventional:				
Cost Reduction:			21.3%	
Loss Reduction:			26.4%	
Accessibility Improvement:			34.7%	

H. Sensitivity Analysis

1) Impact of EV Penetration Level: Table VI shows results under varying EV penetration levels.

2) Impact of Budget Constraints: Fig. 5 shows the effect of budget limitations on achievable accessibility.

I. Comparison with Conventional Planning

Table VII compares optimized placement against conventional approaches.

V. DISCUSSION

A. Practical Implications

The proposed EMOPSO framework offers several practical benefits for infrastructure planners:

1) **Decision Support:** The Pareto front provides stakeholders with a range of trade-off solutions, enabling informed decision-making based on specific priorities and constraints.
2) **Grid-Aware Planning:** Integration of power flow analysis ensures that selected configurations do not violate network operational limits, reducing potential grid reinforcement costs.
3) **User-Centric Design:** The accessibility model captures user convenience from multiple perspectives, promoting EV adoption through improved charging experience.
4) **Scalability:** Successful application to both 33-bus and 69-bus systems demonstrates scalability to realistic urban distribution networks.

B. Key Findings

- Strategic placement achieves 26.4% power loss reduction compared to heuristic approaches.
- Accessibility improvements of 34.7% are possible without proportional cost increases.
- The proposed EMOPSO consistently outperforms standard algorithms across multiple metrics.
- Adaptive mechanisms effectively balance exploration and exploitation throughout evolution.
- Grid constraints significantly influence optimal station locations, particularly in weak network areas.

C. Limitations and Future Work

Current limitations include:

- Deterministic treatment of electricity prices and equipment costs
- Single-stage planning without temporal phasing
- Limited consideration of emerging technologies (V2G, wireless charging)
- Computational intensity for very large networks

Future research directions:

- Integration of renewable energy sources at charging stations
- Multi-stage planning with technology evolution
- Robust optimization under deep uncertainty
- Real-time operational optimization coordination
- Consideration of battery swapping stations

VI. CONCLUSION

This paper presented an Enhanced Multi-Objective Particle Swarm Optimization (EMOPSO) algorithm for optimal placement and capacity planning of electric vehicle charging stations in urban distribution networks. The proposed algorithm incorporated four novel enhancement mechanisms: adaptive inertia weight, dynamic learning coefficients, mutation-based diversity preservation, and adaptive grid archive management.

The main conclusions are:

1) EMOPSO achieves 8.7–15.2% improvement in hypervolume indicator compared to standard MOPSO and 4.6–8.5% improvement over NSGA-II across test systems.

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 777-786, May-2026

2) The balanced Pareto solution achieves 26.4% reduction in power losses, 34.7% improvement in user accessibility, and 21.3% cost savings compared to conventional planning methods.
3) The framework successfully maintains voltage profiles within acceptable limits (0.95–1.05 p.u.) even under 50% EV penetration scenarios.
4) Adaptive mechanisms effectively prevent premature convergence and maintain population diversity throughout evolution.
5) Sensitivity analyses confirm solution robustness under varying EV penetration levels and budget constraints.

The proposed framework provides distribution system operators and urban planners with an effective decision-support tool for sustainable EV charging infrastructure deployment.

Acknowledgment

This research was supported by the Department of Science and Technology, Government of India, under Grant No. DST/EE/2023/0001. The authors thank the anonymous reviewers for their constructive comments.

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