

Parallel Metaheuristic-Based Optimization for Electric Vehicle Charging Station Integration and Sizing in Distribution Systems [†]

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Abstract

The large-scale integration of electric vehicles (EVs) has made the siting and sizing of electric vehicle-charging stations (EVCSs) a critical challenge in distribution systems, as inadequate deployment may compromise secure network operation due to voltage and thermal limit violations. This problem is formulated as a mixed-integer nonlinear programming (MINLP) model, where discrete variables define EVCS locations and charging capacities expressed in terms of the number of EVs served. To address this problem, this paper proposes a unified parallel AC-feasible optimization framework that maximizes EV hosting capacity while explicitly enforcing all operational constraints of the distribution system. Particle Swarm Optimization (PSO), a Population-based Continuous Genetic Algorithm (PGA), and Monte Carlo (MC) optimization are evaluated under a common decision-variable encoding, objective function, AC power-flow evaluator, and constraint-handling strategy, enabling a fair comparison among methodologies under identical operating conditions. The proposed framework is assessed on a modified 33-bus distribution system considering a representative weekly operating scenario and 100 independent runs. Results show that PSO achieves the highest hosting capacity, integrating up to 1246 EVs and an average of 1213.3 EVs, compared with 1225 and 1196.1 EVs for PGA and 1077 and 1049.4 EVs for MC, respectively. All methodologies exhibit standard deviations below 3%, confirming robust and repeatable performance, while requiring less than 1428 s on average to identify feasible planning solutions. In addition, the parallel implementation reduces computational times by 42.22%. These results demonstrate the effectiveness of the proposed framework for identifying high-capacity EVCS planning solutions while preserving secure network operation.

Keywords: electric vehicles; charging stations; distribution systems; optimal planning; mixed-integer nonlinear programming; metaheuristic optimization



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1. Introduction

In recent years, the development of the electric mobility industry has enabled the commercialization of electric vehicles (EVs) with larger battery capacities and longer driving ranges, thereby progressively increasing their penetration in urban areas worldwide [1].

This trend is also observed in Colombia, where EV adoption has expanded significantly in major cities such as Medellín, Cali, and Bogotá. Available data indicate that, by 2025, these three cities account for an aggregated fleet of 25,575 EVs [2], which can be grouped into four representative clusters, denoted as (C_1), (C_2), (C_3), and (C_4) [3], according to battery capacity and driving range.

In this classification, cluster C_1 corresponds to the most robust vehicles, mainly associated with trucks and heavy-duty transportation, whereas cluster C_4 represents hybrid vehicles characterized by lower battery capacities and shorter driving ranges. According to the current composition of the electric vehicle fleet in the main Colombian cities, cluster C_3 represents the predominant vehicle category [4]. These vehicles are commonly associated with Level-2 charging infrastructure, which currently constitutes the most widespread charging technology due to its suitability for residential, commercial, and public charging applications. Therefore, the charging behavior of cluster C_3 and Level-2 charging stations defines the primary operating scenario considered in this study, providing a representative framework for assessing EVCS integration in Colombian distribution networks under current market conditions.

Under these conditions, EVCS integration into distribution systems (DSs) has become a significant challenge, since their deployment increases power demand and may affect secure network operation due to violations of voltage and thermal limits [5]. From a mathematical perspective, this problem is formulated as a mixed-integer nonlinear programming (MINLP) model, in which discrete variables define the EVCS locations and the corresponding EV hosting capacity, expressed as the number of EVs served by each charging station [6].

Several methodologies have been proposed to solve the EVCS planning problem, including exact, predictive, commercial, and metaheuristic approaches [7]. Among them, metaheuristic methods stand out for their flexibility, ease of implementation, and strong performance when dealing with nonlinear, non-convex, and mixed-integer optimization problems [8]. However, several formulations based on genetic algorithms [9], crow search algorithms [10], and particle swarm optimization [11] address the EVCS planning problem only partially and do not explicitly verify all relevant operational constraints of the distribution system, particularly voltage regulation and thermal loading limits. Furthermore, many studies focus on deterministic operating conditions, limiting the assessment of EVCS integration under varying demand scenarios representative of practical network operation.

Therefore, a clear gap remains in the development of EVCS planning methodologies capable of maximizing hosting capacity while explicitly enforcing the main operational constraints of distribution systems under realistic demand conditions. This is particularly relevant because EVCS integration directly modifies network loading patterns, and the achievable hosting capacity depends not only on the selected locations and capacities but also on the temporal variability of the demand profile.

