

Article

Optimizing Algorithms to Allocate Electric Vehicles Based on Charger Types and User Preferences

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Abstract

Electric vehicles (EVs) are crucial for mitigating greenhouse gas emissions in urban transportation. However, their integration requires efficient charging infrastructure and allocation strategies. In this paper, five heuristic algorithms were developed to allocate EVs to urban charging stations. This allocation process incorporates critical constraints, such as user preferences and charger type compatibility, while respecting station capacities governed by power output rules. The proposed methods include four initial allocation heuristics, ranging from capacity-centric and nearest-neighbor approaches to random assignments, complemented by a local search algorithm for solution refinement. To evaluate these heuristics, an optimization model minimizing station establishment and vehicle travel costs was adapted from the literature. Computational experiments were performed on both synthetic instances and real-world case studies. The results indicate that the developed heuristics, especially when enhanced by local search, deliver high-quality, near-optimal solutions within highly competitive computational times. Consequently, this study offers a scalable decision-support tool for urban planners, demonstrating how the joint optimization of infrastructure costs and user preferences can foster sustainable urban mobility and accelerate EV adoption. Ultimately, these findings offer actionable insights for scaling heterogeneous EV infrastructure, fostering urban sustainability and mitigating transport-related carbon emissions.

Keywords: optimization; heuristics; smart grids; electric vehicles; charger types; charging station infrastructure; decision-making tool



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1. Introduction

Electric vehicles are crucial to decarbonizing the transport sector, particularly when integrated with renewable energy grids. This transition is driven by the imperative to mitigate climate change and improve urban air quality. Electric vehicle (EV) sales are the rise globally. In the last decade, EVs—including cars, vans, buses, trucks, and two- or three-wheelers—have reached record growth rates. The global sales trends and projections for 2020–2030 are illustrated in Figure 1, based on data from the IEA (International Energy Agency) [1].

This scenario reflects an energy system based on current and planned policies. Figure 1 illustrates the different vehicle categories: battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs).

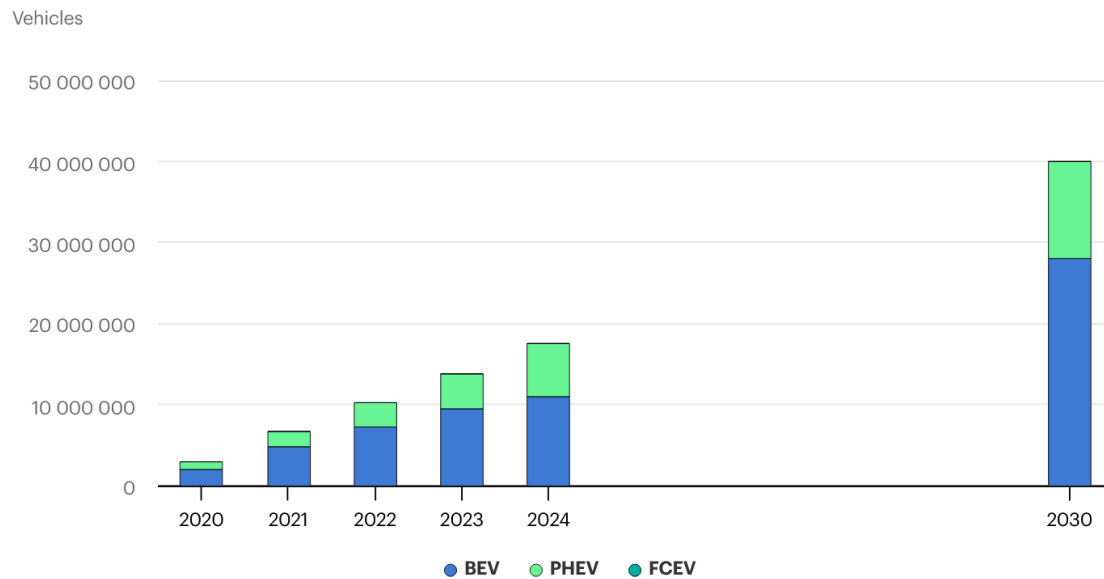


Figure 1. Electric car sales in the world and projections for the 2020–2030 scenario. Source: Adapted from [1].

Brazil has also seen an increase in electric car sales in the last decade, as illustrated in Figure 2. According to IEA [1], sales increased from just 61 vehicles in 2014 to 125,000 in 2024. Sustaining this growth requires expanding the charging infrastructure, including a variety of charger types at each station, as well as reinforcing the electrical grid to support increased demand. In this sense, the electric power system may be affected by the installation of charging stations for electric vehicles. However, a variety of measures are being taken to reduce this impact. For example, in [2], a hybrid system consisting of battery energy storage systems was proposed to improve the operation of the electrical network.

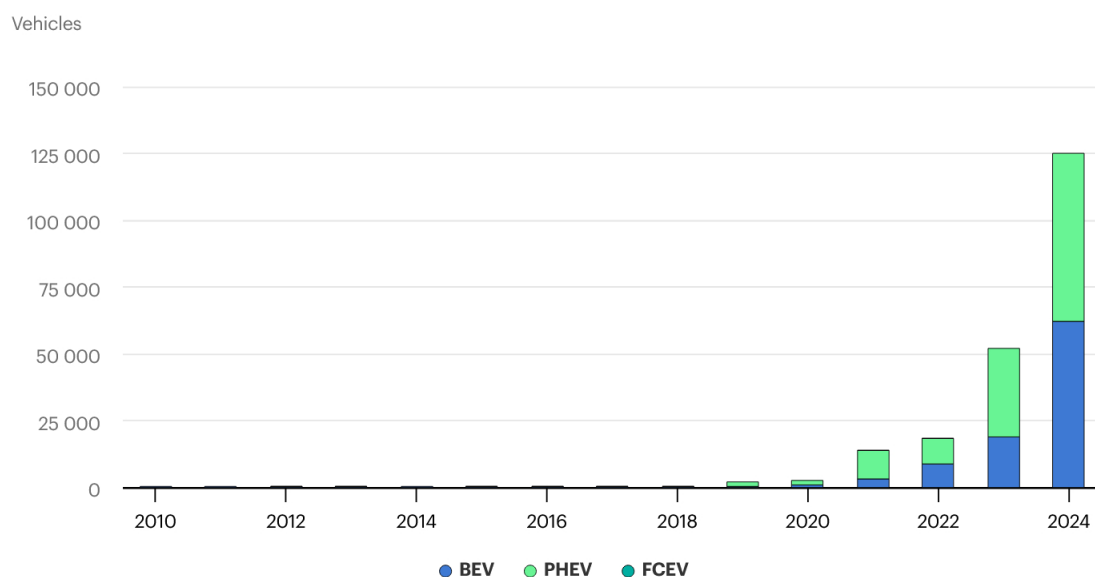


Figure 2. Electric car sales in Brazil from 2021 to 2024. Source: Adapted from [1].

Other works have also been proposed to minimize the challenges associated with the implementation of electric vehicle charging stations [3–6]. In addition, these methods

support the integration of electric vehicle charging stations, improve voltage stability, reduce power losses, and mitigate load spikes. These approaches also offer direct benefits to utilities in terms of cost reduction, transformer loss reduction, and voltage support.

In addition, the use of electric vehicles for mobility in transport is crucial to reducing greenhouse gas emissions, particularly in metropolitan areas around the world. The literature has dedicated considerable attention to the allocation of electric vehicle charging stations in urban areas, considering several metrics such as EV traffic distribution, choice of candidate charging stations, grid energy cost at each charging station, cost and travel time of the electric vehicle to the charging station, availability and specifications of the stations, distance to the charging station, uncertain urban en-route recharging demand, and so on [7–11].

Despite this, although there are several metrics and strategies, to the best of our knowledge, no work allocates charging stations considering different charger types at each station. According to the authors in [12], the optimization models in the literature consider electric vehicle fast chargers, electric vehicle normal chargers, or battery exchange stations. Other papers present several optimization models for the location of electric vehicle charging stations with different strategies for objective functions, constraints, and solution methods [12–15]. In this sense, this paper allocates electric vehicles to charging stations considering different types of charger for slow and fast charging. In addition, user preferences are also introduced to choose charging stations.

There are three charging levels for electric vehicles according to voltage, current, and power requirements, known as Level 1, Level 2, and Level 3 [16]. Level 1 uses a standard 127-volt household outlet, the same type used for common appliances such as phone chargers. This is the slowest EV charging method, adding only a few miles of range per hour of charging. Level 1 charging is best suited for overnight charging or for drivers with low daily mileage needs.

Level 2 uses AC power and offers a faster charging rate than Level 1. This level is commonly found in residential, commercial, and public charging locations and provides a balance between charging speed and convenience. Level 1 and Level 2 chargers operate at lower power levels and are integrated into vehicles. Level 3 is the fastest method of charging electric vehicles. It uses a high-voltage DC power source (typically 400 or 800 volts) to deliver electricity directly to the vehicle battery, bypassing the onboard AC-to-DC converter typical of Level 1 and Level 2. This method significantly reduces charging times, allowing an electric vehicle to reach 80% charge in 20–30 min, compared to several hours with Level 1 or Level 2 charging.

This paper proposes several approaches for the location of electric vehicles to charging stations due to the importance of reducing greenhouse gas emissions through electric vehicles in urban mobility; the extensive literature focusing on charging station allocation in urban areas using metrics such as distance and user preferences; and the rapid growth of electric vehicles worldwide and in Brazil, considering different charging levels at each station. It highlights that the allocation of electric vehicles to charging stations is an NP-hard combinatorial optimization problem [17]. In this context, heuristic algorithms were developed.

In this paper, five heuristic algorithms are developed considering charger types in charging stations within Level 2 and Level 3 charging infrastructures, as well as user preferences. At Level 2, two charger types are considered: Type 2, which is more commonly used in Brazil and follows a European standard, and the AC GB/T Chinese standard, which is similar to Type 2 but uses a different socket connector. For the Level 3 charging infrastructure, three types of charger are considered: CHAdeMO, CCS2 (more commonly used in Brazil), and the DC GB/T Chinese standard. An algorithm assigns vehicles to

charging stations while respecting station capacity, charger types, and user preferences. Another algorithm is based on a nearest-neighbor strategy to assign electric vehicles, while also respecting station capacity, charger types, and user preferences. Two algorithms assign vehicles to charging stations in a random manner, considering the capacity of the station, the types of charger, and user preferences. Finally, an algorithm based on local search is run on the aforementioned algorithms.

The main contributions of this paper are an approach that: (1) the proposed model allocates electric vehicles to charging stations to minimize total infrastructure and operational costs; (2) this optimization accounts for user conveniences, such as charger types and proximity, while strictly respecting the capacity constraints of each station. Additional contributions of this study include: (1) promoting sustainability in cities; (2) providing a framework for the implementation of urban charging infrastructure; (3) contributing to future greenhouse gas emission reductions; (4) introducing innovation by incorporating charger types at charging stations into the optimization model; (5) assisting entrepreneurs in decision-making related to investments in charging station construction; (6) and providing a decision-support tool considering user preferences.

To explicitly highlight the scientific novelty and differentiate this study from existing literature, the core contributions of this paper are threefold. First, unlike traditional models that assume uniform charging infrastructure, our formulation explicitly incorporates distinct charger types at stations directly into the optimization decision. Second, the model simultaneously minimizes total infrastructure and operational costs while strictly satisfying user convenience constraints, such as charger-type compatibility, spatial proximity, and station capacity limits. Finally, we provide a flexible quantitative decision-support tool that reconciles investor capital constraints with dynamic user preferences. By incorporating these realistic constraints into our multi-algorithm framework, decision-makers can select the most suitable algorithm based on their strategic priorities, whether the focus is on minimizing objective function costs, reducing computational runtime, or maximizing the User Preference Success Rate.

The paper is structured as follows. Section 2 describes related work and identifies gaps in the literature. Section 3 presents the mathematical optimization model. Section 4 describes the material and methods, and Section 5 describes the computational results. Section 6 describes the discussion. Finally, Section 6 summarizes the conclusions and proposes directions for future research.

2. Related Work

Research on EV charging infrastructure that has taken place in the last decade can be classified into three main themes: modeling user preferences, allocating infrastructure, dynamic grid pricing, and mitigating grid impact through smart charging. The studies aimed to optimize location, capacity, and costs while also addressing challenges such as demand estimation and user preferences.

The work of [18] not only identified which fast-charging station locations are preferred in a city, but also revealed how users evaluate these locations. The study verified the need to understand how users assess the locations of the fast-charging stations and which criteria are used for preferences. However, the study was limited because participants evaluated only fast-charging stations and did not present a mathematical optimization model with more concrete results, such as station capacity, costs, and charger types.

The paper by [19] developed a genetic algorithm approach for locating electric vehicle charging infrastructure in a city. The approach aims to implement a plan for installing an adequate charging infrastructure to cover future charging demand and reduce the concern of electric vehicle drivers about battery depletion. In this sense, the approach

encourages the widespread adoption of electromobility. The assumptions of the paper were as follows: (1) each charger was considered able to serve only one vehicle; however, stations with charger types such as Type 2 and AC GB/T Chinese standard typically have more than one bay per station; (2) the estimation of charging demand was based on conjecture due to the scarce availability of electric vehicle data, according to the authors. However, the literature provides several datasets related to electric vehicles and charging stations. Another limitation is that the sensitivity analysis was performed by assuming a maximum of only 20 electric vehicle charging stations.

The installation of electric vehicle charging stations can impact the electric power system, and several studies have proposed techniques to mitigate these effects. In [2], battery energy storage systems were used to improve the performance of the electrical network, allowing electric vehicle users and storage systems to participate in demand response programs and improving the stability and efficiency of the grid. In the work of [3], a game-theoretic approach was proposed to develop a smart pricing model and design a mechanism to alleviate network congestion.

The paper by [4] investigated the impact of planning mechanisms within smart grid frameworks when allocating distributed photovoltaic generation units, battery energy storage systems, capacitor banks and electric vehicle charging station facilities. The objective was to improve grid performance through power loss minimization, improved voltage stability, and reduction in voltage deviation. Similarly, Alphonse et al. [5] aimed to reduce energy losses and 24-h voltage deviation while maximizing the weighting of the system to provide charging services to the largest possible number of users.

The work of [6] proposed a smart charging strategy that adapts the charging process to meet both the requirements of the power system and the needs of the users of the electric vehicle. Smart chargers can adjust charging power according to the availability of the grid, the requirements of users, and emergency conditions, enabling electric vehicles to act as flexible grid resources and provide ancillary services. The primary objective of smart charging is to flatten the load profile.

In the work of [15], a methodology was presented to estimate the charging demand of the electric vehicle using graph theory and mathematical modeling. A geographical model was developed based on trip origin–destination data and characteristics of social dimension and validated using real-world charging data. The results were then incorporated into a capacitated maximal coverage location problem to optimize the spatial layout of public charging stations by maximizing their utilization. A limitation of the planning process in [15] is that only Level 2 charging stations were considered. Consequently, the integration of the Level 2 and Level 3 stations in urban areas was not addressed, which does not fully reflect real-world conditions. As a result, vehicles using charger types such as CHAdeMO, CCS2, and the GB/T Chinese standard were not evaluated differently, despite their practical differences.

The paper presented by [8] developed a multi-factor dynamic optimization model using multi-criteria analysis to select the best alternatives to electric vehicle charging within a smart grid, with the goal of supporting higher uptake of mobility based on electric vehicle. According to the authors, the proposed methodology is not limited to comparing alternative charging options at a specific time, as it considers the energy cost as a time-dependent parameter within a predefined dynamic pricing context. A drawback of this work concerns the small number of charging stations and electric vehicles considered, which were 20 and 7, respectively. Another issue relates to dynamic pricing, energy availability, free charging positions, uncertainties in trip time calculation, and other parameters that may compromise the selection of electric vehicle charging options.

In the work of [7], a pricing scheme for electric vehicle charging was presented in a competitive discrete-time dynamic market scenario. In this case, multiple electric vehicle charging stations adopted a pricing model to maximize their profits. This study is relevant due to its pricing scheme for electric vehicle charging, which considers vehicle traffic information, the locations of potential charging stations, waiting times at each station, and grid energy costs. However, the study assumes a highly dynamic environment with frequent short-term fluctuations in prices and other parameters. As a result, the proposed method may not be applicable under certain market conditions.

While some planning models incorporate economic factors, such as the fixed-budget allocation framework proposed by [20] which considers spatial land price disparities, they often introduce significant simplifications. Specifically, their approach treats charging station allocation as a static planning problem, neglecting traffic dynamics, time-of-use electricity pricing, and charging station capacity limits. Furthermore, the assumption of globally optimized traffic flows ignores the individual decision-making process of EV drivers in real-world scenarios. Consequently, there remains a critical research gap in addressing dynamic user behaviors.

The paper by [21] proposed a scheme called the User-Preferences-Based Charging Station Recommendation Scheme, which integrates user preferences with multi-attribute decision-making. The work provides recommendations for the best charging stations available for electric vehicle users. The results indicated good performance in decision-making based on user preferences and reduced sensitivity to abnormal classification when selecting charging stations. Nevertheless, this scheme presents challenges and limitations in implementation, mainly related to data availability, system scalability, and real-time updates.

