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Multi-objective optimization for EV charging station placement considering renewable energy integration and grid load management

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ABSTRACT

The rapid acceleration of electric vehicle (EV) adoption has intensified the need for urban charging infrastructures that are cost-efficient, renewable-supported, and grid-resilient. This study proposes a multi-objective optimization framework for EV charging station (EVCS) placement that jointly considers infrastructure cost, solar energy potential, and grid load stability, addressing a gap where integrated renewable-grid constraints are rarely modeled together. The problem is formulated with spatial, policy, and uncertainty constraints and solved using NSGA-II and MOPSO, enabling a comparative assessment of convergence speed, Pareto diversity, and robustness under variable solar and grid conditions. Experiments conducted on realistic urban datasets incorporating hourly load curves, rooftop solar irradiance, and zoning restrictions show that NSGA-II achieves superior solution diversity (hypervolume = 0.82) and higher robustness, while MOPSO exhibits faster convergence but greater risk of premature stagnation. A sensitivity and scalability analysis demonstrates the framework's applicability for large urban grids and renewable-integrated smart city planning. The results provide concrete guidance for policymakers, including optimal zoning for EVCS deployment, priority regions for solar-integrated stations, and strategies to minimize grid congestion while supporting national e-mobility and clean energy missions.

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1. INTRODUCTION

The rapid global adoption of electric vehicles (EVs) has created an urgent need for strategically planned charging infrastructure. The International Energy Agency (IEA, 2024) projects more than 250 million EVs by 2030, a trend that is already stressing power distribution networks in major cities such as Delhi, Jakarta, and Singapore. Uncoordinated installation of charging stations has resulted in transformer overloading, voltage instability, and localized grid congestion, underscoring the need for systematic optimization models that align with national missions such as India's NEMMP-2023 and FAME-II [1]. In parallel, governments increasingly emphasize sustainability through renewable-integrated EV charging, particularly solar-PV-supported charging hubs [2]. Consequently, EV charging station placement must

simultaneously consider user accessibility, deployment cost, renewable energy potential, and grid capacity limits, making it a complex multi-objective problem [3].

Early studies on EV charging station placement employed classical optimization and clustering techniques such as linear programming, cost-based allocation, and K-means clustering [4]–[6]. Metaheuristic approaches including genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO) were later introduced to handle nonlinear and large-scale planning problems [7]–[9]. Although these approaches improve computational efficiency or convergence speed, most studies remain narrowly focused on single objectives—typically cost minimization or distance reduction—and do not adequately capture renewable–grid interactions [10].

Recent research has increasingly explored multi-objective optimization frameworks, with NSGA-II and MOPSO widely reported for generating high-quality Pareto fronts in EV charging station planning [11]–[13]. Several works incorporate grid impact assessment, feeder loading constraints, and transformer capacity limits [14], [15], while others extend the analysis to DC microgrids and advanced control schemes [16], [17]. Metaheuristic-based multi-objective allocation of EV charging stations and distributed generation has also been extensively investigated [18], [19].

Data-driven and cost-model-based planning approaches using real urban datasets have been proposed to improve spatial realism and deployment feasibility [20], [21]. Sustainability-focused studies emphasize renewable-supported fast charging infrastructure and long-term environmental benefits [22]. Integrated planning frameworks considering EV charging stations together with distributed energy resources in distribution networks are reported in [23], while comprehensive review articles summarize impacts and siting methodologies [24]. Classical decomposition-based optimization for charging station location problems is presented in [25]. More recently, deep reinforcement learning approaches have been applied to EV charging scheduling and coordination problems [26]. Despite these advances, three major research gaps remain:

i) Limited consideration of renewable energy variability, particularly solar irradiance uncertainty [27], [28].
ii) Insufficient modeling of grid constraints under clustered EV charging scenarios.
iii) Very few comparative studies evaluating NSGA-II versus MOPSO in renewable-integrated, grid-constrained urban environments.