In this context, this work proposes a unified parallel optimization framework for EVCS siting and sizing in distribution systems. The proposed framework implements Particle Swarm Optimization (PSO), a Population-based Continuous Genetic Algorithm (PGA), and Monte Carlo (MC) optimization under the same decision-variable encoding, objective function, AC power-flow evaluator, and constraint-handling structure. Rather than combining these methods into a hybrid algorithm, they are evaluated within a common computational framework, enabling a fair comparison in terms of hosting capacity, robustness, repeatability, and computational efficiency. To reduce the computational burden, the objective function and operational constraints are evaluated in parallel through a matrix-based AC power-flow method using successive approximations. The main contributions of this paper are summarized as follows:

- A mixed-integer nonlinear programming model is formulated for the EVCS siting and sizing problem, aiming to maximize the hosting capacity of the distribution system.
- Voltage regulation and thermal loading limits are explicitly incorporated into the AC-feasible evaluation process, ensuring secure network operation.
- A unified parallel optimization framework is proposed to evaluate PSO, PGA, and MC under identical codification, objective function, power-flow evaluation, and constraint-handling procedures.
- A matrix-based 24 h AC power-flow method using successive approximations is integrated into the optimization process to assess the impact of EVCS operation on network performance.
- A representative weekly operating scenario composed of weekday, Wednesday, and weekend demand conditions is incorporated to evaluate EVCS integration under realistic demand variability.
- The proposed framework is validated on a modified 33-bus distribution system through 100 independent runs, allowing the comparison of the evaluated methodologies in terms of hosting capacity, feasibility, robustness, repeatability, and computational efficiency.

The remainder of this paper is organized as follows. Section 2 presents the mathematical formulation of the EVCS planning problem. Section 3 describes the test system and operating scenarios. Section 4 details the proposed optimization framework and the evaluated methodologies. Section 5 discusses the numerical results and comparative analyses. Finally, Section 6 summarizes the main conclusions and future research directions.

2. Mathematical Model for EVCS Planning in Distribution Systems

The proposed model maximizes the installed charging capacity via EVCSs while satisfying the distribution system's main operating constraints. The objective function is defined as follows:

$$FO = \max \left\{ \sum_{i \in \mathcal{N}} P_i^{EVCS} \right\} \quad (1)$$

The objective function in (1) maximizes the total EVCS charging capacity, where P_i^{EVCS} is the installed capacity at bus i . This variable is constrained by (2), where $y_i^{EVCS} \in \{0, 1\}$ indicates whether an EVCS is installed, and $P_i^{EVCS, \min}$ and $P_i^{EVCS, \max}$ are its capacity limits. Thus, if $y_i^{EVCS} = 0$, no capacity is assigned; otherwise, it is bounded within its limits.

$$y_i^{EVCS} P_i^{EVCS, \min} \leq P_i^{EVCS} \leq y_i^{EVCS} P_i^{EVCS, \max} \quad (2)$$

It is important to note that the EVCS capacity is parameterized in terms of the number of EVs assigned to each charging station. Therefore, the optimization process determines both the EVCS location and the corresponding number of vehicles to be supplied. The installed charging capacity at bus i is calculated from the aggregated demand associated with the EVs connected to the EVCS, as follows:

$$P_i^{EVCS} = N_i^{EV} \sum_{h=1}^{\mathcal{H}} D_{EVCS, h}^{C_3} \quad (3)$$

where P_i^{EVCS} is the installed EVCS capacity at bus i , N_i^{EV} is the number of EVs assigned to the charging station installed at that bus, $D_{EVCS, h}^{C_3}$ is the unit charging demand of a representative C_3 vehicle at hour h , and $\mathcal{H}$ is the set of time periods in the 24 h horizon. Thus, the number of EVs reported in the results is directly converted into charging capacity through the hourly demand profile. This relationship allows the objective function to

maximize the total EVCS hosting capacity while preserving the connection between the mathematical model, the normalized charging profile, and the number of EVs served by each station.