The study by [9] introduced a framework based on machine learning to optimize electric vehicle charging considering driver satisfaction through socio-demographic attributes, state of charge, proximity to charging stations, among other factors. However, limitations arise from the use of a specific dataset of electric vehicle users and the absence of real-time data integration. As a result, the generalizability of the findings, as well as the accuracy and applicability of the model, may be affected.

The paper by [10] aimed to minimize the total associated cost of charging by allocating direct current fast chargers at optimal locations to meet the high charging demand. The associated costs include upfront investments in power transmission lines and fast chargers, as well as the value of travel time to the nearest charging stations during the decision period. The model considered uncertain charging demand estimated from real-world traffic flow data and time-varying traffic patterns influenced by weather and seasonal effects. The limitations of this work include the use of only 20 charging stations, the lack of evaluation of electric vehicle penetration rates, and the use of static models that examined only a single time epoch. In addition, the models did not consider the expansion of charging stations with new chargers to accommodate growing charging demand over time.

A recent advancement by [22] introduced a two-stage orderly charging scheduling method via the Supervised Service Matching and Reinforcement Power Dispatch framework. However, their approach presents three major limitations that restrict its real-world scalability. First, the supervised matching network relies heavily on station-specific historical records, making the model highly sensitive to local arrival behaviors and charger configurations, which demands extensive data adaptation or fine-tuning for new deployments. Second, the scope is confined to isolated, single-station real-time scheduling, completely overlooking multi-station coordination, vehicle guidance, and regional grid-level management. Finally, to maintain computational tractability, the authors simplify the charging process into a linear energy update with constant efficiency. This oversimplification neglects

practical battery dynamics, such as nonlinear charging curves and power limits, as well as user-side uncertainties like willingness to wait.

Existing methods in the literature contribute to improving voltage stability, reducing power losses, and preventing load spikes. Additionally, they provide direct benefits to utilities in terms of cost reduction, minimized transformer losses, and voltage support. Nevertheless, the gaps identified in these previous studies motivate the development of algorithms for allocating electric vehicles to charging stations in urban areas. To address this, this paper focuses on optimizing EV allocation, taking into account constraints such as station capacity, infrastructure costs, and user preferences.

3. Optimization of Charging Infrastructure and Algorithmic Strategy

In this section, we present a mathematical optimization model for allocating electric vehicles to charging stations while considering charger types and user preferences. Some examples of solutions obtained by the proposed algorithms are also presented. The optimized parameters and metrics returned by the algorithms for the charging infrastructure are described.

3.1. Mathematical Optimization Model

The mathematical optimization model proposed in this paper is based on the model presented by [13]. To better reflect real-world conditions, the constraints (5) and (6) were added to the literature model. These ensure that both user preferences and charger type specifications are matched between electric vehicles and stations. Thus, the last proposed model selects a set of electric vehicle charging stations from a set of candidate charging station locations, with the objective of minimizing the financial installation cost of the charging stations and the cost of electric vehicle travel. In addition, the proposed model considers different types of chargers for slow and fast charging and preferences of users.

The proposed model includes several constraints. These constraints require that each electric vehicle is covered by a charging station if the station has the appropriate charger type for that electric vehicle and that the capacity of each charging station does not exceed the total demand of the electric vehicles assigned to it. Moreover, user preferences of electric vehicles in choosing charging stations may also be satisfied.

Sets and Parameters:

- J : set of candidate charging station locations, where each station j has a power capacity C_j .
- I : set of electric vehicles, where each vehicle i has a power demand c_i .
- fc_j : financial cost of locating a charging station at location j .
- c_i : power demand of electric vehicle i .
- C_j : total power capacity of the charging station j .
- p_k : user preference k of electric vehicle.
- P_u : available user preferences u at the charging station.
- t_l : charger type l required by electric vehicle.
- T_v : available charger types v at charging station.
- d_{ij} : distance between electric vehicle i and charging station j .

Note: Decision Variables:

- $x_j \in \{0,1\}$: equals 1 if the candidate station j is selected, and 0 otherwise.
- $y_{ij} \in \{0,1\}$: equals 1 if electric vehicle i is assigned to charging station j , and 0 otherwise.

Optimization Model:

$$\min \sum_{j \in J} f c_j x_j + \sum_{i \in I} \sum_{j \in J} d_{ij} y_{ij} \quad (1)$$

$$\text{s.t.} \quad \sum_{j \in J} y_{ij} = 1, \quad \forall i \in I \quad (2)$$

$$y_{ij} \leq x_j, \quad \forall i \in I, \forall j \in J \quad (3)$$

$$\sum_{i \in I} c_i y_{ij} \leq C_j x_j, \quad \forall j \in J \quad (4)$$

$$y_{ij, p_k} \leq x_{j, p_u}, \quad p_k \in P_u, \quad \forall i \in I, \forall j \in J \quad (5)$$

$$y_{ij, t_l} \leq x_{j, T_v}, \quad t_l \in T_v, \quad \forall i \in I, \forall j \in J \quad (6)$$

$$x_j \in \{0, 1\}, \quad \forall j \in J \quad (7)$$

$$y_{ij} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J \quad (8)$$

Minimum Distance Constraint Between Charging Stations:

- r : minimum allowable distance between any two charging stations.
- $dist_{kj}$: distance between charging stations k and j .

$$r x_k x_j \leq dist_{kj}, \quad \forall k, j \in J, k \neq j \quad (9)$$

The optimization model does not use the minimum distance constraint between charging stations with radius r described above. This is because, in the preliminary results, the majority of charging stations already exhibited a high spatial dispersion. According to [13], the minimum value of r was set to 1 km. The final results presented in this paper showed that the distance $dist_{kj}$ between charging stations for all instances was greater than or equal to 1 km.

The objective function in (1) minimizes the total financial cost of charging station installation and the total distance traveled by electric vehicles to access the selected charging stations. Constraints (2) and (3) ensure that each electric vehicle is assigned to exactly one charging station. Constraint (4) ensures that the total demand assigned to charging station j does not exceed its capacity C_j . Constraints (5) ensure that an electric vehicle i with preference k is assigned to charging station j with preference set P_u if and only if $p_k \in P_u$. Constraints (6) ensure that an electric vehicle i with charger type l is assigned to charging station j with charger type set T_v only if $t_l \in T_v$. Finally, constraints (7) and (8) define the integrality requirements of the binary decision variables.

3.2. Examples of Solutions with Optimized Parameters

Figure 3 shows an example of a solution obtained using a strategy that uses the nearest-neighbor-based algorithm with 20 electric vehicles and 6 charging stations (20EV–6CS). More details about this strategy can be seen in Procedure 1. This algorithm assigns electric vehicles while respecting the capacity of each charging station, the charger types available at the charging stations, and user preferences. The complete results are presented in Table 1, which includes all performance metrics. Table 2 details the charger types and user preferences for each charging station and each electric vehicle.