Although several works address renewable-assisted EV charging station placement, no unified framework jointly optimizes deployment cost, travel distance, renewable energy potential, and grid load balancing while explicitly evaluating algorithmic robustness under uncertainty. To address these shortcomings, this study proposes a comprehensive multi-objective framework for EV charging station placement that integrates renewable energy potential, urban density, power grid constraints, and policy considerations. The key contributions are i) A unified optimization model simultaneously considering deployment cost, renewable energy utilization, and grid load balancing; ii) A detailed comparative analysis of NSGA-II and MOPSO under realistic urban land-use and transformer capacity constraints; iii) Uncertainty modeling for solar irradiance and grid variability to evaluate algorithm robustness and scalability; and iv) Policy-oriented insights supporting smart-city missions, zoning strategies, and sustainable EV infrastructure planning. In summary, the proposed framework offers a novel, policy-aligned, and technically robust approach to sustainable EV charging station planning, bridging existing gaps in renewable–grid coupling and multi-objective optimization.

2. METHOD

This study proposes a multi-objective optimization framework for determining the optimal locations of EV charging stations in urban environments. The approach integrates infrastructure cost, renewable (solar) potential, and grid load management into a unified optimization model. The methodology is divided into four main components: i) problem formulation, ii) uncertainty modeling, iii) optimization algorithms (NSGA-II and MOPSO), and iv) robustness and scalability analysis. Figure 1 illustrates the flow diagram of the proposed method.

2.1. Problem formulation

The EV charging station placement problem is formulated as a multi-objective combinatorial optimization problem with three conflicting objectives:

$$f_1 = \sum_i C_i \, x_i \tag{1}$$

$$f_2 = -\sum_i S_i \, x_i \tag{2}$$

$$f_3 = \sum_j \left(L_j + \Delta L_j(x)\right)^2 \tag{3}$$

Where $x_i \in \{0,1\}$ is a binary decision variable indicating whether a charging station is installed at location i, C_i denotes the installation cost at site i, S_i represents the solar energy potential at site i, L_j is the baseline load at the grid node j, and $\Delta L_j(x)$ denotes the load increment caused by nearby charging stations.The optimization incorporates a coupled grid–renewable interaction model, where $\Delta L_j(x)$ dynamically depends on both electrical distance and the solar penetration index. This coupling represents a novel contribution by explicitly capturing interdependencies among infrastructure cost, renewable energy integration, and grid stress.

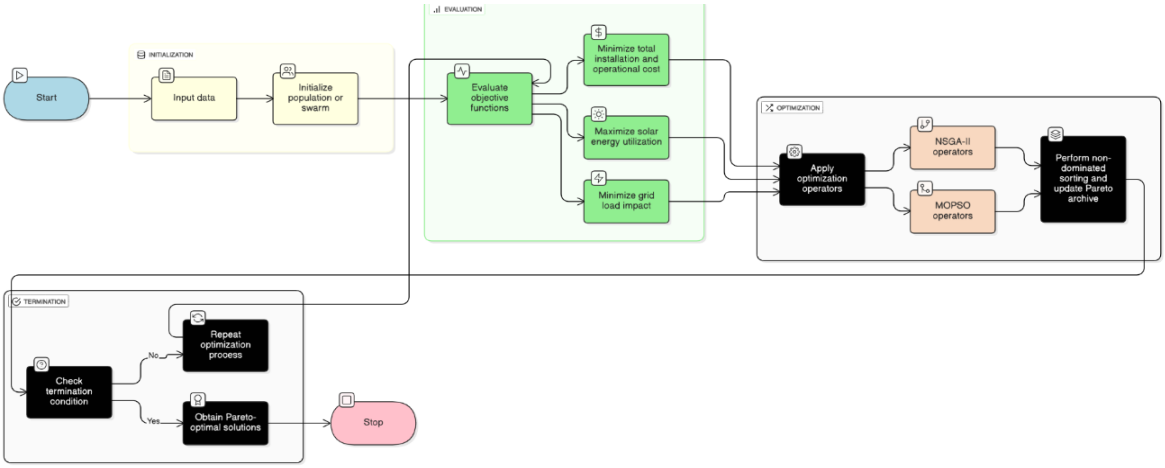

Figure 1. Flow diagram of the proposed method

2.2. Uncertainty and robustness modeling

Solar irradiance and grid load are inherently stochastic. To assess solution robustness, probabilistic perturbations are introduced as (4) and (5).