The optimal siting and sizing of EVCSs are subject to the electrical operating constraints of the distribution system:

$$p_{ih}^g - p_{ih}^d - p_{ih}^{EVCS} = \sum_{j \in \mathcal{N}} Y_{ij} v_{ih} v_{jh} \cos(\delta_{ih} - \delta_{jh} - \theta_{ij}) \quad (4)$$

$$p_{ih}^{EVCS} = P_i^{EVCS} D_{EVCS_h}^{C3} \quad (5)$$

$$q_{ih}^g - q_{ih}^d = \sum_{j \in \mathcal{N}} Y_{ij} v_{ih} v_{jh} \sin(\delta_{ih} - \delta_{jh} - \theta_{ij}) \quad (6)$$

$$P_i^{g,\min} \leq p_{ih}^g \leq P_i^{g,\max} \quad (7)$$

$$Q_i^{g,\min} \leq q_{ih}^g \leq Q_i^{g,\max} \quad (8)$$

$$V_i^{\min} \leq v_{ih} \leq V_i^{\max} \quad (9)$$

$$|i_{ijh}| \leq I_{ij}^{\max} \quad (10)$$

Equations (4) and (6) represent the active and reactive power balance at each node i and time period h , where p_{ih}^g and q_{ih}^g are the active and reactive power supplied by the conventional source, and p_{ih}^d and q_{ih}^d correspond to the demand. The EVCS demand p_{ih}^{EVCS} is modeled as a function of the installed charging capacity P_i^{EVCS} and the normalized demand hourly profile $D_{EVCS_h}^{C3}$, associated with cluster C_3 under Level 2 charging, as defined in (5) and illustrated in Figure 1. This charging level and vehicle cluster are considered because they represent the most common EV charging behavior in Colombia, given their adequate balance of charging speed, installation cost, and compatibility with urban electrical infrastructure [12]. The right-hand side represents the active and reactive nodal power injections computed from the network admittance matrix, where Y_{ij} is the admittance magnitude between nodes i and j , v_{ih} and v_{jh} are the voltage magnitudes, and δ_{ih} , δ_{jh} , and θ_{ij} are the corresponding voltage and admittance angles. In addition, Equations (7) and (8) define the operating limits of the conventional source, while Equations (9) and (10) ensure voltage regulation and thermal limits in the distribution lines, respectively.

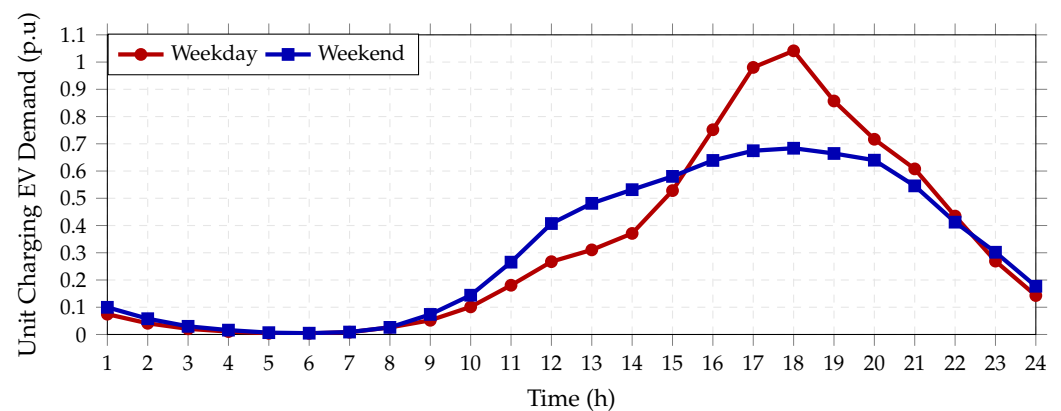


Figure 1. Comparison of the Level 2 EV charging demand profile for weekday and weekend scenarios.

3. Test System Description

In this work, an adapted version of the classical 33-bus distribution system is used as the test system. This model preserves the original electrical configuration and parameter

data, including 33 buses, 32 branches, and base values of 12.66 kV and 1000 kVA, while incorporating updated line parameters and maximum current limits reported in [13].

In addition, 33% of the network buses are considered as candidate locations for EVCS installation, following the recommendation reported in [4,14]. These nodes, highlighted in green in Figure 2, were not selected randomly but correspond to the predefined candidate set of the benchmark test system. This assumption reflects a realistic planning stage in which technically and spatially feasible locations are identified before the optimization process. Although adopted here to ensure consistency with the reference benchmark, the candidate-node set can be adapted according to the technical and operational requirements of other distribution systems.