Procedure 1 Nearest Neighbor Based Algorithm

```

1: procedure NEARESTNEIGHBOR( $CS, EV, D$ )      ▷  $CS$ : set of charging stations,  $EV$ : an
   electric vehicle,  $D$ : distance matrix
2:   Choose an arbitrary starting charging station  $cs_{start} \in CS$ 
3:    $cs_{best} \leftarrow cs_{start}$                 ▷  $cs_{best}$ —the best selected station
4:    $d_{min} \leftarrow d(EV, cs_{start})$           ▷  $d_{min}$ —minimum distance from  $EV$  to  $cs_{start}$ 
5:    $Unvisited \leftarrow CS \setminus \{cs_{start}\}$ 
6:   while  $Unvisited$  is not empty do
7:     Find  $cs_{node} \in Unvisited$  and calculate  $d(EV, cs_{node})$ 
8:     if  $d(EV, cs_{node}) < d_{min}$  then
9:        $d_{min} \leftarrow d(EV, cs_{node})$ 
10:       $cs_{best} \leftarrow cs_{node}$ 
11:    end if
12:    Remove  $cs_{node}$  from  $Unvisited$ 
13:  end while
14:  return  $cs_{best}$                           ▷ Return the best selected station
15: end procedure

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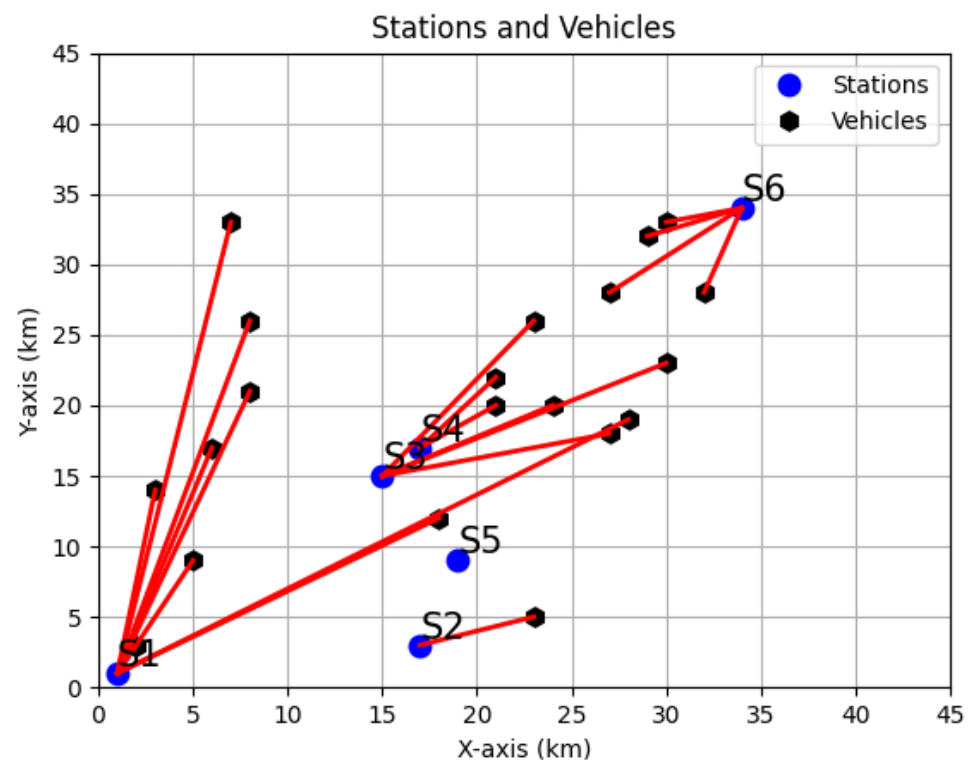


Figure 3. Example of a solution using the algorithm based on nearest neighbors (20EV-6CS). Source: Authors (2026).

From Tables 1 and 2, it can be observed that for Electric Vehicle 13 the user preference was not satisfied. Therefore, the UPSR was 95%. The solution is feasible since each electric vehicle is allocated to a charging station. The minimum distance among all stations was equal to 3 km, indicating a good spatial dispersion of the charging stations.

The total kW capacity of the opened charging stations was 1295 kW, while the total kW demand of the electric vehicles was 1736 kW. As a result, some vehicles must be queued for charging, particularly at Charging Station 1. It is highlighted that all electric vehicles have fast charger types, except Vehicle 6. The developed algorithms support post-allocation analysis of the charging infrastructure. In the example above, Charging Station 1 could increase its capacity and number of chargers if an entrepreneur decides to

invest. Such an investment could solve the vehicle queuing issue. In this case, the electric vehicles were allocated to Charging Station 1 because the algorithm is based on the nearest-neighbor strategy.

Table 1. Complete results of an instance with 20 electric vehicles and 6 charging stations.

Objective Function Cost	2567
Financial Cost of the Opened Charging Stations	2300 thousands US\$
kW Cost of the Opened Charging Stations	1295 kW
kW Cost of the Vehicles	1736 kW
Number of bays (charges)	23
Number of charges Type 2	0
Number of charges GB/T Chinese AC	6
Number of charges CHAdeMO	7
Number of charges CCS2	8
Number of charges GB/T Chinese DC	2
Computational time	0.017 s
Feasibility	The solution is feasible
The User Preference Success Rate (UPSR)	95.0%
The minimum distance among all stations	3 km
Total of candidate charging stations	6
Total of selected (opened) charging stations	5

Source: Authors (2026).

Table 2. Details about charger types and user preferences as input data for instance with 20 electric vehicles and 6 charging stations.

Charging Station: 1, Charger Types: 1, 2, 3, 4, and 5, User Preferences: 1, 2, and 3	Charging Station: 2, Charger Types: 1, 2, 3, 4, and 5, User Preferences: 1, 2, and 3	Charging Station: 3, Charger Types: 1, 2, 3, 4, and 5, User Preferences: 1, 2, and 3	Charging Station: 4, Charger Types: 1, 2, 3, 4, and 5, User Preferences: 1, 2, and 3	Charging Station: 5, Charger Types: 1, 2, 3, 4, and 5, User Preferences: 1, 2, and 3	Charging Station: 6, Charger Types: 1, 2, 3, 4, and 5, User Preferences: 1, 2, and 3
Vehicle: 3 charger type: 4 user preference: 2	Vehicle: 13 charger type: 2 user preference: 1	Vehicle: 4 charger type: 4 user preference: 2	Vehicle: 1 charger type: 4 user preference: 2		Vehicle: 2 charger type: 4 user preference: 1
Vehicle: 12 charger type: 4 user preference: 2		Vehicle: 14 charger type: 5 user preference: 2	Vehicle: 19 charger type: 3 user preference: 2		Vehicle: 8 charger type: 3 user preference: 3
Vehicle: 7 charger type: 3 preference: 2		Vehicle: 11 charger type: 3 preference: 2			Vehicle: 17 charger type: 3 preference: 2
Vehicle: 16 charger type: 5 user preference: 2		Vehicle: 10 charger type: 2 user preference: 1			Vehicle: 15 charger type: 3 user preference: 1
Vehicle: 6 charger type: 2 user preference: 3					
Vehicle: 9 charger type: 4 user preference: 1					
Vehicle: 18 charger type: 4 user preference: 2					
Vehicle: 5 charger type: 3 user preference: 3					
Vehicle: 20 charger type: 4 user preference: 1					

Source: Authors (2026).

However, the other algorithms assign vehicles to charging stations while respecting the capacity of each charging station, thereby avoiding charging queues. Therefore, the total kW capacity of the opened charging stations will be greater than the total kW demand of

the vehicles. Charging Station 5 was not selected. In this sense, the financial cost of the opened charging stations was lower than the cost of selecting all candidate stations.

Another perspective on Charging Station 1 (CS1) is related to the scheduling of electric vehicles at this station. For example, CS1 can simultaneously charge a first group of vehicles, namely vehicles 3, 6, 7, and 16, due to its maximum capacity of 301 kW and a maximum of five charger types. Charger type 1 is not used because there is no vehicle with a power demand of 19 kW allocated to this station. After the first group finishes charging at CS1, a second group of vehicles (vehicles 5 and 12) can be charged. Subsequently, CS1 charges a third group (vehicle 9 only), followed by a fourth group (vehicle 18 only), and finally a fifth group (vehicle 20 only).

The predicted total time to charge all vehicles at CS1 is 2 h, according to estimates based on the charging curve shown in Figure 4. However, five vehicles of Class 4 (CCS2, 150 kW, DC) are charged in a predicted total time of 1 h and 40 min, as shown in Table 3. It is highlighted that the majority of electric vehicle users charge their batteries up to approximately 80% state of charge. Therefore, the predicted total time for charging all vehicles at CS1 is expected to be shorter. When the battery reaches 80% state of charge, the charging speed decreases significantly, and it takes considerably longer to charge from 80% to 100%, as illustrated in Figure 5.

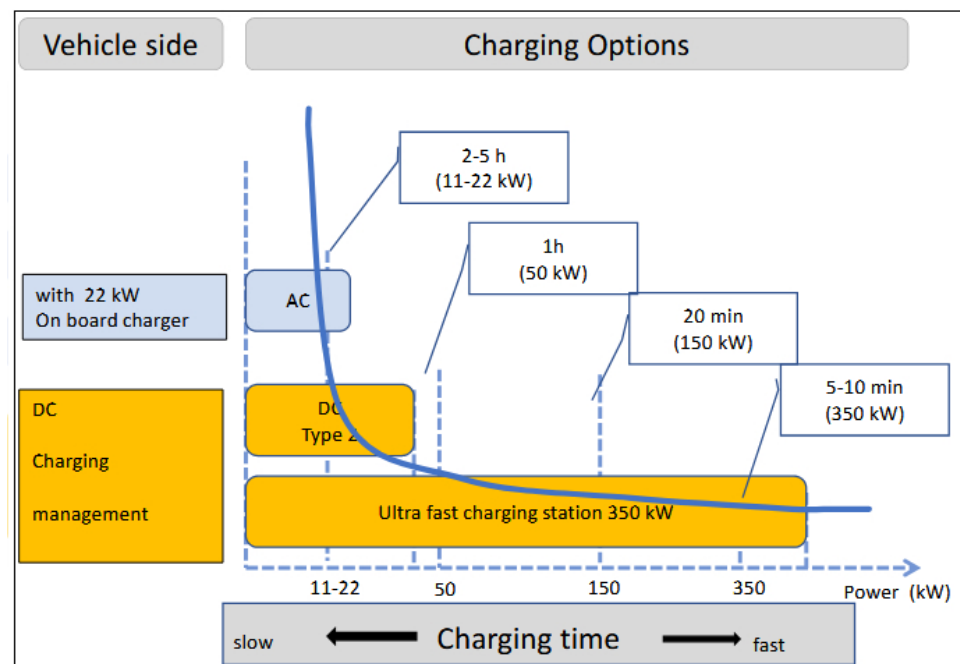


Figure 4. The correlation between charging capacity and charging time. Source: Adapted from [23].

Table 3. Distribution of vehicles in CS1 with the class of charger types and estimated charging time.

	Class 1: Type 2, 19 kW (AC)	Class 2: GB/T Chinese, 22 kW (AC)	Class 3: CHAdeMO 50 kW (DC)	Class 4: CCS2 150 kW (DC)	Class 5: GB/T Chinese, 60 kW (DC)
Vehicle: 3				20 min	
Vehicle: 12				20 min	
Vehicle: 7			1 h		
Vehicle: 16					1 h
Vehicle: 6		2 h			
Vehicle: 9				20 min	
Vehicle: 18				20 min	
Vehicle: 5			1 h		
Vehicle: 20				20 min	

Source: Authors (2026).

Table 4 presents another example of a solution obtained using an algorithm that respects the capacity and charger types at each charging station, as well as user preferences. The complete results, including all performance metrics, are shown in Table 4. From Table 4, it can be observed that all electric vehicles complied with user preferences, resulting in a UPSR of 100%. The solution is feasible, as each electric vehicle is allocated to a charging station. The minimum distance among all stations was equal to 3 km, indicating a good dispersion of charging stations. The total kW capacity of the opened charging stations was 1637 kW, while the total kW demand of the electric vehicles was 1559 kW. Therefore, no vehicle needs to wait in a charging queue, since the station capacities exceed the total demand.

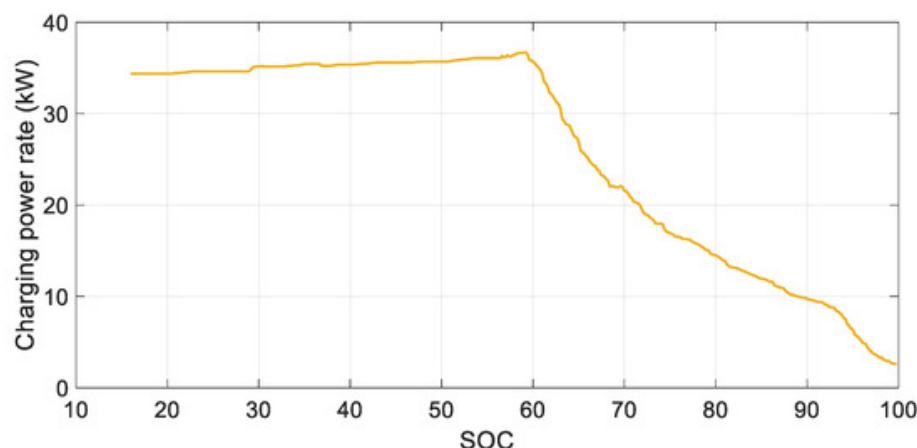


Figure 5. Typical charging profile of an electric vehicle under a DC fast-charging system. Adapted from [24].

Figure 6 shows an example of a solution obtained using the capacity-priority-based algorithm with 25 electric vehicles and 11 charging stations (25EV–11CS). As shown in Figure 6, some charging stations were not selected. In particular, charging stations 7, 8, 9, and 10 were not selected.

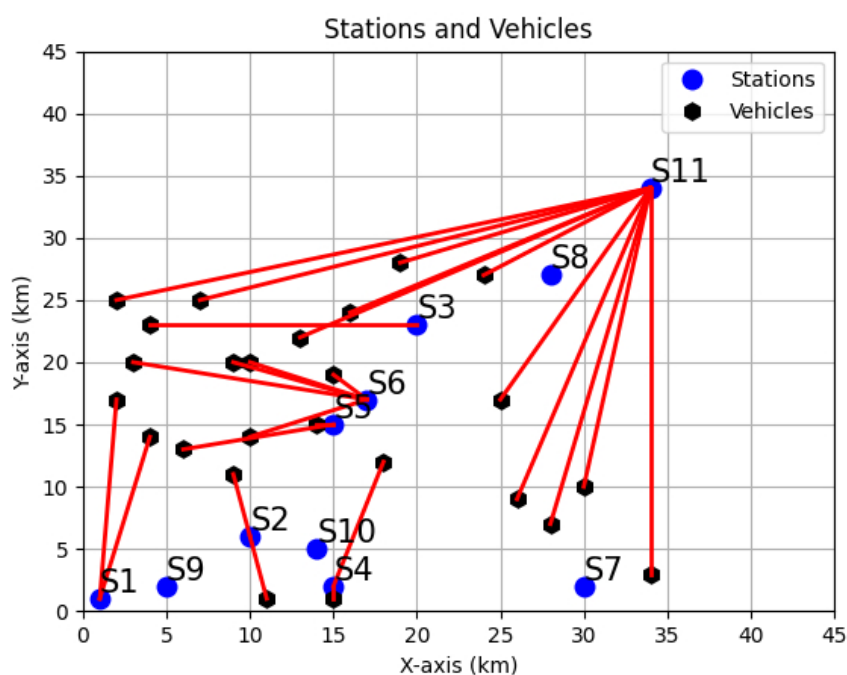


Figure 6. Example of a solution using the algorithm based on the capacity (25EV–11CS). Source: Authors (2026).

Table 4. Complete results of an instance with 25 electric vehicles and 11 charging stations.

Objective Function Cost	3380
Financial Cost of the Opened Charging Stations	3000 thousands US\$
kW Cost of the Opened Charging Stations	1637 kW
kW Cost of the Vehicles	1559 kW
Number of bays (charges)	39
Number of charges Type 2	6
Number of charges GB/T Chinese AC	22
Number of charges CHAdeMO	3
Number of charges CCS2	7
Number of charges GB/T Chinese DC	1
Computational time	0.065 s
Feasibility	The solution is feasible
The User Preference Success Rate (UPSR)	100.0%
The minimum distance among all stations	3 km
Total of candidate charging stations	11
Total of selected (opened) charging stations	7

Source: Authors (2026).

4. Material and Methods

This section presents the approach used to generate the problem instances, including data such as charging station capacity, electric vehicle demand, station financial cost, charger types, user preferences, and the range of Cartesian coordinates for vehicles and charging stations. In addition, the implemented data values for each instance and the performance metrics used to evaluate the developed algorithms are described. In this work, five algorithms were developed for allocating electric vehicles to charging stations while considering station capacity, charger types, and user preferences.

The specifications provided in the following sections ensure the reproducibility of the algorithms and generated instances. The environment was developed in the Python programming language on an Intel-based system, both of which are described in further detail in the Section 5.

4.1. System Boundaries and Operational Scope

To ensure methodological clarity across the comprehensive analysis presented in this study, the operational framework is governed by a well-defined set of system boundaries and computational constraints:

- **Infrastructure Dimension:** The planning model targets static charging station allocation within a predetermined set of candidate urban coordinates, isolating the algorithmic performance from dynamic real-time traffic routing or power grid distribution variables.
- **Scale-Adaptive Computational Budgets:** The algorithmic scope transitions deterministically based on instance scale. The local search operates fully with an $O(n^4)$ complexity bound for instances up to 150 vehicles, whereas it automatically adapts to a strict computational budget capped at $K = 50$ iterations for large-scale deployments (≥ 200 vehicles).
- **Multi-Objective Evaluation Axes:** The framework restricts its multi-criteria assessment precisely to three performance pillars: mathematical objective function cost, computational execution time, and user satisfaction quantified via the User Preference Success Rate.

By maintaining this comprehensive architecture within explicitly mapped boundaries, the framework provides a robust and non-fragmented evaluation of the trade-offs between investor capital constraints and user preferences.

4.2. Approach to Generate the Instances

To evaluate the optimization model, an algorithm was used to generate instances in which the positions of charging stations and electric vehicles are randomly distributed in a planar region. Each charging station instance is composed of a text file, where each line contains an identifier for the station, the total power (capacity) of the charging station, the financial cost for station installation, the charger types available at the station, the Cartesian coordinates, and user preferences.

For the electric vehicle instances, a similar text file was also created, following the same structure used for charging stations. In this case, each line contains an identifier for the vehicle, the power demand, the charger type, the Cartesian coordinates, and a user preference. More details about electric vehicle charging stations are presented as follows.

It is highlighted that the Cartesian coordinate data for electric vehicles are generated in the same way as for charging stations. The planar region considered is a square area of 34 km by 34 km, totaling 1156 km². This area approximately corresponds to the cities of the Greater Vitória Metropolitan Region—Vitória, Vila Velha, Serra, and Cariacica—with a total area of 1135 km² at State of Espírito Santo in Brazil [25]. Each electric vehicle and each charging station has Cartesian coordinates (x, y) generated from a discrete uniform distribution in the range [0, 34]. The power infrastructure of the Greater Vitória Metropolitan Region comprises 38 generation projects with a total installed capacity of 417.31 MW (data as of 1 April 2026) [26]. Compared to the 2.46 MW demand for charging stations identified in Table 18, this capacity reflects an energy surplus for the region. In total, Espírito Santo accounts for 1821.93 MW of capacity from 105 active projects.

According to the literature, the financial cost for installing charging stations is as follows: for AC semi-fast charging stations, the cost ranges from 30,000 to 160,000 USD per bay, with each bay having several types of connectors; for DC fast charging stations, the cost ranges from 80,000 to 120,000 USD per bay, where each bay has one type of connector [27,28].

In this sense, an installation cost of 100,000 USD per bay was adopted for both AC and DC charging stations. Each bay is composed of a single charger type. Thus, in an AC charging station, a bay has one charger type with two connectors, allowing two electric vehicles to be charged simultaneously using the same charger type. In a DC charging station, a bay has one connector per charger type, and only one electric vehicle can be charged at a time. A maximum of five charger types was considered for each charging station. Therefore, the maximum cost of each charging station is 500 thousand USD for both AC and DC charging stations.

Electric vehicle charging power levels were considered as Level 2 (semi-fast) and Level 3 (fast), using three-phase systems for both AC and DC power supply [29]. In addition, both AC and DC connectors were considered, totaling five charger types [30–33]. Thus, a maximum of five charger types was defined for each charging station. Two AC charger types and three DC charger types are described as follows. The power levels (in kW) were selected from a commercial perspective:

- Class 1—Type 2 (European standard, used in Brazil), AC charger, 22 kW maximum power, considered as 19 kW.
- Class 2—GB/T Chinese standard (two plugs for DC and AC), similar to Type 2 but with a different connector, AC charger, 28 kW maximum power, considered as 22 kW.
- Class 3—CHAdeMO, DC charger, 50 to 400 kW, considered as 50 kW.
- Class 4—CCS2, DC charger, capable of up to 350 kW (widely used in Brazil), considered as 150 kW.
- Class 5—GB/T Chinese standard (two plugs for DC and AC), DC charger, 60 to 237 kW, considered as 60 kW.

Thus, the total power (capacity) of each charging station depends on the number and type of chargers installed. For example, if a charging station has Class 1 and Class 2 chargers, the total power is 41 kW. On the other hand, if a charging station has all five classes, the total power is 301 kW. A numerical identifier was assigned to each charger class. In the text file, a number or a set of numbers is written in each line to identify the charger type of a vehicle or the charger types of a station. Class 1 is associated with number 1, Class 2 with 2, Class 3 with 3, and so on.

In recent decades, user preferences and behaviors related to strategic locations—such as shopping centers for fast-charging stations, traffic flow, distance, and energy price—have been shown to significantly impact the optimization of electric vehicle charging station placement and operation [9,18,21].

In this context, a user-centric approach combined with optimization of candidate stations promotes broader adoption of electric vehicles. Moreover, it ensures that charging infrastructure aligns with user needs and supports the development of a sustainable electric vehicle charging ecosystem.

Therefore, in this work, three user preferences were considered: energy price, convenience store availability, and traffic flow. A charging station can have up to three user preferences. A numerical identifier was assigned to each preference: energy price is associated with number 1, convenience store with 2, and traffic flow with 3. Let a list of elements $(1, 2, 3, \dots, n)$, where the list contains n elements. For each charging station, a discrete uniform distribution in the range $[1, 3]$ was used to generate the associated preference numbers. Thus, a charging station may have one preference (1), (2), or (3); two preferences (1 2), (1 3), or (2 3); or all three preferences (1 2 3). However, for each electric vehicle, only a single user preference was assigned: (1), (2), or (3). This single-preference strategy was adopted because it is more realistic.

To guarantee model feasibility and ensure that no vehicle remains unassigned during the fallback loops (see, Figures 8 and 9), the experimental layout is designed with three strategic universal charging stations, located at both ends and in the center of the planar region. These three stations are equipped to satisfy all possible user preferences. Consequently, the strict enforcement of constraints (5) and (6) is always maintained without causing infeasibility.

Tables 5 and 6 present examples of charging station and electric vehicle data, respectively, corresponding to a single line in the instance text file. Table 5 shows a line containing the station identifier (4), total power (41), installation cost (200), charger types available (1, 2), Cartesian coordinates (11, 5), and user preferences (1, 3) associated with the charging station. Table 6 shows a line containing the vehicle identifier (5), the power demand (150), the charger type (4), the Cartesian coordinates (3, 30), and a user preference (2), associated with the electric vehicle user, corresponding to a preference for a convenience store.

The metrics used to evaluate the algorithms for each instance were the objective function cost, the financial cost of the opened charging stations (thousand dollars), the power capacity cost of the opened charging stations (kW), the total power demand of the vehicles to be charged (kW), the number of bays, a detailed description of the number of chargers in each class, computational time, solution feasibility, the UPSR (User Preference Success Rate), the minimum distance among all stations, and the total number of selected (opened) charging stations. Tables 1 and 4 show examples of metrics that are outputs of the algorithms.

Table 5. An example of data for a charging station.

Data of a Line	Units	Implemented Values	Example of a Line
Station Id	Integer number	1, 2, ..., n	4
Capacity	kW	19 to 301	41
Financial cost	US\$ thousands	100 to 500	200
Charger types (T_v)	Class 1, Class 2, Class 3, Class 4, Class 5	$v = 1, 2, 3, 4$, and 5	1 and 2 ($T_{1,2}$)
Cartesian coordinates	x-integer number, y-integer number	1 to 34, 1 to 34	$x = 11$ and $y = 5$
User preferences (P_u)	energy price cost, convenience store, and traffic flow	$u = 1, 2$, and 3	1 and 3 ($P_{1,3}$)

Source: Authors (2026).

Table 6. An example of data for an electric vehicle.

Data of a Line	Units	Implemented Values	Example of a Line
Vehicle Id	Integer number	1, 2, ..., m	5
Capacity	kW	19, 22, 50, 60, and 150	150
Charger type (t_l)	Class 1, Class 2, Class 3, Class 4, Class 5	$l = 1, 2, 3, 4$, and 5	4 (t_4)
Cartesian coordinates	x—integer number, y—integer number	1 to 34, 1 to 34	$x = 3$ and $y = 30$
User preferences (p_k)	energy price cost, convenience store, and traffic flow	$k = 1, 2$, and 3	2 (p_2)

Source: Authors (2026).

When the algorithm refers to the random allocation of electric vehicles to charging stations, the average objective function cost and its standard deviation are reported. UPSR is a metric that measures the percentage of users in each instance whose preferences were successfully satisfied as specified at the start. The UPSR evaluates the percentage of electric vehicle users whose initial charging preferences were successfully satisfied by their assigned charging stations. Based on the condition that each vehicle is allocated to exactly one station, the metric is mathematically defined as follows:

$$\text{UPSR} = \left(\frac{1}{|V|} \sum_{v \in V} \mathbb{I}_{\{\exists s \in S : v \in s.V \wedge v.pv \in s.Ps\}} \right) \times 100 \quad (10)$$

where:

- V and S denote the sets of vehicles and charging stations, respectively;
- $|V|$ represents the total number of vehicles;
- $s.V$ is the set of vehicles assigned to station s ;
- $v.pv$ represents the initial preference established by the user of vehicle v ;
- $s.Ps$ is the set of user preferences supported by station s ;
- $\mathbb{I}_{\{\cdot\}}$ is the indicator function that outputs 1 if the condition is satisfied, and 0 otherwise.

A higher UPSR indicates superior user satisfaction, reflecting a larger proportion of users whose initial choices were successfully met. From a decision-making perspective, the UPSR does not rely on a static, universal quantitative threshold to determine infrastructure quality across different regional scales. Instead, it serves as a dynamic, context-dependent performance indicator. The optimal value of UPSR is determined by the specific trade-offs established during the optimization process, balancing investor capital constraints (e.g., the cost of opening new candidate stations) against computational constraints and user satisfaction targets. Consequently, rather than assessing infrastructure

through an arbitrary fixed baseline, planners can leverage the UPSR to analyze varying trade-off fronts between service quality and budget limitations.

4.3. Algorithms for Allocating Electric Vehicles to the Stations

Five algorithms were developed to allocate electric vehicles to urban charging stations, considering factors such as charger types and user preferences. Each algorithm applies a specific strategy: one focuses on station capacities, another uses a nearest-neighbor approach (Procedure 1), and the remaining two assign vehicles randomly. In addition, a local search algorithm was designed to improve the solutions produced by these initial methods.

The Procedure 1 is an algorithm that uses the nearest-neighbor strategy is a simple greedy heuristic where an electric vehicle starts at a chosen charging station and repeatedly visits the closest unvisited one. After visiting all stations, it returns to the best-positioned station, typically the one nearest to the vehicle's starting point. After returning the optimal charging station choice, this station is assigned to the electric vehicle. In each instance, all electric vehicles select their respective charging stations based on the best available option.

Time-of-Use (ToU) tariffs are asset optimization tools that incentivize grid usage during off-peak hours, typically overnight, improving system efficiency and reducing costs for all users. This approach to intelligent resource management is already standard for industrial and large-scale energy consumers. Although electric vehicle drivers follow various routines, low charging station operators' fees or reduced kilowatt-hour rates from utilities could trigger a "rush" of electric vehicle owners looking to charge their batteries simultaneously. Consequently, the charging infrastructure must be scaled to handle these peak loads.

Furthermore, Vehicle-to-Grid (V2G) technology allows EVs to support grid stabilization rather than merely drawing power. Through V2G, vehicles can supply energy back to the grid during peak demand. Therefore, a large number of interconnected EVs could ultimately serve as a decentralized solution for grid stability, functioning as a massive, distributed battery system. Therefore, the methodology proposed in this paper used to evaluate the algorithms assumes that all electric vehicles charge their batteries simultaneously at the selected stations. This assumption represents a worst-case scenario in a metropolitan area. In this sense, charging stations can be scaled to accommodate all electric vehicle users based on their preferences and types of chargers.

Figure 7 and Algorithms 1–5 below describe the pseudocode for each routine and/or algorithm used in this paper. First, we describe the objects contained in the *Vehicle* and *ChargingStation* classes. It can be observed that both classes contain an identifier, capacity, charger types, Cartesian coordinates, and user preferences. Figure 7 shows the two classes mentioned above, along with their attributes and values set by a constructor. The first method, called Algorithm 1 (AVtoCSCapacity), assigns vehicles to charging stations while respecting the capacity of each charging station, the charger types available at each station, and user preferences (Algorithm 1). Algorithm 1 reads the data from an instance of each vehicle and stores the input in an array called *Vehicles*.

Similarly, it reads the data from an instance of each charging station and stores the input in an array called *ChargingStations*. After that, the algorithm sorts the vehicles by battery capacity in descending order and also sorts the charging stations by capacity in descending order. Next, each vehicle is allocated to a charging station. Finally, the algorithm returns the vehicle-to-station assignments by setting the attributes *NChargStation* and *CSVehicles* of the *Vehicle* and *ChargingStation* classes, respectively.