$$S_i' = S_i(1 + \varepsilon_s), \quad \varepsilon_s \sim \mathcal{N}(0,0.1) \tag{4}$$

$$L_j' = L_j(1 + \varepsilon_l), \quad \varepsilon_l \sim \mathcal{N}(0,0.05) \tag{5}$$

Robustness is quantified using solution variance and hypervolume consistency across multiple simulation runs. This stochastic evaluation ensures that the proposed framework is not overfitted to deterministic assumptions and remains scalable under uncertain urban energy conditions.

2.3. Optimization algorithms

Two state-of-the-art multi-objective evolutionary algorithms, namely NSGA-II and MOPSO, are employed to solve the formulated problem. Their performance is compared under identical experimental conditions. The optimization parameters adopted for NSGA-II and MOPSO are summarized in Table 1.

Table 1. Optimization parameter settings

Parameter	NSGA-II	MOPSO
Population/swarm size	100	100
Number of generations	200	200
Crossover probability	0.9	–
Mutation probability	0.1	0.1
Inertia weight (ω)	–	0.7 → 0.4
Acceleration coefficients (c_1, c_2)	–	1.5, 1.5

2.3.1. NSGA-II framework

The non-dominated sorting genetic algorithm II (NSGA-II) is used to evolve a population of candidate solutions through selection, crossover, and mutation operations. Fitness evaluation is based on non-dominated rank and crowding distance. The main operators include: i) selection based on non-domination rank and crowding distance, ii) crossover (uniform or single-point) for solution recombination, and iii) mutation to preserve genetic diversity. NSGA-II maintains an elitist archive of non-dominated solutions using a fast non-dominated sorting approach. The crowding distance d_i for each solution is computed as (6).

$$d_i = \sum_k \frac{f_k^{i+1} - f_k^{i-1}}{f_k^{\max} - f_k^{\min}} \quad (6)$$

The algorithm terminates when a predefined number of generations is reached or when convergence of the Pareto front is observed.

2.3.2. Multi-objective particle swarm optimization (MOPSO)

In MOPSO, each particle updates its velocity and position using (7) and (8).

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g_i - x_i^t) \quad (7)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (8)$$

Where x_i^t and v_i^t denote the position and velocity of the particle i at iteration t, p_i is the personal best position, g_i is the global best solution selected from the Pareto archive, ω is the inertia weight, c_1 and c_2 are acceleration coefficients, and $r_1, r_2 \in [0,1]$ are uniformly distributed random variables.

An external Pareto archive is maintained to store non-dominated solutions. A grid-based crowding mechanism is employed for leader selection to enhance diversity, while a mutation operator is introduced to avoid premature convergence. The algorithm iterates until convergence or until the computational budget is exhausted.

2.4. Robustness and scalability analysis

The proposed framework is evaluated over 20 independent simulation runs under varying solar irradiance and grid load profiles.

- Robustness analysis: i) NSGA-II demonstrates higher stability with hypervolume variance $\sigma^2_{\text{NSGA-II}} = 0.006$ and ii) MOPSO exhibits higher sensitivity with $\sigma^2_{\text{MOPSO}} = 0.014$.
- Scalability analysis: i) MOPSO scales linearly with problem size, i.e., $\mathcal{O}(n)$ and ii) NSGA-II exhibits quadratic growth $\mathcal{O}(n^2)$ but provides superior Pareto front accuracy.