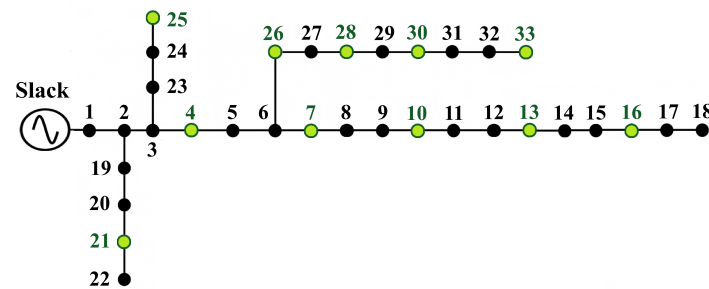


Figure 2. Electrical diagram of the modified 33-bus test system. The green nodes correspond to the predefined candidate set of the benchmark test system.

To represent demand variability, this work uses an average daily load profile from the local operator in Medellín, including typical weekdays, Wednesday, and weekend conditions, as shown in Figure 3. In addition, between 70 and 3000 EVs are supplied by the EVCSs. Based on these limits and the charging profile in Figure 1, the bounds $P_i^{EVCS,min}$ and $P_i^{EVCS,max}$ are defined. Therefore, the problem is to determine the number of EVs to charge at each station while satisfying the demand profile and all operational constraints of the distribution system. The analysis considers integrating three EVCSs to identify the most effective solution methodology and to evaluate the network's maximum hosting capacity.

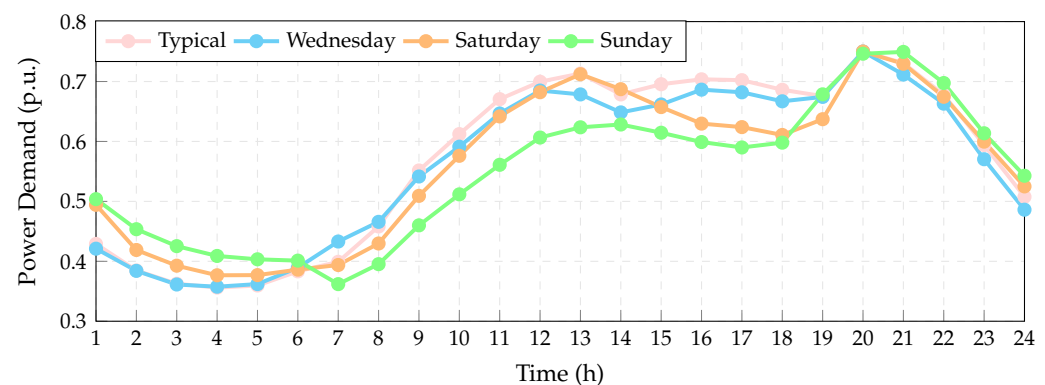


Figure 3. Daily power demand profiles for a representative average week from Medellín, Colombia [15].

4. Optimization Methodology

To solve the EVCS integration and sizing problem, the coding shown in Figure 4 is used. It includes two parts: the bus location of the EVCSs and their charging capacity. In this example, three EVCSs are considered, but the coding can be extended according to the network requirements.

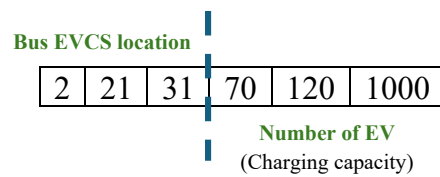


Figure 4. Proposed codification for EVCS location and sizing.

This work employs the Monte Carlo (MC) method [16], the Genetic Algorithm (PGA) [17], and Particle Swarm Optimization (PSO) [18] as solution methodologies, following the iterative procedures reported in the cited references. The algorithm parameters were not selected empirically; instead, they were obtained through a preliminary tuning stage based on an external PSO optimizer following the methodology described in [19]. This procedure allows the identification of parameter combinations that improve solution quality, robustness, and repeatability for the EVCS planning problem. The resulting tuned parameters adopted in this work are summarized in Table 1.

Table 1. Tuned parameters of the evaluated optimization methodologies.