```

CLASS Vehicle
  // Define variables
  ATTRIBUTES:
    Id : Integer
    BatteryCapacity: Integer
    NChargStation = Integer
    Type = Integer
    XCoordinate = Integer
    YCoordinate = Integer
    UserPreference= Integer
  // Define constructor (initialization method)
  CONSTRUCTOR (id, capacity, type, x, y, userp)
    SET Id TO id
    SET BatteryCapacity TO capacity
    SET NChargStation TO None
    SET Type TO type
    SET XCoordinate TO x
    SET YCoordinate TO y
    SET UserPreference TO userp

CLASS ChargingStation
  // Define variables
  ATTRIBUTES:
    Id: Integer
    Capacity: Integer
    Cost: Integer
    CSVehicles: Integer Value Array
    Types = Integer Value Array
    XCoordinate = Integer
    YCoordinate = Integer
    UserPreferences= Integer Value Array
  // Define constructor (initialization method)
  CONSTRUCTOR (id, capacity, cost, types, x, y, userpre)
    SET Id TO id
    SET Capacity TO capacity
    SET Cost TO cost
    SET CSVehicles TO None
    SET Types TO types
    SET XCoordinate TO x
    SET YCoordinate TO y
    SET UserPreferences TO userpre

```

Figure 7. The Vehicle and ChargingStation classes and their attributes. Source: Authors (2026).

It is important to note that Algorithm 1 operates strictly as a constructive phase aimed at generating an initial feasible solution. Its primary focus is to satisfy hard constraints, such as station capacities and charger types. Because it prioritizes feasibility, Algorithm 1 passively assigns vehicles, which may initially yield suboptimal selections regarding travel distance (d_{ij}), i.e., the distance between electric vehicle i and charging station j , and establishment costs (fc_j), which represent the financial costs of locating a charging station at location j . However, this initial assignment serves as the starting point for the subsequent Local Search phase (Algorithm 5), which is fully responsible for actively optimizing Objective Function (1) by minimizing travel and station costs.

The second method, called Algorithm 2 (AVtoCSNN), uses a nearest-neighbor strategy to assign electric vehicles to charging stations, while attempting to respect station capacity, charger types, and user preferences (Algorithm 2).

First, Algorithm 2 sets the input data into the Vehicles and ChargingStations arrays. Then, it calculates the minimum distance from each vehicle to the stations and allocates each vehicle to the nearest station while respecting station capacities. Next, the algorithm considers charger types and user preferences. Finally, it returns the vehicle assignments by setting the attributes NChargStation and CSVehicles of the Vehicle and ChargingStation classes, respectively.

Algorithm 1 Called AVtoCSCapacity. Source: Authors (2026).

```

1: procedure AVtoCSCAPACITY(Vehicles, ChargingStations)
  // Sort arrays in descending order
2:   SORT(Vehicles, BatteryCapacity, descending)
3:   SORT(ChargingStations, Capacity, descending)

  // First allocation pass based on capacity and constraints
4:   for  $i \leftarrow 1$  to length(Vehicles) do
5:     for  $j \leftarrow 1$  to length(ChargingStations) do
6:       if Vehicles[ $i$ ].BatteryCapacity  $\leq$  ChargingStations[ $j$ ].Capacity and
Vehicles[ $i$ ].Type  $\in$  ChargingStations[ $j$ ].Types and Vehicles[ $i$ ].UserPreference  $\in$ 
ChargingStations[ $j$ ].UserPreferences then
7:         ChargingStations[ $j$ ].CSVehicles  $\leftarrow i$ 
8:         Vehicles[ $i$ ].NChargStation  $\leftarrow j$ 
9:         ChargingStations[ $j$ ].Capacity  $\leftarrow$  ChargingStations[ $j$ ].Capacity –
Vehicles[ $i$ ].BatteryCapacity
10:        break
11:      end if
12:    end for
13:  end for

  // Fallback pass to ensure all vehicles get a charging station
14:  for  $i \leftarrow 1$  to length(Vehicles) do
15:    if Vehicles[ $i$ ].NChargStation = None then
16:      for  $j \leftarrow 1$  to length(ChargingStations) do
17:        if Vehicles[ $i$ ].Type  $\in$  ChargingStations[ $j$ ].Types and
Vehicles[ $i$ ].UserPreference  $\in$  ChargingStations[ $j$ ].UserPreferences then
18:          ChargingStations[ $j$ ].CSVehicles  $\leftarrow i$ 
19:          Vehicles[ $i$ ].NChargStation  $\leftarrow j$ 
20:          break
21:        end if
22:      end for
23:    end if
24:  end for

25:  return Vehicles, ChargingStations
26: end procedure

```

The third method, called Algorithm 3 (AVtoCSRandom), uses a random strategy to allocate vehicles to charging stations, while respecting station capacity and charger types (Algorithm 3). Algorithm 3 sets the inputs in the same way as Algorithms 1 and 2. Then, at each iteration, for a given vehicle, the algorithm selects a random number between 1 and m using a uniform distribution, where m is the total number of stations. Let s number be the selected number. The vehicle is assigned to the station with identifier (Id) equal to s number if the station capacity and charger type constraints are satisfied. In this case, user preferences are omitted because, under a randomized choice, some vehicles may not find a station that satisfies their preferences in a given iteration. Finally, the algorithm returns all vehicle-to-station assignments.

Algorithm 2 Called AVtoCSNN. Source: Authors (2026).

```

1: procedure AVtoCSNN(Vehicles, ChargingStations)
  // Initialization and nearest-station allocation pass
2:   for  $i \leftarrow 1$  to length(Vehicles) do
3:      $closestStation \leftarrow \text{None}$ 
4:      $closestDistance \leftarrow \infty$ 
5:     for  $j \leftarrow 1$  to length(ChargingStations) do
6:        $distance \leftarrow \text{EUCLIDIS}(x[i], y[i], x[j], y[j])$  ▷ Euclidean distance
7:       if  $distance < closestDistance$  and  $Vehicles[i].Type \in$ 
         ChargingStations[ $j$ ].Types then
8:          $closestStation \leftarrow j$ 
9:          $closestDistance \leftarrow distance$ 
10:      end if
11:    end for
12:     $j \leftarrow closestStation$ 

    // Allocate based on station capacity
13:    if  $Vehicles[i].BatteryCapacity \leq ChargingStations[j].Capacity$  and
       $Vehicles[i].NChargStation = \text{None}$  then
14:       $ChargingStations[j].CSVehicles \leftarrow i$ 
15:       $Vehicles[i].NChargStation \leftarrow j$ 
16:       $ChargingStations[j].Capacity \leftarrow ChargingStations[j].Capacity -$ 
         $Vehicles[i].BatteryCapacity$ 
17:    end if
18:  end for

  // Fallback pass to ensure all vehicles get a charging station
19:  for  $i \leftarrow 1$  to length(Vehicles) do
20:    if  $Vehicles[i].NChargStation = \text{None}$  then
21:      for  $j \leftarrow 1$  to length(ChargingStations) do
22:        if  $Vehicles[i].Type \in ChargingStations[j].Types$  and
           $Vehicles[i].UserPreference \in ChargingStations[j].UserPreferences$  then
23:           $ChargingStations[j].CSVehicles \leftarrow i$ 
24:           $Vehicles[i].NChargStation \leftarrow j$ 
25:          break
26:        end if
27:      end for
28:    end if
29:  end for

30:  return Vehicles, ChargingStations
31: end procedure

```

Because Algorithm 3 contains random elements, a fourth method, called Algorithm 4 (AVtoCSMainRandom), was implemented and executed 10 times (Algorithm 4). Algorithm 4 returns the best solution, the average solution, and the standard deviation. At each execution of Algorithm 4, it is necessary to retain the original values contained in the Vehicles and ChargingStations arrays. First, Algorithm 4 executes Algorithm 3 once and sets this result as the initial best solution. The best cost is stored in the variable bestrcost and saved in an array called listvalues. Next, Algorithm 4 runs multiple times, evaluating the generated solutions and saving each cost value in listvalues. Whenever a solution generated by Algorithm 3 improves the quality of the current best solution, the best solution is updated. Finally, the algorithm returns the best solution, the average cost, and the standard deviation.

Algorithm 3 Called AVtoCSRandom. Source: Authors (2026).

```

1: procedure AVtoCSRANDOM(Vehicles, ChargingStations)
2:    $m \leftarrow \text{length}(\text{ChargingStations})$ 

   // Random allocation pass based on capacity and type constraints
3:   for  $i \leftarrow 1$  to  $\text{length}(\text{Vehicles})$  do
4:     SEED ▷ Generate new seed
5:      $snumber \leftarrow \text{RANDOM.UNIFORM}(1, m)$  ▷ Choose a random number in uniform distribution
6:     for  $j \leftarrow 1$  to  $\text{length}(\text{ChargingStations})$  do
7:       if  $\text{ChargingStations}[j].Id = snumber$  then
8:         if  $\text{Vehicles}[i].BatteryCapacity \leq \text{ChargingStations}[j].Capacity$  and  $\text{Vehicles}[i].Type \in \text{ChargingStations}[j].Types$  then
9:            $\text{ChargingStations}[j].CSVehicles} \leftarrow i$ 
10:           $\text{Vehicles}[i].NChargStation} \leftarrow j$ 
11:           $\text{ChargingStations}[j].Capacity} \leftarrow \text{ChargingStations}[j].Capacity} - \text{Vehicles}[i].BatteryCapacity$ 
12:          break
13:        end if
14:      end if
15:    end for
16:  end for

   // Fallback pass to ensure all vehicles get a charging station
17:  for  $i \leftarrow 1$  to  $\text{length}(\text{Vehicles})$  do
18:    if  $\text{Vehicles}[i].NChargStation = \text{None}$  then
19:      for  $j \leftarrow 1$  to  $\text{length}(\text{ChargingStations})$  do
20:        if  $\text{Vehicles}[i].Type \in \text{ChargingStations}[j].Types$  then
21:           $\text{ChargingStations}[j].CSVehicles} \leftarrow i$ 
22:           $\text{Vehicles}[i].NChargStation} \leftarrow j$ 
23:          break
24:        end if
25:      end for
26:    end if
27:  end for

28:  return Vehicles, ChargingStations
29: end procedure

```

A method known as AVtoCSLSearch is used to optimize the results of the AVtoC-SCapacity, AVtoCSNN, and AVtoCSMainRandom algorithms. This method is a local search algorithm designed to find improved solutions within a given search space. Local search algorithms are powerful tools for solving optimization problems [34]. Algorithm 5 (AVtoCSLSearch), when performing the local search, respects the capacity of each charging station, the charger types available at each station, and user preferences Algorithm 5. First, in Algorithm 5, the current cost obtained from Algorithm 1, 2, or 4 is set as the best solution. Next, at each iteration of Algorithm 5, a vehicle may migrate to another charging station, provided that the capacity, charger type, and user preference constraints of the target station are satisfied. If moving a vehicle from one station to another improves the solution cost, the current solution is updated and maintained as the best solution.

Algorithm 4 Called AVtoCSMainRandom. Source: Authors (2026).

```

1: procedure AVTOCSMAINRANDOM(Vehicles, ChargingStations)
  // Retain the original heterogeneous value arrays
2:   NewVehicles  $\leftarrow$  Vehicles
3:   NewChargingStations  $\leftarrow$  ChargingStations

4:   sum  $\leftarrow$  0
5:   max  $\leftarrow$  10                                ▷ Maximum iterations for Algorithm 3

6:   bestSolution  $\leftarrow$  EVALSOL(AVtoCSRandom)
7:   bestrcost  $\leftarrow$  COST(AVtoCSRandom)
8:   sum  $\leftarrow$  sum + bestrcost
9:   LISTVALUES(bestrcost)                          ▷ Store initial best cost in array

10:  for i  $\leftarrow$  1 to max − 1 do
  // Reset to original arrays before each iteration
11:    Vehicles  $\leftarrow$  NewVehicles
12:    ChargingStations  $\leftarrow$  NewChargingStations

13:    partialSolution  $\leftarrow$  EVALSOL(AVtoCSRandom)
14:    partialcost  $\leftarrow$  COST(AVtoCSRandom)
15:    sum  $\leftarrow$  sum + partialcost
16:    LISTVALUES(partialcost)

17:    if partialcost < bestrcost then
18:      bestSolution  $\leftarrow$  partialSolution
19:      bestrcost  $\leftarrow$  partialcost
20:    end if
21:  end for

22:  average  $\leftarrow$  sum / max
23:  stdevvalue  $\leftarrow$  STDEV(listvalues)              ▷ Standard deviation

24:  return bestSolution, average, stdevvalue
25: end procedure

```

The Algorithm 5 systematically explores the solution space to minimize Objective Function (1). To do so, we define a swap-based neighborhood structure, denoted as $N(fs)$. For any current feasible solution fs , a neighbor solution $fs' \in N(fs)$ is generated by evaluating the exchange of a vehicle assigned to one charging station with another vehicle assigned to a different station. Regarding the computational complexity, the worst-case time complexity of Algorithm 5 is bounded by $O(n^4)$. This is mathematically justified by the exhaustive neighborhood exploration mechanism, which employs four nested loops to evaluate all possible swap combinations: the first loop iterates over all charging stations, the second over the vehicles assigned to each station, the third over all candidate charging stations, and the fourth over the vehicles assigned to each candidate station. Assuming n represents the upper bound for both the number of stations and the maximum number of vehicles assigned to a single station, the complete pairwise evaluation demands $O(n \times n \times n \times n) = O(n^4)$ operations.

To rigorously evaluate the performance of the proposed stochastic algorithm (Algorithm 4), we established a comparative framework in accordance with standard evaluation protocols for combinatorial optimization [35]. When direct state-of-the-art competitors are not readily available or adaptable for a specific problem setting, it is methodologically essential to benchmark the proposed method against strong structural baselines rather than simple random generation. Therefore, we designed two deterministic

algorithms (Algorithms 1 and 2) to serve as our established methodological baselines. Furthermore, to ensure a high standard of competitive performance across the board, all algorithms, both the baselines and the proposed Algorithm 4, were enhanced with the same local search procedure (Algorithm 5). This framework objectively measures the intelligence and efficiency of the proposed stochastic approach against robust, established strategies.

Algorithm 5 Called AVtoCSLSearch. Source: Authors (2026).