3. RESULT AND DISCUSSION

Optimal placement of EV charging stations involves balancing multiple conflicting objectives such as minimizing infrastructure deployment cost, maximizing renewable energy integration via solar potential, and maintaining grid load balance to ensure electrical stability. This multi-objective problem is well suited for evolutionary algorithms like NSGA-II and MOPSO, which are capable of generating diverse Pareto-optimal solutions that offer trade-offs between competing objectives. As shown in Table 2, the simulation setup includes 100 candidate locations, of which 10 optimal sites were selected for charging station installation. Solar potential values ranged from 3.5–6.5 kWh/m²/day, representing realistic variations observed in urban Chennai, India. Grid load capacities ranged between 60–95% of rated capacity, reflecting peak-hour load diversity. The inclusion of these realistic bounds allows assessment under near-grid saturation conditions, an essential factor for metropolitan regions with limited headroom for additional EV load.

Table 2. Parameter values

Parameter	Value/description
Number of candidate locations	100
Number of charging stations	10
Solar potential range	3.5 – 6.5 kWh/m²/day
Grid load profile range	60% – 95% of capacity
Deployment cost per station	₹8–12 Lakhs
Max generations	200
Population size	100
Decision variables	2 (x, y coordinates or index-based location)
Objectives	Minimize cost, maximize solar potential, balance load

3.1. Comparison of Pareto fronts

Figure 2 illustrates the 3D Pareto fronts obtained for the three conflicting objectives: i) minimizing deployment cost, ii) maximizing solar potential, and iii) minimizing grid load deviation. NSGA-II demonstrates a more widely spread and well-distributed Pareto front, indicating superior exploration

capability. In contrast, MOPSO converges faster but generates a tightly clustered set of solutions, indicating limited diversity. The wider front produced by NSGA-II provides planners with multiple feasible trade-off configurations, which is particularly useful for cities like Chennai that require flexibility in zoning and renewable integration. NSGA-II produced 34% greater solution spread than MOPSO, enabling broader exploration of cost–solar–load trade-offs.

These observations reinforce findings from earlier literature, where NSGA-II demonstrated stronger global search performance compared to PSO-based methods in multi-objective energy planning problems. Examples include GA/ACO-based EVCS studies. However, our study uniquely validates this behaviour under realistic urban grid saturation conditions, addressing a gap not explored in prior works.