Parameter	MC	PGA	PSO
Population size (N_i)	52	10	37
Maximum iterations ($t_{\max}$)	561	584	414
Mutation rate (n_M)	–	2	–
Cognitive coefficient (C_1)	–	–	0.5789
Social coefficient (C_2)	–	–	1.9172
Maximum inertia ($W_{\max}$)	–	–	0.8433
Minimum inertia ($W_{\min}$)	–	–	0.2195
Velocity factor (μ)	–	–	60.5145

All methodologies employ a matrix-based hourly power-flow method based on successive approximations [20] to evaluate the effects of EVCS location and sizing on DS operation. To improve computational performance, the objective function and operational constraints of all individuals within each population are evaluated simultaneously through a parallel process implemented in MATLAB using the parfor tool. The pseudocode of Algorithm 1 summarizes the general methodology employed for the three solution approaches, which differ only in the solution update stage.

Algorithm 1 General methodology for EVCS siting and sizing

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1: Read system and EVCS data
2: Initialize solutions (according to the selected method)
3: for each iteration or simulation do
4:   for each solution do
5:     Define EVCS location and size
6:     Run hourly power flow with MSA by using parallel process
7:     Evaluate objective function and constraints
8:   end for
9:   Update solutions (MC/GA/PSO)
10: end for
11: Return the best solution

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The optimization was performed using the selected representative demand profile over a 24 h horizon. The additional profiles are included to illustrate demand variability in the Colombian distribution context; however, the reported numerical comparison among

MC, PGA, and PSO corresponds to the same demand scenario, so that all methods are evaluated under identical operating conditions.

5. Results and Discussion

To establish a reference operating condition, base case, the distribution system was evaluated without EVCS installation, i.e., with zero integrated EVs and considering only the conventional demand profiles. Table 2 summarizes the main operating indicators throughout the week.

Table 2. Baseline operating condition without EVCS integration.

Day	EVs	Losses (kWh/day)	$V_{\min}$ (p.u.)	$V_{\max}$ (p.u.)	Max. Loading (%)
Monday	0	1671.05	0.9295	0.9676	73.54
Tuesday	0	1671.05	0.9295	0.9676	73.54
Wednesday	0	1594.33	0.9295	0.9675	73.54
Thursday	0	1671.05	0.9295	0.9676	73.54
Friday	0	1671.05	0.9295	0.9676	73.54
Saturday	0	1583.41	0.9295	0.9657	73.54
Sunday	0	1491.75	0.9295	0.9671	73.48
Weekly Total	0	11,353.68	–	–	–

The baseline scenario represents the original operation of the distribution system without EVCS integration, i.e., with zero installed charging capacity and no EVs connected. Under these conditions, all technical constraints are satisfied, with voltages ranging between 0.9295 p.u. and 0.9676 p.u. and a maximum feeder loading of 73.54%, leaving an available thermal margin of 26.46%.

Regarding network performance, daily energy losses vary between 1491.75 kWh/day and 1671.05 kWh/day, resulting in a total weekly loss of 11,353.68 kWh. These results confirm that the network operates securely under conventional demand conditions and provide a suitable reference for quantifying the impact of EVCS integration on hosting capacity, voltage regulation, and feeder loading.

This analysis considers the integration of three EVCSs within the distribution network. Table 3 presents the best solution identified by each optimization methodology, detailing the optimal EVCS locations and the corresponding number of EVs served at each station. Under these conditions, PSO achieved the highest integration capacity, reaching 1246 EVs, compared with 1225 EVs with PGA and 1077 EVs with MC. This represents an improvement of 1.71% over PGA and 15.69% over MC. In addition, a clear correlation is observed in the selected nodes, since buses 4, 25, and 26 appear repeatedly in the best solutions, suggesting favorable electrical conditions for EVCS installation. In particular, PSO selects buses 26, 25, and 4, obtaining a more effective distribution of EVs among the most suitable nodes and, consequently, a higher total integration capacity while satisfying all operational constraints of the network.

Table 3. Optimal EVCS locations and number of EVs served by each method.

Method	Bus 1	Bus 2	Bus 3	EVs 1	EVs 2	EVs 3	Total EVs	Energy Losses (kWh)
MC	26	28	4	385	244	448	1077	14,317.90
PGA	4	25	30	938	139	148	1225	13,811.08
PSO	26	25	4	536	161	549	1246	14,329.47

The baseline case registered total weekly losses of 11,353.68 kWh, whereas EVCS integration increased this value to 14,317.90 kWh, 13,811.08 kWh, and 14,329.47 kWh for MC, PGA, and PSO, respectively, corresponding to increments between 21.64% and 26.21%.