```

1: procedure AVtoCSLSEARCH(Vehicles, ChargingStations)
2:   icost  $\leftarrow$  TCost(ChargingStations, Vehicles) ▷ Initial cost
3:   bestcost  $\leftarrow$  icost

   // Local search procedure by swapping vehicle assignments
4:   for s  $\leftarrow$  1 to length(ChargingStations) do
5:     for all v  $\in$  ChargingStations[s].CSVehicles do
6:       // Swap vehicle i from station j with vehicle l from station k
7:       N(fs)  $\leftarrow$  Swap vehicle Vehicles[i] and vehicle Vehicles[l]

8:       if i  $\neq$  l and j  $\neq$  k and Vehicles[i].Type  $\in$  ChargingStations[k].Types and
       Vehicles[l].Type  $\in$  ChargingStations[j].Types and Vehicles[i].UserPreference  $\in$ 
       ChargingStations[k].UserPreferences and Vehicles[l].UserPreference  $\in$ 
       ChargingStations[j].UserPreferences then
9:         if pcost < bestcost then
10:          bestcost  $\leftarrow$  pcost
11:          return bestcost
12:         end if
13:       end if
14:     end for
15:   end for
16: end procedure

```

5. Computational Results

A set of small-, medium-, and large-sized instances was randomly selected to evaluate the developed algorithms. The number of electric vehicles ranges from 20 to 1000, and the number of charging stations ranges from 6 to 300. The generated instances follow the procedure described in the previous section, “Approach to generate the instances.” The results obtained by the algorithms were computed on an Intel(R) Core(TM) i7 processor at 2.20 GHz, with 8 GB of RAM, running a 64-bit Windows operating system. The algorithms were developed using the Python programming language, version 3.13.5.

5.1. Results from Algorithms 1, 2, and 4 for Small- and Medium-Sized Instances

Tables 7 and 8 present the results obtained by Algorithm 1 (AVtoCSCapacity) for small- and medium-sized instances. In Table 7, the first column lists the instances, where the first number before the letter “V” represents the number of vehicles and the second number before the string “CS” represents the number of charging stations. For example, the instance 20V–6CS contains 20 electric vehicles and 6 candidate charging stations. Table 7 also reports, in the second column, the objective function cost; in the third column, the financial cost of the opened charging stations; and in the fourth column, the power capacity cost of the opened charging stations (kW). The last three columns show the computational time, the UPSR, and the total number of opened charging stations, respectively.

Table 8 shows, in the first column, the same instances as Table 7, with details on the number of charges in each class. The second column of Table 8 shows the total number of charges for Class 1 (Type 2), the third column shows the total number of charges for Class 2 (GB/T Chinese AC), and the fourth column shows the total number of charges for Class 3

(CHAdEMO). The last columns show the total number of charges for Class 4 (CCS2) and Class 5 (GB/T Chinese DC), respectively.

Table 7. Output values by Algorithm 1 (AVtoCSCapacity).

Instances	Objective Function Cost	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations
20V-6CS	2933	2600	1386	0.009	100.0	6
25V-7CS	3108	2700	1546	0.043	100.0	6
25V-11CS	3380	3000	1637	0.055	100.0	7
30V-20CS	3425	3000	1806	0.155	100.0	6
35V-20CS	5006	4500	2709	0.416	100.0	9
40V-20CS	4993	4500	2709	0.597	100.0	9
45V-20CS	6313	5900	3373	1.299	100.0	13
50V-20CS	5812	5300	3191	2.957	100.0	11
55V-30CS	6168	5500	3311	3.766	100.0	11
60V-30CS	8076	7700	4457	5.826	100.0	17
65V-30CS	8206	7700	4457	6.244	100.0	17
70V-30CS	8554	7900	4498	6.575	100.0	18
75V-30CS	8511	7900	4498	22.195	100.0	18
80V-40CS	9820	9200	5540	19.676	100.0	20
85V-40CS	9908	9200	5540	23.400	100.0	20
90V-40CS	10,251	9600	5781	33.575	100.0	21
95V-40CS	10,462	9600	5781	40.977	100.0	21
100V-40CS	12,494	11,700	6418	47.246	100.0	28
150V-80CS	17,462	16,400	9874	345.544	100.0	34

Source: Authors (2026).

Table 8. The number of charges resulting from Algorithm 1 (AVtoCSCapacity).

Instances	Type 2	GB/T Chinese AC	CHAdEMO	CCS2	GB/T Chinese DC
20V-6CS	0	6	7	8	2
25V-7CS	6	22	3	7	1
25V-11CS	6	22	3	7	1
30V-20CS	14	14	7	4	5
35V-20CS	10	18	8	7	6
40V-20CS	10	26	6	7	9
45V-20CS	10	34	6	12	5
50V-20CS	18	36	8	9	6
55V-30CS	16	26	16	10	8
60V-30CS	16	16	17	19	8
65V-30CS	14	36	18	14	8
70V-30CS	28	38	16	15	6
75V-30CS	24	36	20	17	8
80V-40CS	22	40	18	21	10
85V-40CS	26	28	26	21	11
90V-40CS	30	32	28	20	11
95V-40CS	28	48	23	23	11
100V-40CS	32	40	21	30	13
150V-80CS	38	88	33	38	16

Source: Authors (2026).

Tables 9 and 10 show the results obtained by Algorithm 2 (AVtoCSNN) for small- and medium-sized instances. The description of the columns in Tables 9 and 10 is similar to that of Tables 7 and 8, respectively. We observe that the UPSR in Table 7 was equal to 100.0% for all instances, whereas the values in Table 9 varied between 60% and 95%. In most cases, the objective function values in Table 7 were lower than those in Table 9. The computational time of 345.544 s was significant only for the instance 150V–80CS in Table 7. However, the computational times in Table 9 were generally lower than those in

Table 7. Tables 8 and 10 illustrate the need for different charger types at charging stations to naturally accommodate different electric vehicles in real-world scenarios.

Table 9. Output values by Algorithm 2 (AVtoCSNN).

Instances	Objective Function Cost	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations
20V-6CS	2567	2300	1295	0.016	95.00	5
25V-7CS	2450	2200	1245	0.009	68.00	5
25V-11CS	3074	2800	1427	0.041	96.00	7
30V-20CS	5278	5100	2623	0.013	60.00	13
35V-20CS	6044	5700	2984	0.221	85.71	14
40V-20CS	6349	6100	3225	0.078	72.50	15
45V-20CS	7351	7000	3777	0.202	77.78	17
50V-20CS	6316	5800	2965	0.562	92.00	15
55V-30CS	8035	7700	4257	0.546	80.00	19
60V-30CS	9465	9100	4800	0.331	86.67	24
65V-30CS	9176	8700	4521	0.599	86.15	23
70V-30CS	9392	8800	4371	1.651	85.71	25
75V-30CS	8925	8300	4280	2.460	82.67	22
80V-40CS	12,143	11,700	6090	1.934	76.25	30
85V-40CS	12,482	11,800	6009	4.595	83.53	31
90V-40CS	12,383	11,700	6090	4.089	82.22	30
95V-40CS	12,397	11,600	5871	5.834	76.84	31
100V-40CS	10,863	9800	5084	6.158	88.00	26
150V-80CS	22,990	22,200	11,443	39.405	75.33	59

Source: Authors (2026).

Table 10. The number of charges resulting from Algorithm 2 (AVtoCSNN).

Instances	Type 2	GB/T Chinese AC	CHAdEMO	CCS2	GB/T Chinese DC
20V-6CS	0	6	7	8	2
25V-7CS	6	22	3	7	1
25V-11CS	6	22	3	7	1
30V-20CS	14	14	7	4	5
35V-20CS	10	18	8	7	6
40V-20CS	10	26	6	7	9
45V-20CS	10	34	6	12	5
50V-20CS	18	36	8	9	6
55V-30CS	16	26	16	10	8
60V-30CS	16	16	17	19	8
65V-30CS	14	36	18	14	8
70V-30CS	28	38	16	15	6
75V-30CS	24	36	20	17	8
80V-40CS	22	40	18	21	10
85V-40CS	26	28	26	21	11
90V-40CS	30	32	28	20	11
95V-40CS	28	48	23	23	11
100V-40CS	32	40	21	30	13
150V-80CS	38	88	33	38	16

Source: Authors (2026).

Tables 11 and 12 show the results obtained by Algorithm 4 (AVtoCSMainRandom) for small- and medium-sized instances. The description of the columns in Table 11 is similar to that of Table 7, with the addition of two columns: the average objective function cost and the standard deviation. The columns in Table 12 are identical to those in Table 8. We observe in Table 11 that the planning of candidate charging stations was efficient, since the number of opened charging stations is lower than the number of candidate stations in all instances. It is also observed that the UPSR was greater than 95.0% for 14 out of 19 instances. The computational time of 299.348 s was significant only for the instance

150V–80CS, with 150 vehicles and 80 candidate charging stations. The computational time reported in Table 11 corresponds to the sum of all ten runs performed by Algorithm 4.

Table 11. Output values by Algorithm 4 (AVtoCSMainRandom).

Instances	Objective Function Cost	Standard Deviation	The Best Cost of Objective Function	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations
20V-6CS	2887.3	184.93	2470	2100	1085	0.014	90.00	5
25V-7CS	3054.1	130.02	2701	2300	1264	0.042	96.00	6
25V-11CS	3441.4	298.78	2974	2600	1355	0.048	96.00	7
30V-20CS	6802.7	577.27	5624	5300	2843	0.221	100.0	13
35V-20CS	6743.1	474.16	5421	5000	2742	0.288	94.29	12
40V-20CS	7429.1	888.26	6246	5800	3134	0.414	90.00	14
45V-20CS	7806.8	569.25	6685	6200	3116	0.691	88.89	16
50V-20CS	8536.0	329.2	7525	7000	3777	1.615	96.00	17
55V-30CS	9062.3	415.44	7634	7000	3446	2.057	96.36	20
60V-30CS	9103.3	598.55	7512	6800	3567	3.743	98.33	17
65V-30CS	9766.5	569.55	8323	7400	3887	3.965	96.92	19
70V-30CS	10,080.1	733.8	7978	7200	3528	7.467	95.71	20
75V-30CS	10,272.3	482.8	8340	7700	4057	20.768	98.67	21
80V-40CS	12,776.5	493.08	11,341	10,600	5448	21.177	98.75	28
85V-40CS	13,242.1	649.12	11,698	10,500	5416	9.525	92.94	28
90V-40CS	13,579.8	547.54	11,885	10,900	5439	17.185	96.67	29
95V-40CS	13,875.1	667.55	11,570	10,500	5457	30.623	95.79	27
100V-40CS	14,193.2	537.24	12,662	11,600	6040	47.964	99.00	30
150V-80CS	23,951.4	586.11	21,770	20,200	10,559	299.348	99.33	53

Source: Authors (2026).

Table 12. The number of charges resulting from Algorithm 4 (AVtoCSMainRandom).

Instances	Type 2	GB/T Chinese AC	CHAdEMO	CCS2	GB/T Chinese DC
20V-6CS	0	6	7	8	2
25V-7CS	6	22	3	7	1
25V-11CS	6	22	3	7	1
30V-20CS	14	14	7	4	5
35V-20CS	10	18	8	7	6
40V-20CS	10	26	6	7	9
45V-20CS	10	34	6	12	5
50V-20CS	18	36	8	9	6
55V-30CS	16	26	16	10	8
60V-30CS	16	16	17	19	8
65V-30CS	14	36	18	14	8
70V-30CS	28	38	16	15	6
75V-30CS	24	36	20	17	8
80V-40CS	22	40	18	21	10
85V-40CS	26	28	26	21	11
90V-40CS	30	32	28	20	11
95V-40CS	28	48	23	23	11
100V-40CS	32	40	21	30	13
150V-80CS	38	88	33	38	16

Source: Authors (2026).

Table 12 illustrates the need for different charger types in charging stations to naturally accommodate different electric vehicles in the real world.

Figure 8 shows a comparison among Algorithms 1, 2 and 4 for small- and medium-sized instances. In general, Algorithm 1 achieves better performance when the objective function cost and UPSR are considered. From another perspective, Algorithm 2 achieves the best computational time. We highlight that the best objective function cost was obtained by Algorithm 4, considering the total computational time of ten runs of the algorithm.

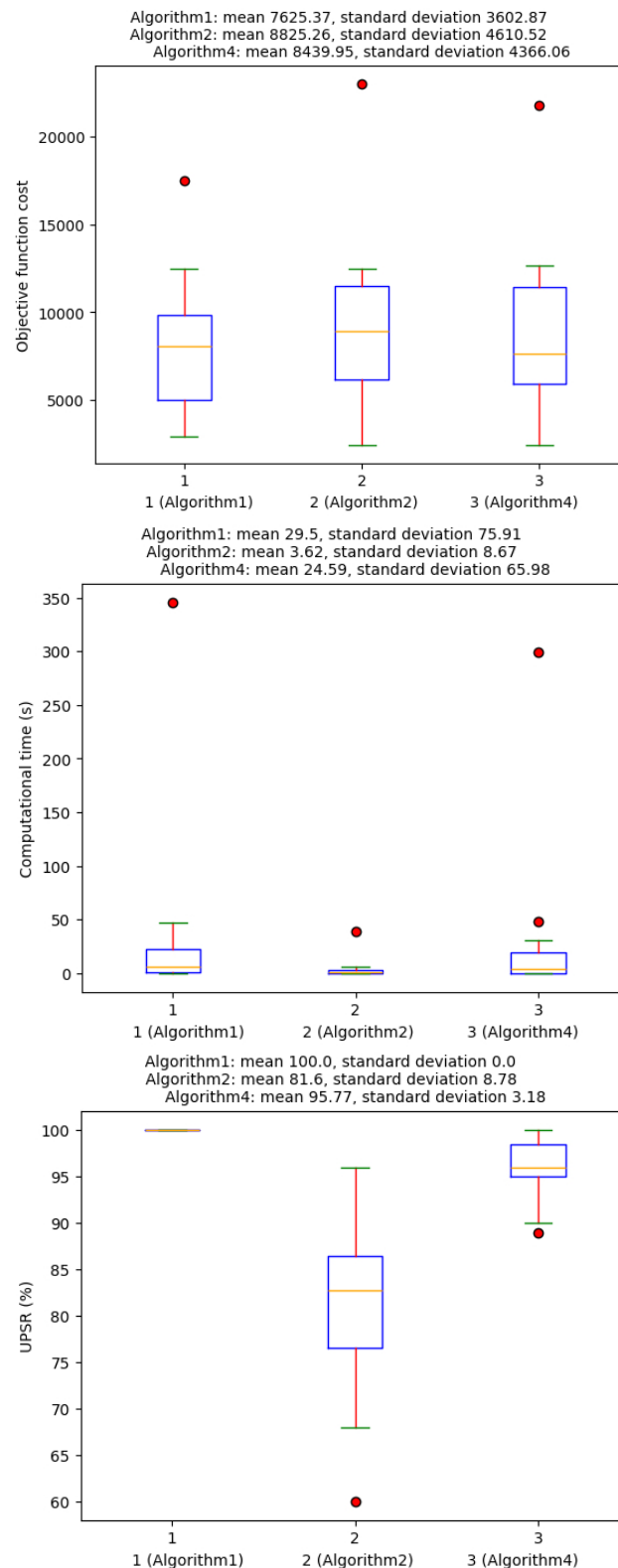


Figure 8. Comparison between Algorithms 1, 2 and 4 for instances of small and medium size. Source: Authors (2026).

5.2. Settings Parameters in the Local Search

It should be noted that the polynomial complexity of the local search algorithm is of order $O(n^4)$, corresponding to fourth-order polynomial complexity. Since performance is not affected for small- and medium-sized instances with 150 electric vehicles or fewer, no parameter adjustments were made. Therefore, for large-sized instances with 200 or more

vehicles, the number of local search iterations was limited to a maximum value (maxim) of 50 for Algorithms 1, 2 and 4. This maximum value was adopted based on preliminary tests. Mathematically, this bounds the effective operational complexity of the search phase, effectively reducing the scale of the algorithm's execution from an open-ended fourth-order polynomial growth to a controlled operational bound verified through preliminary sensitivity analysis. This guarantees that computational tractability is preserved as the number of electric vehicles scales up.

Figure 9 shows the application of local search to Algorithms 1, 2 and 4, highlighting improvements in the solutions over several iterations ($k = 1, 2, \dots, m$). At iteration $k = 0$, the value is obtained without applying local search and corresponds to the output of Algorithms 1, 2, or 4. The results shown in Figure 9 were obtained for small-, medium-, and large-sized instances. For large-sized instances, the value of $k = 50$ was fixed. More details about large-sized instances are provided in the following sections. The percentage gap shown in Figure 9 is calculated as follows: $Gap = 100 * (OFC - BEST) / BEST$, where OFC is the value of the objective function cost calculated in iteration k, and BEST is the best objective function cost of Algorithms 1, 2, or 4.