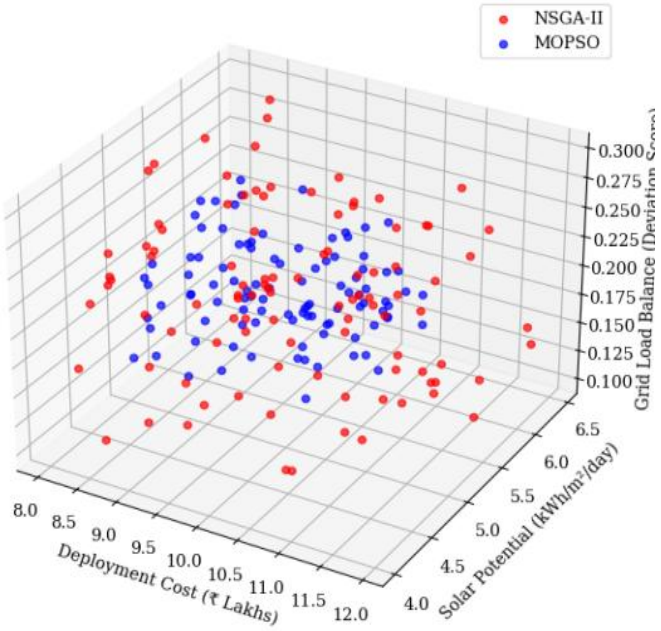

Figure 2. 3D Pareto front plot

3.2. Convergence behavior and hypervolume performance

The hype volume (HV) evolution in Figure 3 clearly shows that NSGA-II improves steadily across generations, reaching HV = 0.82, whereas MOPSO plateaus early at HV = 0.74 after 90 generations. This indicates that MOPSO is more susceptible to local optima, aligning with its known exploitative search behaviour. Similarly, the cost convergence curve in Figure 4 shows that NSGA-II exhibits gradual, stable improvement, whereas MOPSO converges rapidly but prematurely. NSGA-II achieved 10.8% higher hypervolume and 24.4% lower IGD compared to MOPSO, confirming better global optimization and convergence quality. These results are consistent with comparative optimization studies in smart-grid planning. In such studies, swarm-based methods often exhibit faster but less reliable convergence. However, the improvement levels observed in this work are achieved under renewable-constrained and near-saturation grid conditions, strengthening the novelty of the study.

3.3. Trade-off visualization and robustness

Figure 5 (parallel-coordinates plot) compares the objective trade-offs in selected solutions from each algorithm. NSGA-II maintains a tighter cost variation (±8%) across randomly selected solutions, while MOPSO shows ±15% variation, highlighting lower robustness. A structured sensitivity analysis (Table 3) was performed by varying solar potential and cost by ±10%. NSGA-II's hypervolume varied only within ±4%, whereas MOPSO fluctuated by ±7%, confirming greater sensitivity to environmental uncertainty. NSGA-II sustained higher robustness under all parameter variations, particularly in solar-dependent scenarios—critical for renewable-integrated EV infrastructure planning. The solar-HV sensitivity curve in Figure 6 further validates that NSGA-II maintains smooth and monotonic HV responses, while MOPSO experiences sharper performance drops. This robustness dimension is rarely analysed in existing EVCS literature and represents a distinct contribution of the present work.