This behavior is expected, since the additional demand introduced by the charging stations increases network power flows and, consequently, energy losses. As loss minimization is not an objective of the proposed optimization framework, these increments should be interpreted as a natural consequence of achieving higher EV hosting capacities while maintaining all voltage and thermal constraints within their admissible limits.

Table 4 summarizes the statistical performance of the evaluated methodologies over 100 independent runs. The MC approach achieved the lowest average hosting capacity, integrating 1049.4 EVs, while also presenting the highest computational burden with an average processing time of 1427.51 s. Although its standard deviation remained below 2%, its reduced solution quality limits its suitability for the EVCS planning problem.

Table 4. Statistical performance of the optimization methodologies over 100 independent runs.

Method	Average EVs	Coefficient of Variation (%)	Processing Time (s)
MC	1049.4	1.96	1427.51
PGA	1196.1	2.44	171.10
PSO	1213.3	2.60	504.55

The PGA significantly improved the hosting capacity, reaching an average of 1196.1 EVs while requiring only 171.10 s on average, making it the fastest methodology among those evaluated. This result highlights its ability to provide competitive solutions with excellent computational efficiency.

PSO achieved the highest average hosting capacity with 1213.3 integrated EVs. Compared with PGA, PSO increased the hosting capacity by approximately 17 EVs on average, corresponding to an improvement of 1.44%. Although PSO exhibited the largest standard deviation (2.60%), the difference with respect to PGA (2.44%) was marginal, indicating comparable robustness and repeatability. Furthermore, the observed variability remained below 3% in all cases, confirming stable convergence behavior across repeated executions.

Although PSO required a higher computational effort than PGA, the EVCS planning problem corresponds to a long-term planning task in which the quality of the final solution is typically prioritized over execution time. Under this perspective, PSO is the preferred methodology because it consistently achieved the highest average hosting capacity. Nevertheless, if computational efficiency is considered through the ratio between average hosting capacity and processing time, PGA becomes the most efficient alternative, achieving 6.99 EVs/s compared with 2.40 EVs/s for PSO and 0.74 EVs/s for MC.

An additional comparison between serial and parallel implementations showed an average reduction in computational time of 42.22%, confirming the benefits of parallel processing for the EVCS planning problem. The achieved speedup depends on the available hardware resources and the number of workers employed. All simulations were performed in MATLAB R2025b using 4 parallel workers on a Lenovo IdeaPad S340-14IIL laptop equipped with an Intel® Core™ i5-1035G4 processor and 8 GB of RAM.

Figure 5 presents the worst voltage profile over the 24 h horizon and the maximum loading of each distribution line obtained from the EVCS planning solutions. These results correspond to the most critical operating conditions identified after EVCS integration and provide a direct verification of the voltage and thermal constraints enforced by the optimization model. The minimum voltage is observed at hour 20, reaching 0.9206 p.u., while the maximum voltage reaches 0.9633 p.u. during low-demand periods. Consequently, all bus voltages remain within the admissible operating range throughout the scheduling horizon. Likewise, the highest line loading occurs in line 3, reaching 99.98% of its thermal capacity without violating the corresponding thermal limit. These results confirm that the proposed framework is capable of maximizing EV hosting capacity while preserving secure

network operation, ensuring compliance with all technical constraints even under the most demanding operating conditions.

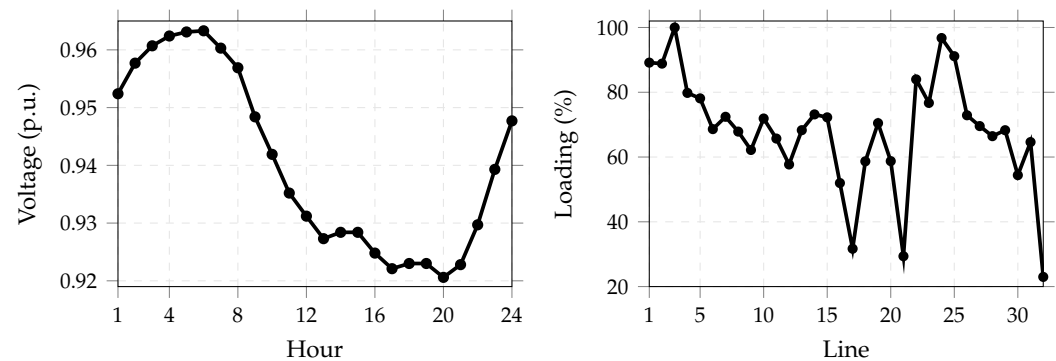


Figure 5. Worst voltage profile during the 24 h horizon and maximum line loading in the distribution system.