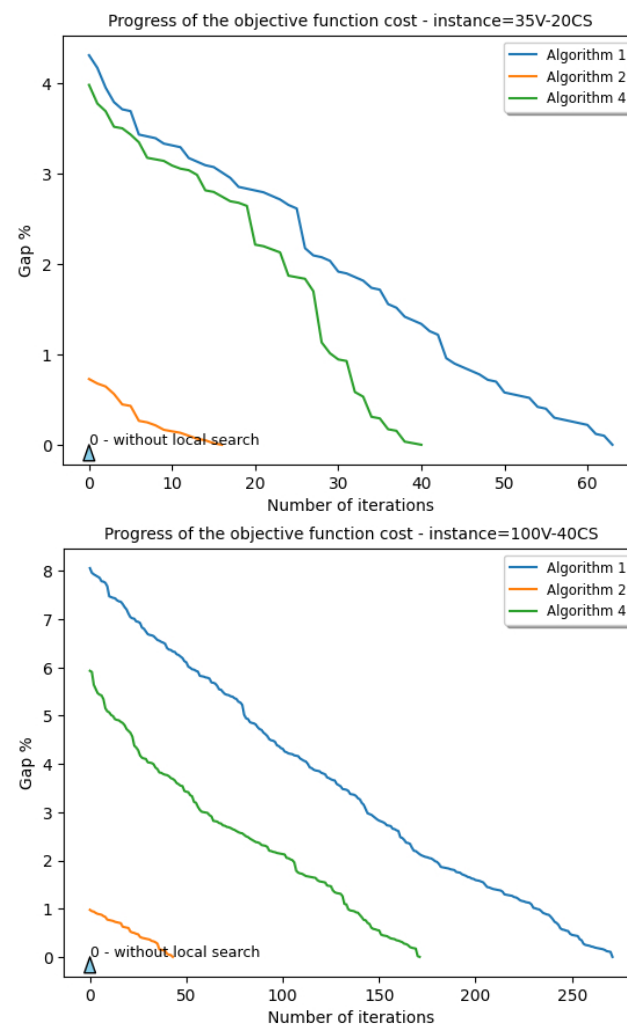


Figure 9. Cont.

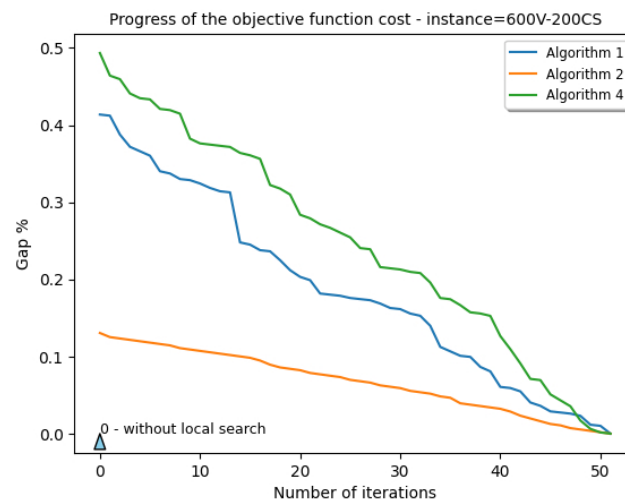


Figure 9. Effect of local search on Algorithms 1, 2 and 4. Source: Authors (2026).

5.3. Analysis and Results of Algorithm 3 (AVtoCSRandom)

We evaluate the performance of Algorithm 3 in terms of the probability of finding good solutions for the problem of allocating electric vehicles to charging stations. In this sense, Algorithm 3 was executed up to 1000 times. Next, the mean and standard deviation method was used to calculate upper and lower bounds by considering three standard deviations from the mean to remove outliers, under the assumption that the data are Gaussian distributed [36]. When the third standard deviation is considered, 99.7% of the values are expected to be normal based on this property.

Afterward, the Shapiro–Wilk statistical test was applied to verify whether the null hypothesis of normality is rejected or accepted [37]. The Shapiro–Wilk test statistic ranges from 0 to 1, where values closer to 1 indicate a better fit to a normal distribution. Let p be the associated p -value of the test and $\alpha = 0.05$. Thus, if $p > \alpha$, the data are assumed to follow a normal distribution (the null hypothesis is not rejected). Otherwise, the data are assumed not to follow a normal distribution (the null hypothesis is rejected).

Finally, the performance of Algorithm 3 is evaluated using statistical analysis. In this context, three plots were generated from the data of Algorithm 3 (executed up to 1000 times): the cumulative distribution function, the histogram, and the probability density function. Figures 10 and 11 show the statistical analysis of Algorithm 3 for several randomly selected instances, while Table 13 presents a summary of this analysis. We observe in Table 13 that the results of Algorithm 3 (random variable values) for all evaluated instances likely follow a normal distribution, with very few outliers.

Table 13. Summary of the statistical analyses shown in Figures 10 and 11.

Instances	Number of Vehicles	Number of Candidate Stations	p	Number of Outliers
1	30	20	0.355	1
2	40	20	0.059	1
3	100	40	0.067	3
4	1000	300	0.293	2

Source: Authors (2026).

Algorithm 3 supports decision-makers in choosing a target value for the objective function and, consequently, a target value for the financial cost of future opened charging stations. In this sense, Algorithm 3 can be combined with the cumulative distribution function to select an instance that meets a pre-established target value for the objective function.

Thus, it becomes possible to estimate, with a given probability, the likelihood of reaching a charging station configuration that considers both charger types and user preferences.

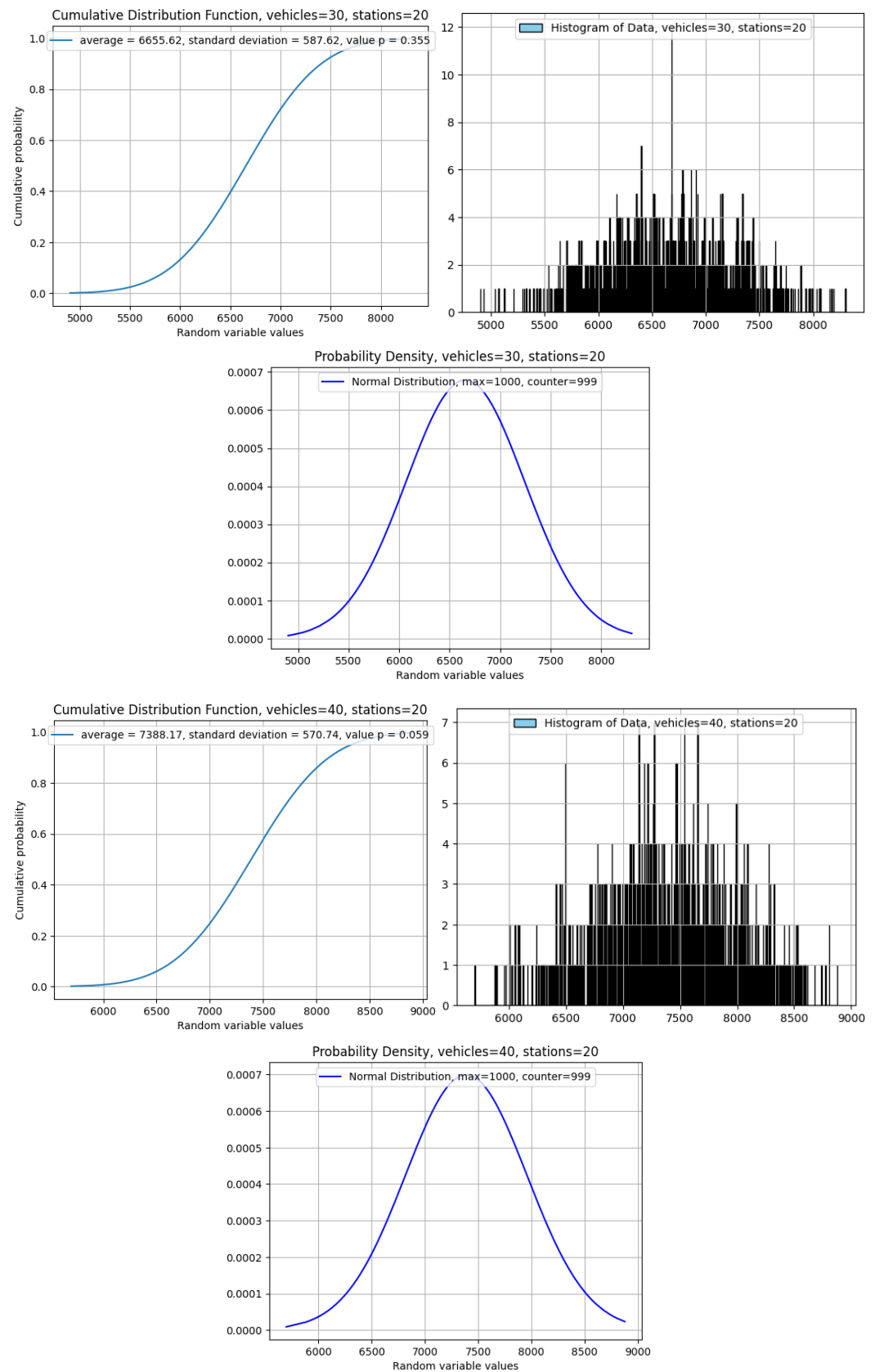


Figure 10. A statistical examination of the performance of Algorithm 3 (Part I). Source: Authors (2026).

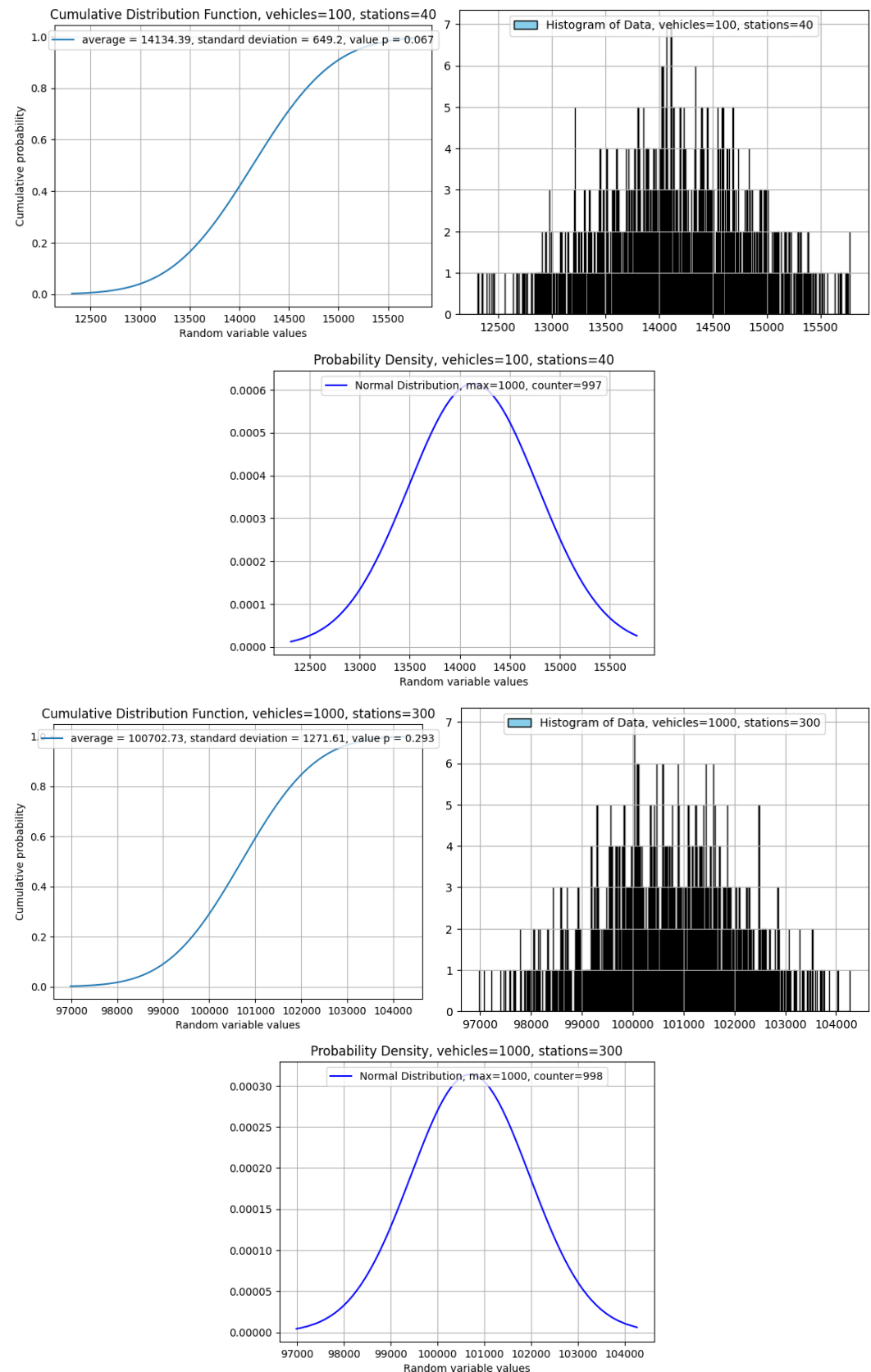


Figure 11. A statistical examination of the performance of Algorithm 3 (Part II). Source: Authors (2026).

5.4. Results of Algorithms for a Case Study Based on Real Station Data and Synthetic Profiles

The algorithms were applied to synthetic profiles and real-world data from the Greater Vitória metropolitan region. The data are described in Table 14. Table 14 shows, in the

first column, the station identifier; in the second, the city; and in the third, the charger types. The last columns present the latitude, longitude, and station power, respectively. Specifically, station locations and charger types are extracted directly from the real-world infrastructure, whereas vehicle demands, specific locations, and user preferences are synthetically generated to test algorithm robustness under various scenarios. The adoption of synthetic data aims to evaluate scalability, assess peak scenarios that may occur in the real world, and ensure users' privacy and sensitive data protection.

Table 14. Data from charging stations of Greater Vitória.

Station ID	City	Charger Types	Latitude	Longitude	Station Power (kW)
1	Vila Velha	Type 2	−20.409060	−40.333161	22
2	Vitória	Type 2	−20.251161	−40.27247	22
3	Serra	Type 2	−20.220606	−40.356912	22
4	Cariacica	Type 2	−20.253245	−40.373174	22
5	Vila Velha	Type 2	−20.393218	−40.317711	22
6	Vila Velha	Type 2	−20.353477	−40.343126	22
7	Vila Velha	Type 2	−20.373858	−40.310085	22
8	Vila Velha	Type 2	−20.373297	−40.307688	22
9	Vila Velha	Type 2	−20.347334	−40.320705	22
10	Vila Velha	CCS2	−20.358033	−40.310132	150
11	Vila Velha	Type 2	−20.352475	−40.298665	22
12	Vila Velha	Type 2	−20.352012	−40.293359	22
13	Vila Velha	Type 2	−20.342632	−40.288782	22
14	Vila Velha	Type 2	−20.336094	−40.288256	22
15	Vila Velha	Type 2	−20.335475	−40.28631	22
16	Vila Velha	Type 2	−20.333876	−40.28764	22
17	Vila Velha	Type 2	−20.328248	−40.273485	22
18	Serra	Type 2	−20.162278	−40.24211	22
19	Serra	Type 2	−20.183230	−40.25555	22
20	Serra	Type 2	−20.193008	−40.265762	22
21	Serra	Type 2	−20.194092	−40.251988	22
22	Serra	Type 2	−20.193243	−40.242816	22
23	Serra	Type 2	−20.236249	−40.278745	22
24	Serra	Type 2	−20.239868	−40.274375	22
25	Vitória	Type 2	−20.249650	−40.272463	22
26	Vitória	Type 2	−20.252005	−40.26671	22
27	Vitória	CCS2	−20.263765	−40.263473	150
28	Vitória	Type 2	−20.265661	−40.267128	22
29	Vitória	Type 2	−20.263118	−40.294646	22
30	Vitória	Type 2	−20.263568	−40.296352	22
31	Vitória	Type 2	−20.265325	−40.29499	22
32	Vitória	Type 2	−20.271823	−40.287563	22
33	Vitória	Type 2	−20.273495	−40.300599	22
34	Vitória	Type 2	−20.276654	−40.294585	22
35	Vitória	Type 2, CHAdeMO and CCS2	−20.280591	−40.288085	222
36	Vitória	Type 2	−20.280293	−40.301198	22
37	Vitória	Type 2	−20.280904	−40.297527	22
38	Vitória	Type 2	−20.282778	−40.3018	22
39	Vitória	Type 2	−20.284794	−40.302427	22
40	Vitória	CCS2	−20.297201	−40.300667	150
41	Vitória	Type 2	−20.299842	−40.303395	22
42	Vitória	Type 2	−20.302286	−40.303137	22
43	Vitória	Type 2	−20.301043	−40.295374	22
44	Vitória	Type 2	−20.301011	−40.295548	22
45	Vitória	Type 2	−20.301082	−40.295768	22
46	Vitória	CCS2	−20.303917	−40.29207	150

Table 14. Cont.

Station ID	City	Charger Types	Latitude	Longitude	Station Power (kW)
47	Vitória	Type 2	−20.306331	−40.302381	22
48	Vitória	Type 2	−20.306842	−40.296078	22
49	Vitória	Type 2	−20.307756	−40.314322	22
50	Vitória	Type 2	−20.311703	−40.30351	22
51	Vitória	Type 2	−20.311614	−40.300534	22
52	Vitória	CCS2	−20.310387	−40.29673	150
53	Vitória	Type 2	−20.316752	−40.29926	22
54	Vitória	Type 2	−20.316023	−40.297811	22
55	Vitória	Type 2	−20.314045	−40.293977	22
56	Vitória	Type 2	−20.315281	−40.29306	22
57	Vitória	Type 2	−20.315000	−40.290333	22
58	Vitória	Type 2	−20.313205	−40.289324	22
59	Vitória	CCS2	−20.313528	−40.287142	150
60	Vitória	Type 2	−20.311994	−40.286701	22
61	Vitória	Type 2	−20.311780	−40.287036	22
62	Cariacica	Type 2	−20.337325	−40.379494	22
63	Cariacica	Type 2	−20.339269	−40.382012	22
64	Cariacica	Type 2	−20.335329	−40.390831	22
65	Cariacica	CCS2	−20.349339	−40.38678	150
66	Cariacica	Type 2	−20.342781	−40.399999	22
67	Cariacica	Type 2	−20.343155	−40.402848	22

Source: Adopted from [38].

Tables 15–17 show the results of the algorithms for instances using data from charging stations in Greater Vitória (Table 14). The description of the columns in Tables 15–17 is similar to that of Table 7.

The computational time in Table 17 corresponds to the sum of all ten runs performed by Algorithm 4. Data related to the instances in Tables 15–17, including vehicles, user preferences, and financial costs of stations, were generated according to the Section 4. In this case, it was assumed that each Type 2 bay has only one connector.

The Universal Transverse Mercator (UTM) coordinate system was used to convert latitude and longitude information into Cartesian coordinates (x, y). UTM is suitable for mapping small areas where accurate distance measurements are required.

Electric vehicles were distributed within a metropolitan area of 459 km², with x-coordinates ranging from 353 km to 370 km. The y-coordinates ranged from 7743 km to 7770 km.

We observe in Tables 15–17 that the 68 available stations cannot satisfactorily serve all 40 electric vehicles. Although the 40V–67CS instance presents a UPSR of 100%, vehicles are still required to wait in a queue for charging services.

As a result, the expected increase in future demand—where all vehicles may charge simultaneously—will require the opening of additional charging stations.

We highlight that the results presented in Tables 15–17 assume that all electric vehicles charge their batteries simultaneously at the selected (opened) stations, representing a worst-case scenario for the Greater Vitória metropolitan area. Therefore, the charging stations are required to accommodate all electric vehicles according to user preferences.

We also evaluated an alternative scenario with two instances, 170V–67CSmod and 184V–67CSmod, using Algorithm 1, since all UPSR values were equal to 100% for the instances in Table 15. In this scenario, all charging stations satisfy all user preferences, and each Type 2 bay has two connectors.

It was further assumed that only 70% of electric vehicles would charge their batteries at the stations. In this sense, this scenario differs from the previous worst-case scenario for the metropolitan area. All other input data follow the Section 4.

Table 15. Output values by Algorithm 1 (AVtoCSCapacity) for case study.

Instances	Objective Function Cost	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations	Vehicles Queue in the Stations
30V-67CS	15,149	15,000	1072	0.332	100.0	28	No
40V-67CS	19,757	19,500	1654	1.198	100.0	37	Yes
50V-67CS	23,357	23,000	1808	1.707	100.0	44	Yes
60V-67CS	27,355	27,000	2240	3.651	100.0	52	Yes
70V-67CS	32,393	32,000	2460	7.725	100.0	62	Yes

Source: Authors (2026).

Table 16. Output values by Algorithm 2 (AVtoCSNN) for case study.

Instances	Objective Function Cost	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations	Vehicles Queue in the Stations
30V-67CS	9732	9500	830	0.154	90.0	17	Yes
40V-67CS	10,920	10,500	1002	0.268	95.0	19	Yes
50V-67CS	12,075	11,500	1302	0.779	92.0	21	Yes
60V-67CS	14,062	13,500	1390	1.219	96.67	25	Yes
70V-67CS	15,666	15,000	1456	0.974	95.71	28	Yes

Source: Authors (2026).

Table 17. Output values by Algorithm 4 (AVtoCSMainRandom) for case study.

Instances	Objective Function Cost	Standard Deviation	The Best Cost of Objective Function	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations	Vehicles in Queue in the Stations
30V-67CS	12,246.9	1092.6	10,733	10,500	746	0.275	86.67	19	Yes
40V-67CS	14,804.3	958.75	13,331	13,000	856	1.126	97.5	24	Yes
50V-67CS	16,318.0	1013.44	14,928	14,500	922	1.231	80.0	27	Yes
60V-67CS	18,122.4	971.79	16,464	16,000	1116	5.986	90.0	30	Yes
70V-67CS	20,986.5	917.81	19,076	18,500	1354	5.597	91.43	35	Yes

Source: Authors (2026).

By comparing the data in Table 18 with Table 15, we conclude that investing in infrastructure upgrades at the 67 existing charging stations in Greater Vitória makes it possible to accommodate a larger number of electric vehicles. Therefore, considering a future increase in electric vehicles and a charging demand of 70%, the current stations could serve up to 127 vehicles.

Table 18. Output values by Algorithm 1 with demands.

Instances	Objective Function Cost	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	Total of Opened Charging Stations	Charger Number of Type 2	Charger Number of CHAdeMO	Charger Number of CCS2
* 170V-67CSmod	33,045	32,000	2460	0.538	62	109	1	8
* 184V-67CSmod	34,537	33,500	2270	1.366	65	120	1	6

* UPSR equal to 100%; no vehicles in queue for charging; different vehicles. Source: Authors (2026).

The results are shown in Table 18, with a UPSR of 100% for all instances and no vehicles remaining in a queue at the charging stations. For the 170V–67CSmod instance, 118 electric vehicles were able to charge at the stations, while for the 184V–67CSmod instance, 127 vehicles were served. We note that the electric vehicles differ between instances. The kW cost of the opened charging stations for the 184V–67CSmod instance was lower due to the number of CCS2 chargers.