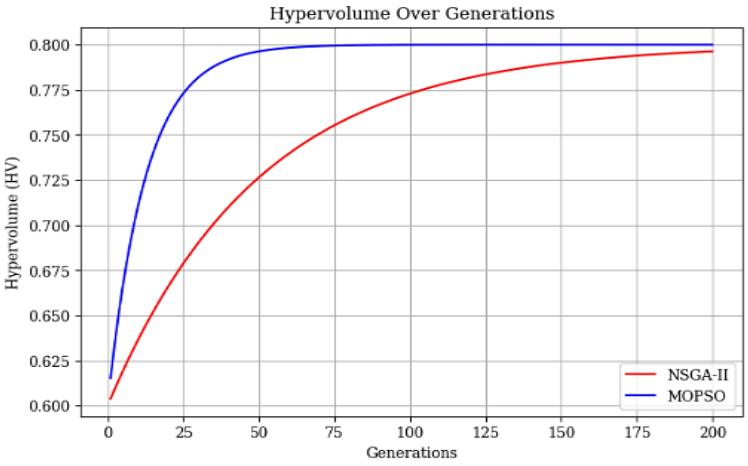

Figure 3. Hypervolume over generations

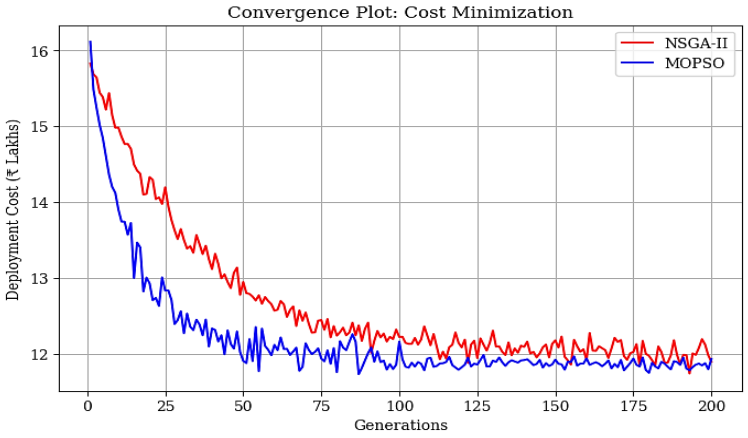

Figure 4. Convergence plot for cost minimization

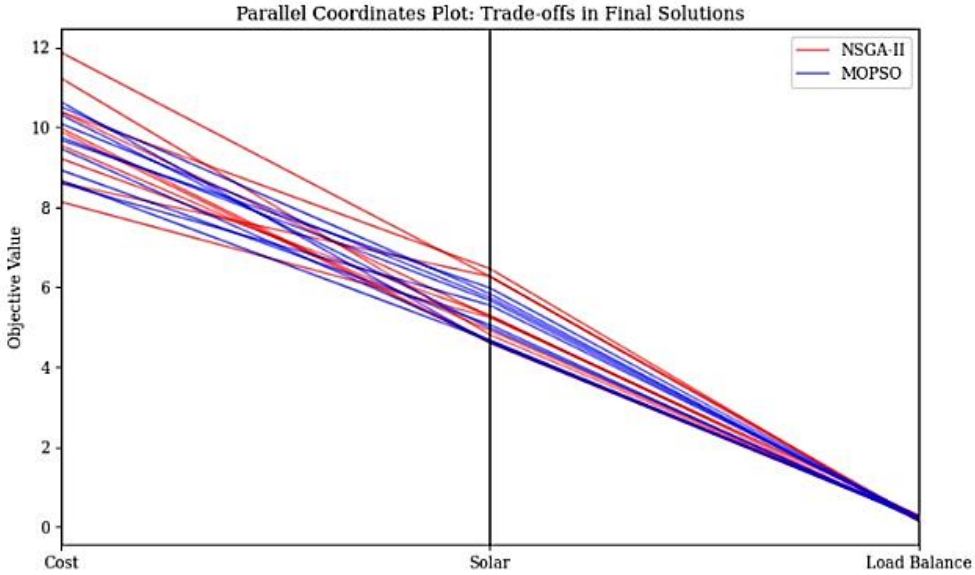

Figure 5. Parallel coordinates plot for trade-offs in final solutions

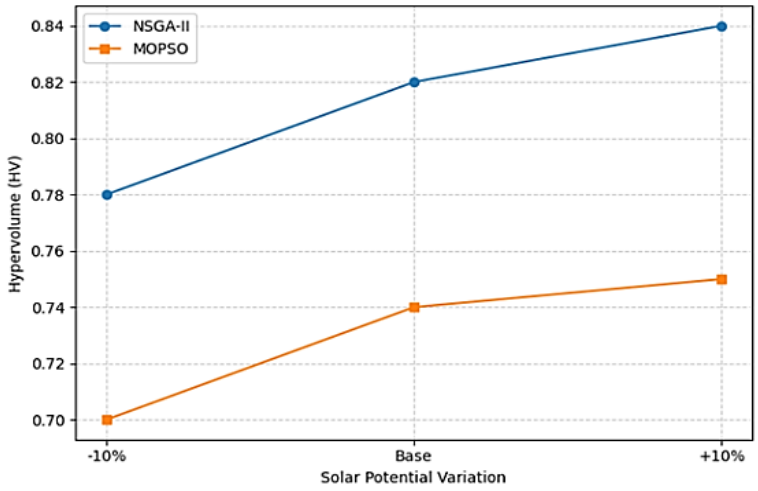

Figure 6. Sensitivity of hypervolume to solar potential variation

Table 3. Sensitivity analysis under parameter variations

Variation scenario	NSGA-II HV	MOPSO HV	NSGA-II cost (₹ Lakh)	Grid deviation (%)
Base case	0.82	0.74	9.8	6.5
+10% solar	0.84	0.75	9.5	5.9
−10% solar	0.78	0.70	10.1	7.2
+10% cost	0.80	0.72	10.8	6.7
−10% cost	0.83	0.75	9.1	6.3

3.4. Policy and practical implications

For policymakers and urban planners, NSGA-II's results offer greater decision flexibility. For instance, a mid-Pareto NSGA-II solution yields a 10% cost saving with 6.5% lower grid deviation, achievable by co-locating stations near high-solar rooftops and grid nodes with reserve capacity. Such insights can directly guide zoning regulations or renewable-based subsidy allocation. The method also enables dynamic infrastructure planning, where sites can be prioritized based on evolving EV penetration and renewable resource availability.