To further evaluate the network hosting capacity, an additional analysis was performed using the PSO solution. The number of EVCSs was progressively increased from a single station until voltage or thermal constraint violations were observed. This assessment identifies the practical limits of EVCS integration and provides additional insight into the impact of charging-station penetration on distribution system operation.

Table 5 presents the impact of increasing the number of EVCSs on the hosting capacity and technical performance of the distribution system. Starting from the base case, the progressive deployment of charging stations increases the EV hosting capacity from 1110 EVs with a single EVCS to a maximum of 1385 EVs with six EVCSs. This behavior indicates that distributing the charging demand among a larger number of stations operating at lower individual capacities allows a more effective utilization of the available network resources, increasing the total EV penetration while maintaining compliance with the operational constraints.

Table 5. Impact of EVCS penetration on network hosting capacity.

EVCSs	EVs	Losses (kWh)	$V_{\min}$ (p.u.)	Load _{max} (%)	Feas.
Base	0	11,353.68	0.9294	73.54	Yes
1	1110	13,157.44	0.9242	99.9977	Yes
2	1283	13,527.79	0.9237	99.9749	Yes
3	1278	13,727.67	0.9233	99.9812	Yes
4	1338	14,129.85	0.9214	99.9786	Yes
5	1380	14,183.43	0.9214	99.9747	Yes
6	1385	13,991.97	0.9223	99.9734	Yes
7	1328	14,646.58	0.9198	99.9999	Yes
8	1484	15,786.05	0.9171	137.94	No

Regarding network performance, weekly energy losses increase from 11,353.68 kWh in the base case to values between 13,157.44 kWh and 14,646.58 kWh for the feasible EVCS scenarios. This growth is expected due to the additional charging demand; however, the increase remains controlled when compared with the significant improvement in hosting capacity. In terms of technical feasibility, all solutions with up to seven EVCSs satisfy the voltage and thermal constraints, maintaining minimum voltages above 0.9198 p.u. and maximum line loadings at or below their admissible limits.

When eight EVCSs are installed, the hosting capacity reaches 1484 EVs; however, the maximum feeder loading increases to 137.94%, violating the thermal constraint and

rendering the solution infeasible. Therefore, the limiting factor of the system is not voltage regulation but feeder loading. This result suggests that additional EV integration could be achieved through network reinforcement measures, such as conductor repowering or feeder upgrading by the distribution system operator, which would increase the available thermal capacity and enable higher EV hosting levels.

6. Conclusions

This work proposed a unified parallel optimization framework for EVCS siting and sizing in distribution systems. The proposed AC-feasible MINLP model maximizes EV hosting capacity while enforcing voltage and thermal constraints, and incorporates a representative weekly operating scenario to account for demand variability.

The results demonstrated that the framework can identify EVCS locations and capacities that effectively exploit the available network hosting capacity while preserving secure operation. The best solution enabled the integration of 1246 EVs without violating any operational constraints.

The statistical analysis based on 100 independent runs confirmed the robustness and repeatability of the evaluated methodologies, with standard deviations below 3%. Among the tested approaches, PSO achieved the highest average hosting capacity (1213.3 EVs), outperforming PGA and MC while maintaining comparable solution variability. Although PGA exhibited superior computational efficiency, achieving the best solution-time ratio, the EVCS planning problem addressed in this work corresponds to a long-term planning task in which maximizing hosting capacity is the primary objective. Under this criterion, PSO provided the most effective solution. Additionally, the parallel implementation reduced computational times by 42.22%, highlighting the benefits of high-performance computing for large-scale EVCS planning studies.

Future research should consider the integration of multiple EV clusters as the participation of clusters (C_1), (C_2), and (C_4) increases and approaches the levels currently observed for cluster (C_3). This extension will require EVCS planning models capable of representing heterogeneous charging behaviors, battery capacities, and demand patterns. Additionally, the proposed formulation could be extended toward a multi-objective framework that simultaneously maximizes EV hosting capacity while minimizing energy losses, operational impacts, and computational effort. Due to the nonlinear and conflicting nature of these objectives, advanced high-performance optimization techniques will be required to efficiently solve the resulting large-scale planning problem.

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