Next, we evaluated the dynamic behavior throughout a 24-h period, considering various EV user preferences. The time slots and preferences were defined based on data selected from Vitória, chosen because its traffic demand exceeds that of neighboring cities. Consequently, there is a significant flow of electric vehicles from surrounding cities toward the capital, Vitória. The data were gathered in March 2026. For each hourly range, it was assumed that the majority of users indicated a single preference. Consequently, five instances were generated according to Table 19. For example, the second row of Table 19 presents the maximum number of available EVs and candidate charging stations for the 0:00 to 6:00 time slot; in this scenario, 75% of users prioritize the energy price and 80% of charging stations can meet this specific demand.

Similar logic applies to the other instances, which incorporate different types of user preferences. Additionally, it was assumed that a maximum of 70% of the 184 total EVs would charge at these stations during the day. Thus, this scenario provides a more realistic representation of the metropolitan area compared to the previous worst-case scenario. Table 19 also presents other priorities of electric vehicle users in different time slots, where charging stations prioritize fulfilling these preferences.

Table 19. Input data for Greater Vitória instances considering 24-h dynamic behavior.

ID	Instance	No. EVs Available	Candidate CSs	Time Slot	User Preference Type of EVs	Preference Fulfillment of CSs
1	184V-67CSprice75EV_price80CS	184	67	0:00–6:00	75% (energy price)	80% (energy price)
2	184V-67CStraffic50EV_traffic60CS	184	67	6:01–8:00	50% (traffic flow)	60% (traffic flow)
3	184V-67CSstore80EV_store50CS	184	67	8:01–17:00	80% (convenience store)	50% (convenience store)
4	184V-67CStraffic60EV_traffic50CS	184	67	17:01–20:00	60% (traffic flow)	50% (traffic flow)
5	184V-67CSprice70EV_price70CS	184	67	20:00–24:00	70% (energy price)	70% (energy price)

Source: Authors (2026).

Table 20 shows the results obtained from Algorithm 1 for instances based on Greater Vitória data, considering dynamic behavior over a 24-h period, according to input data from Table 19. As shown in Table 20, charging stations can operate in different time slots to meet the preferences set by EV users.

Table 20. Algorithm 1 results for Greater Vitória instances: 24-h dynamic behavior analysis.

ID	Objective Function Cost	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	Total of Opened Charging Stations	Charger Number of Type 2	Charger Number of CHAdeMO	Charger Number of CCS2	Number of Vehicles
* 1	32,967	32,000	2204	0.681	62	113	1	6	120
* 2	29,975	29,000	1816	6.540	56	122	0	3	125
* 3	25,836	25,000	1640	0.577	48	93	0	4	97
* 4	28,597	27,500	1750	5.966	53	118	0	3	121
* 5	31,474	30,500	2010	0.703	59	109	1	5	115

* UPSR equal to 100%; no vehicles in queue for charging; different vehicles. Source: Authors (2026).

5.5. Results from Algorithms 1, 2, and 4 for Large Size Instances

Tables 21–26 present the results of the algorithms for large-size instances. The description of the columns in Tables 21, 23 and 25 is similar to that of Table 7. The computational time reported in Table 25 corresponds to the sum of the ten runs performed by Algorithm 4. The Cartesian coordinates of vehicles and stations, financial costs, vehicle and station capacities, and user preferences for the instances in Tables 21, 23 and 25 were generated according to the Section 4. We observe that the UPSR in Table 21 is equal to 100.0% for all instances.

Table 21. Output values by Algorithm 1 (AVtoCSCapacity) for large size instances.

Large Instances	Objective Function Cost	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations
200V-80CS	25,165	21,900	12,380	0.793	100.0	50
200V-100CS	25,549	22,200	11,845	1.301	100.0	55
250V-100CS	32,255	27,800	13,288	20.670	100.0	78
300V-120CS	38,242	33,000	17,654	35.440	100.0	84
350V-120CS	42,157	35,400	18,264	18.502	100.0	94
400V-150CS	52,979	46,100	23,323	9.557	100.0	123
450V-150CS	54,494	46,100	23,323	112.521	100.0	123
500V-180CS	60,077	50,200	25,328	119.628	100.0	138
550V-180CS	60,933	50,200	25,328	136.785	100.0	138
600V-200CS	69,378	58,000	28,540	101.613	100.0	160
650V-200CS	71,399	58,400	28,622	61.359	100.0	162
700V-200CS	72,245	58,400	28,622	64.001	100.0	162
750V-220CS	80,169	64,800	32,012	45.519	100.0	182
800V-220CS	80,588	64,800	32,012	76.123	100.0	182
850V-220CS	82,081	64,800	32,012	112.567	100.0	182
900V-250CS	92,184	74,200	37,175	137.267	100.0	205
950V-250CS	93,670	74,200	37,175	98.145	100.0	205
1000V-250CS	94,608	74,200	37,175	214.024	100.0	205
1000V-300CS	10,6204	86,100	41,139	61.521	100.0	249

Source: Authors (2026).

The description of the columns in Tables 22, 24 and 26 is similar to that of Table 8. Table 22 highlights a contrast between the instances: (a) 200V-80CS and 200V-100CS, and (b) 1000V-250CS and 1000V-300CS. In these cases, 80 and 250 charging stations have sufficient capacity to accommodate 200 and 1000 electric vehicles, respectively. Therefore, there is no need to increase the number of candidate stations in the instances 200V-80CS and 1000V-250CS.

Table 22. The number of charges from Algorithm 1 (AVtoCSCapacity) for large size instances.

Large Instances	Type 2	GB/T Chinese AC	CHAdeMO	CCS2	GB/T Chinese DC
200V-80CS	56	100	50	49	23
200V-100CS	56	100	50	49	23
250V-100CS	56	132	63	59	34
300V-120CS	78	142	77	75	38
350V-120CS	84	174	96	83	42
400V-150CS	106	202	94	105	47
450V-150CS	118	252	95	113	57
500V-180CS	106	270	108	131	73
550V-180CS	142	286	144	128	64
600V-200CS	182	290	163	138	63
650V-200CS	182	320	185	140	74
700V-200CS	188	352	162	161	107
750V-220CS	206	382	185	174	97
800V-220CS	204	418	196	190	103
850V-220CS	228	398	219	203	115
900V-250CS	208	472	215	237	108
950V-250CS	244	442	231	249	127
1000V-250CS	248	536	244	228	136
1000V-300CS	248	536	244	228	136

Source: Authors (2026).

As shown in Table 23, the UPSR varies between 69.50% and 83.18%. These values are significantly lower than those reported in Table 21, where all instances achieved a UPSR of 100%. This indicates that Algorithm 1 outperforms Algorithm 2 with respect to the UPSR metric. However, when considering the objective function cost, Algorithm 2 generally performs better than Algorithm 1, except for the instance 200V-80CS.

Table 23. Output values by Algorithm 2 (AVtoCSNN) for large size instances.

Large Instances	Objective Function Cost	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations
200V-80CS	25,615	23,900	12,677	35.284	69.50	61
200V-100CS	25,670	23,900	11,930	52.251	75.50	66
250V-100CS	25,517	22,900	11,594	96.771	80.80	64
300V-120CS	35,645	33,300	16,928	216.355	76.33	94
350V-120CS	35,183	31,800	16,601	212.107	80.29	87
400V-150CS	43,260	39,600	20,714	348.177	74.25	104
450V-150CS	44,555	40,100	20,767	392.713	74.00	107
500V-180CS	48,599	43,700	22,348	817.926	77.00	124
550V-180CS	52,251	46,900	23,413	791.425	74.73	139
600V-200CS	55,942	49,200	24,240	763.471	75.00	140
650V-200CS	57,752	50,200	25,219	949.204	76.92	141
700V-200CS	59,328	51,000	25,300	1351.537	74.57	146
750V-220CS	68,048	58,700	29,483	2615.568	81.20	169
800V-220CS	67,306	57,500	29,019	3193.908	82.12	165
850V-220CS	70,617	59,600	29,925	2758.392	83.18	171
900V-250CS	74,835	63,300	32,719	2243.176	78.22	175
950V-250CS	77,576	65,400	33,572	3434.811	80.11	180
1000V-250CS	76,827	63,500	32,642	1763.833	79.10	176
1000V-300CS	85,758	73,400	35,649	1960.157	77.10	217

Source: Authors (2026).

Table 24. The number of charges from Algorithm 2 (AVtoCSNN) for large size instances.

Large Instances	Type 2	GB/T Chinese AC	CHAdemo	CCS2	GB/T Chinese DC
200V-80CS	56	100	50	49	23
200V-100CS	56	100	50	49	23
250V-100CS	56	132	63	59	34
300V-120CS	78	142	77	75	38
350V-120CS	84	174	96	83	42
400V-150CS	106	202	94	105	47
450V-150CS	118	252	95	113	57
500V-180CS	106	270	108	131	73
550V-180CS	142	286	144	128	64
600V-200CS	182	290	163	138	63
650V-200CS	182	320	185	140	74
700V-200CS	188	352	162	161	107
750V-220CS	206	382	185	174	97
800V-220CS	204	418	196	190	103
850V-220CS	228	398	219	203	115
900V-250CS	208	472	215	237	108
950V-250CS	244	442	231	249	127
1000V-250CS	248	536	244	228	136
1000V-300CS	248	536	244	228	136

Source: Authors (2026).

Table 23 shows that 176 charging stations have sufficient capacity to accommodate 1000 electric vehicles; therefore, there is no need to increase the number of candidate stations for the instance 1000V-250CS. For this instance, Table 24 indicates the following distribution of chargers: 248 Type 2, 536 GB/T Chinese AC, 244 CHAdemo, 228 CCS2, and 136 GB/T Chinese DC. These large-size instances illustrate planning scenarios for charging station networks with diverse charging technologies.

Such diversity is essential due to differences among electric vehicle manufacturing industries. Electric vehicle production is a complex process involving multiple sectors beyond vehicle assembly, including battery manufacturing and the production of key components such as motors, inverters, and, in particular, charging systems.

We observe in Table 25 that the UPSR varied between 71.82% and 81.87%, which is significantly lower than the values in Table 21, where all instances achieved 100%. Thus, Algorithm 1 outperformed Algorithm 4 with respect to the UPSR metric. Table 26 also shows diversity across instances in terms of the resulting number of chargers, namely Type 2, GB/T Chinese AC, CHAdeMO, CCS2, and GB/T Chinese DC. This diversity is particularly important given the multiple manufacturing industries involved in electric vehicle production.

Table 25. Output values by Algorithm 4 (AVtoCSMainRandom) for large size instances.

Instances	Objective Function Cost	Standard Deviation	The Best Cost of Objective Function	Financial Cost of the Opened Charging Stations (Thousands US\$)	Cost of the Opened Charging Stations (kW)	Comp. Time (s)	UPSR (%)	Total of Opened Charging Stations
200V-80CS	27,450.9	635.80	26,077	22,000	11,353	10.485	73.00	59
200V-100CS	26,329.7	1013.11	24,660	20,400	9960	10.209	81.00	58
250V-100CS	29,300.0	615.12	27,923	22,800	11,300	7.210	74.40	66
300V-120CS	37,815.2	1099.87	36,465	30,100	16,081	8.002	79.33	79
350V-120CS	40,150.5	1075.66	38,743	31,100	16,462	6.967	77.71	84
400V-150CS	49,061.8	911.91	47,125	39,000	19,894	33.517	80.00	106
450V-150CS	51,686.7	1517.58	48,560	39,600	20,298	17.521	75.11	110
500V-180CS	55,374.9	638.52	54,405	43,900	22,637	14.019	74.80	121
550V-180CS	58,232.2	999.99	56,479	45,000	23,130	18.900	71.82	124
600V-200CS	65,838.8	1323.8	63,775	51,200	25,293	46.423	75.17	147
650V-200CS	68,956.9	981.63	67,279	53,800	26,848	39.801	76.00	154
700V-200CS	70,181.4	972.55	67,914	53,200	26,387	21.384	78.57	151
750V-220CS	77,031.2	1001.50	75,095	59,100	29,724	25.798	81.87	170
800V-220CS	78,544.9	667.91	77,519	61,100	30,308	64.588	80.25	178
850V-220CS	80,140.0	783.16	78,498	60,300	30,047	64.565	79.76	175
900V-250CS	88,618.1	1165.95	87,285	68,700	34,815	34.628	76.33	195
950V-250CS	91,469.1	498.13	90,461	70,300	35,278	35.306	78.84	202
1000V-250CS	92,073.1	1148.18	90,393	69,600	35,110	36.917	75.90	202
1000V-300CS	99,954.5	1198.35	97,633	76,600	36,857	32.648	76.80	229

Source: Authors (2026).

Table 26. The number of charges from Algorithm 4 (AVtoCSMainRandom) for large size instances.

Large Instances	Type 2	GB/T Chinese AC	CHAdeMO	CCS2	GB/T Chinese DC
200V-80CS	56	100	50	49	23
200V-100CS	56	100	50	49	49
250V-100CS	56	132	63	59	34
300V-120CS	78	142	77	75	38
350V-120CS	84	174	96	83	42
400V-150CS	106	202	94	105	47
450V-150CS	118	252	95	113	57
500V-180CS	106	270	108	131	73
550V-180CS	142	286	144	128	64
600V-200CS	182	290	163	138	63
650V-200CS	182	320	185	140	74
700V-200CS	188	352	162	161	107
750V-220CS	206	382	185	174	97
800V-220CS	204	418	196	190	103
850V-220CS	228	398	219	203	115
900V-250CS	208	472	215	237	108
950V-250CS	244	442	231	249	127
1000V-250CS	248	536	244	228	136
1000V-300CS	248	536	244	228	136

Source: Authors (2026).