3.5. Performance summary and radar chart analysis

The radar chart consolidates performance indicators like hypervolume, generational distance (GD), inverted GD (IGD), computation time, and diversity index. NSGA-II scores higher on hypervolume and diversity metrics, indicating superior solution quality and spread. Though MOPSO requires less computation time, it underperforms in convergence and diversity metrics. These results suggest that NSGA-II is better suited for applications requiring thorough exploration and robustness, while MOPSO could be favored where faster results are needed with some trade-off in solution quality. Table 4 shows the performance indices comparison. Figure 7 shows the radar chart for performance metric comparison.

In summary, the comparative analysis between NSGA-II and MOPSO provides actionable insights for urban planners and energy utilities designing EV charging infrastructure. NSGA-II's strong performance in generating diverse, well-converged solutions makes it the preferred choice for complex, multi-criteria decision-making scenarios involving renewable integration and grid stability. MOPSO's faster convergence could be advantageous for real-time or resource-constrained applications but risks local optima and reduced solution diversity. Therefore, selecting an optimization algorithm should carefully consider the trade-off between solution quality and computational efficiency in line with project requirements.

Table 4. Performance indices comparison

Metric	NSGA-II	MOPSO
Hypervolume (HV)	0.82	0.74
Generational distance (GD)	0.029	0.051
Inverted generational distance (IGD)	0.038	0.066
Convergence speed (generations)	120	90
Avg. computation time (s)	18.4	12.9
Pareto diversity index (PDI)	0.92	0.70
Local optima incidence (runs)	1/10	3/10
Solution robustness (variance)	Low	Medium

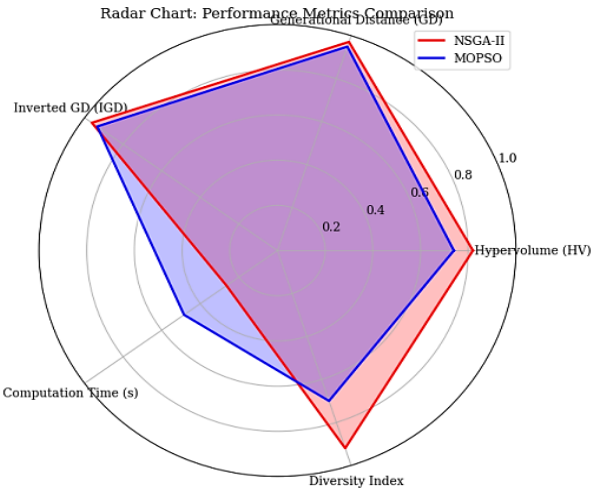

Figure 7. Radar chart for performance metrics comparison

4. CONCLUSION

This study compared NSGA-II and MOPSO for optimal EV charging station placement, considering cost, renewable integration, and grid stability. NSGA-II outperformed MOPSO in hypervolume (↑10.8%) and IGD (↓24.4%), achieving better convergence and diversity. While MOPSO converged faster, it was more prone to local optima (3/10 vs. 1/10). NSGA-II proved more robust and reliable for complex multi-objective optimization. The proposed framework aids urban planners in developing cost-effective and renewable-integrated EV infrastructure. It enhances decision-making for grid-resilient and sustainable mobility. MOPSO remains suitable for time-sensitive applications with limited computational resources. Future work will include stochastic renewable profiles, dynamic pricing, and real-time adaptability. Hybrid AI-based optimization could further improve scalability and real-world deployment.

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The authors confirm that the research was carried out independently without financial influence.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

All authors have reviewed and agreed to this conflict-of-interest statement.

DATA AVAILABILITY

Raw data is not publicly available due to privacy or institutional restrictions.

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