We evaluated the long-term penetration rate of electric vehicles for large-size instances and its impact on opened charging stations, as shown in Figure 12. The data were obtained from Tables 21, 23 and 25, considering Algorithms 1, 2 and 4. The least squares method was used to determine the best-fitting line by minimizing the sum of squared differences between observed and predicted values [39]. The resulting equation is given by $cs = mv + b$, where cs is the number of opened charging stations, v is the number of vehicles, $m = 0.18$,

and $b = 28.21$. The least squares method provides a useful decision-making tool for investors when forecasting future infrastructure needs.

The penetration rate was interpreted as an increase in electric vehicle adoption every six months, with a growth rate of approximately 10% per semester. Based on this rate, the number of vehicles increases from 200 to 1000 over a period of 102 months, implying the need to expand the number of opened charging stations from approximately 50 to 200, according to the best-fitting line in Figure 12. Applying this penetration rate to the 67 current charging stations in the Greater Vitória metropolitan area using the instance in Table 18 (184V-67CSmod), a medium-term strategy indicates that the network would need to expand to approximately 115 stations within the next 60 months to serve about 478 electric vehicles. If this growth rate persists, stakeholders would need to invest in the construction of 48 additional charging stations to ensure adequate service for electric vehicle users.

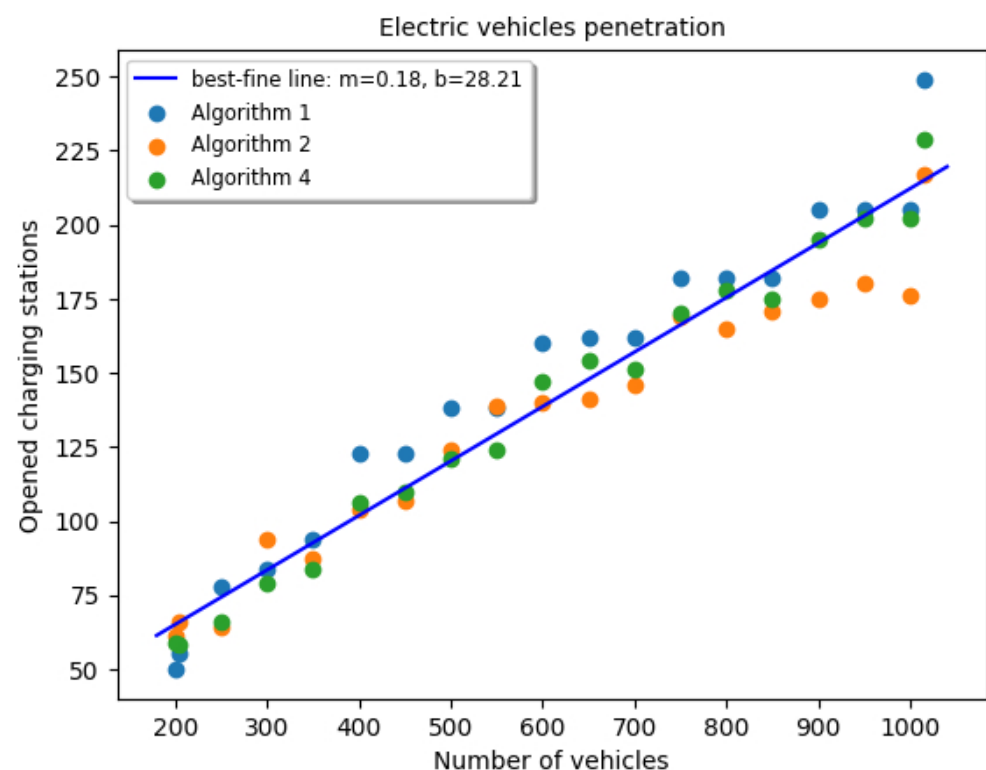


Figure 12. Evaluation of penetration rate of electric vehicles. Source: Authors (2026).

Algorithms 1, 2 and 4 are compared for instances of large size in Figure 13. The Algorithm 2 obtains the best performance when it is considered the cost of the objective function.

However, Algorithm 1 achieved the best performance when evaluating the UPSR, while Algorithm 4 obtained the best computational time. It is worth emphasizing that the plotting of Algorithm 4 considered the best objective function cost along with the total computational time accumulated over ten runs of the algorithm.

As presented in this study, multiple instances were developed to account for various scenarios. These can be adapted to different periods of the day or week where user preferences such as energy pricing, convenience stores, and traffic patterns are desired. Highlights that vehicle charging units remain integrated within the EVs. The algorithms demonstrate high robustness and low computational overhead. Since each instance can be adjusted with specific user preference parameters, the system is able to deliver near-instantaneous results using dynamic optimization.

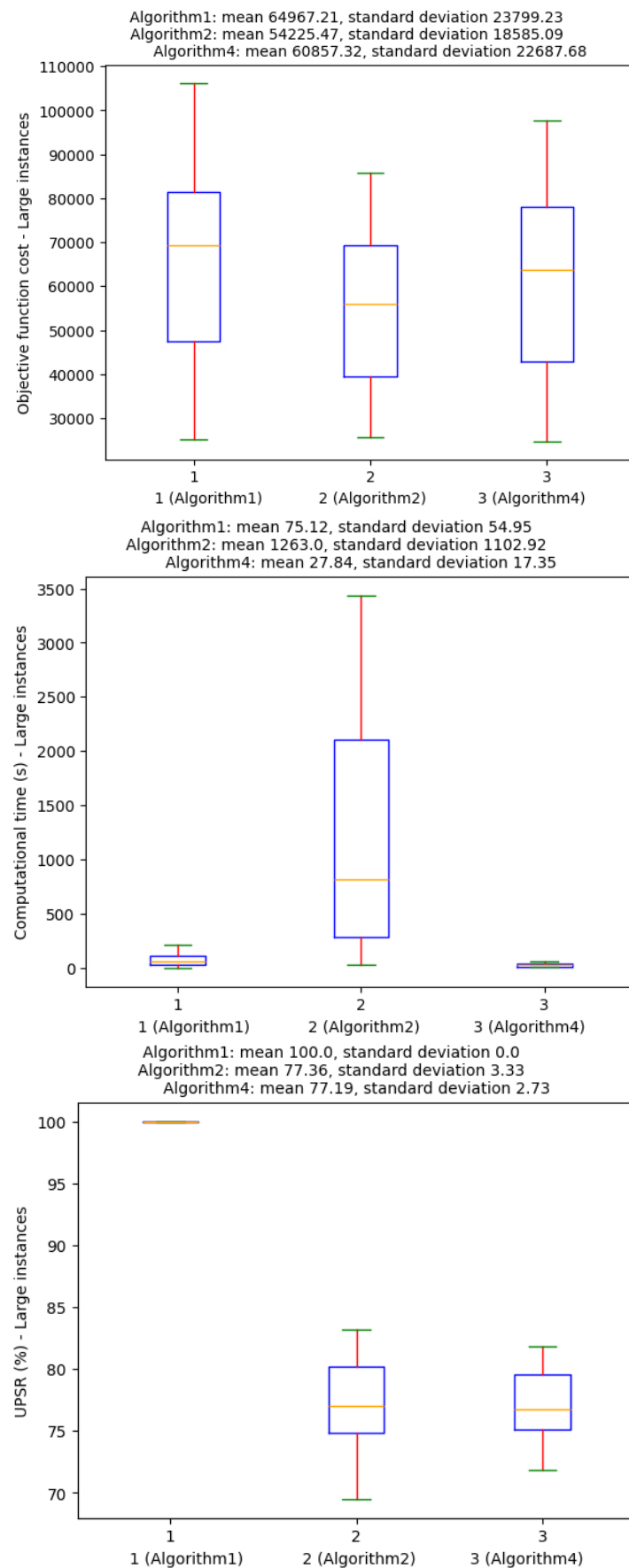


Figure 13. Comparison between Algorithms 1, 2 and 4 for instances of large size. Source: Authors (2026).

5.6. Theoretical Interpretability and Computational Complexity

The charging station allocation problem tackled in this framework is inherently NP-hard, making the derivation of universal analytical optimality bounds computationally intractable for large-scale regional deployments. To address this limitation, five distinct allocation strategies were designed as heuristic mechanisms, trading absolute mathematical optimality for practical computational efficiency.

The theoretical foundation of these strategies rests on their algorithmic design paradigms, balancing exploration and exploitation through a dedicated local search mechanism shared by both the deterministic and randomized variants. To guarantee strict computational tractability, the local search adapts dynamically to the problem scale. Let n denote the number of vehicles in the instance. For smaller to medium problem scales (up to 150 vehicles), the local search explores the neighborhood structure thoroughly, resulting in a formal worst-case computational complexity of $O(n^4)$.

However, to mitigate the polynomial growth of $O(n^4)$ in larger environments, the framework imposes a structural iteration ceiling for instances containing 200 or more vehicles. In these large-scale scenarios, the local search execution is strictly capped at a maximum of $K = 50$ iterations. This boundary restrains the computational complexity to a controlled scale of $O(K \cdot n^3)$ or $O(K \cdot n)$ depending on the primary allocation loop, effectively preventing combinatorial explosion.

This multi-strategy design provides a robust, quantitatively bounded decision-support tool. Rather than relying on an unconstrained search, planners can select the specific allocation strategy based on the immediate operational focus: minimizing objective function costs, reducing computational execution times under scaled networks, or strictly maximizing the UPSR.

6. Discussion

The adoption of electric vehicles contributes significantly to the reduction of greenhouse gas emissions by replacing petroleum-based energy sources with cleaner alternatives. This transition is further supported by the integration of renewable energy sources, such as photovoltaic systems, into the energy matrix. In addition, user motivation to access charging stations is influenced by factors such as the availability of convenience stores, low traffic flow, and charging costs. However, the diversity of electric vehicles, driven by multiple manufacturing industries, introduces challenges for charging infrastructure planning.

Electric vehicle manufacturing is a complex process that involves several industrial sectors beyond automobile companies, including battery production, power electronics, and charging technologies. In this context, charging infrastructure—particularly public charging stations—plays a crucial role in the EV ecosystem. Such infrastructure comprises both hardware components (charging units, connectors, and charger types) and software systems that manage charging networks. Consequently, effective planning of charging stations is essential to meet the growing demand for EVs while considering charger types and user preferences.

This work presented several heuristic algorithms for allocating electric vehicles to charging stations. Extensive computational experiments were conducted using small-, medium-, and large-scale instances, including a case study based on real-world data. The number of electric vehicles ranged from 20 to 1000, while the number of charging stations varied from 6 to 300. This diversity of instance sizes enabled the evaluation of algorithmic performance under different levels of complexity and granularity. Furthermore, the penetration rate of electric vehicles was analyzed over a long-term horizon to assess its impact on the number of opened charging stations.

All proposed algorithms account for station capacity and charger types, but each emphasizes different priorities: proximity to charging stations, user preferences, or minimizing the number of opened candidate stations. As a result, stakeholders can select solutions based on investment strategies, user satisfaction, or trade-offs among capacity, charger diversity, and proximity. For example, a solution achieving 90% UPSR may be considered acceptable compared to a 100% UPSR solution if the latter requires significantly higher infrastructure costs due to the opening of additional charging stations.

Statistical analyses were performed using a randomized algorithm, while two deterministic algorithms were evaluated with distinct priorities. Randomness plays a fundamental role in many scientific fields, including physics, biology, and economics [40]. In combinatorial optimization, randomized algorithms can improve both solution quality and computational efficiency. In this work, deterministic algorithms were compared with a randomized version, demonstrating that the proposed deterministic approaches outperform random starting procedures when considering the objective function cost, thereby validating the proposed methodology.

For small- and medium-sized instances, Algorithm 1 achieved better performance in terms of objective function cost, whereas Algorithm 2 outperformed Algorithm 1 with respect to computational time. For large-scale instances, Algorithm 2 yielded the best results in terms of objective function cost, while Algorithm 1 consistently achieved the highest UPSR. Algorithm 4, in turn, exhibited superior computational time performance for the majority of instances. These results demonstrate the robustness of the proposed approaches across multiple performance metrics.

All parameters of the algorithms, such as calibrations, methods, and strategies, along with the instances and scenarios, were described in detail in the Sections 4 and 5. Consequently, the reproducibility of this study is guaranteed.

All algorithms proved to be efficient in terms of memory usage, exhibiting low RAM consumption across all instance sizes. Algorithms 1 and 2 were particularly efficient for small- and medium-sized instances; however, their computational requirements increased for large-scale problems. Therefore, as future work, we propose the development of a local search algorithm with polynomial complexity lower than $O(n^4)$.

The main limitations of this study stem from the worst-case assumption that all electric vehicles require charging simultaneously. Although this assumption is conservative, an alternative scenario was evaluated using real-world data with a charging demand of 70% of vehicles. While charging queues may arise in some cases, they are assumed not to significantly inconvenience users. Another limitation is that each user can select only one preference (traffic, convenience stores, or energy price). In addition, to maintain computational tractability, the proposed model abstracts certain real-world EV charging dynamics. Practical deployments, however, must account for stochastic vehicle arrivals and queueing times, non-linear battery charging kinetics (e.g., reduced speed above 80% SoC), and fluctuating electricity tariffs (Time-of-Use pricing). Future extensions will focus on incorporating these dynamic operational factors, accommodating diverse user preferences, and modeling complex charging demand scenarios to better reflect real-world behavior.

7. Conclusions and Future Work

This paper presented optimization algorithms for the strategic allocation of electric vehicles to charging stations, addressing a critical bottleneck in the transition toward sustainable, low-carbon urban transportation. By integrating critical real-world constraints such as station capacity, heterogeneous charger types, and multi-faceted user preferences (including traffic flow, convenience amenities, and charging costs), we developed a suite of heuristic algorithms capable of resolving small- to large-scale instances containing up to

1000 EVs and 300 charging stations. The rigorous computational validation, complemented by a case study using real-world data, demonstrated that the proposed deterministic approaches significantly outperform randomized starting procedures, thereby validating the structural design of the developed search mechanisms.

From a managerial and policymaking perspective, this work provides valuable decision-support tools. Rather than offering a single, rigid optimal solution, our framework empowers network operators and urban planners to navigate key trade-offs between infrastructure investment and user satisfaction. Specifically, the analysis of the UPSR revealed that accepting a slight compromise in user satisfaction (e.g., targeting a 90% UPSR instead of 100%) can yield substantial capital expenditure savings by avoiding the deployment of redundant, high-cost candidate stations. Furthermore, the diverse performance profiles of the algorithms, where Algorithm 1 excels in solution quality for smaller instances and Algorithm 2 offers superior computational efficiency at scale, enable planners to deploy tailored optimization tools depending on their specific operational demands and computational resources.

Despite its contributions, certain limitations of this study outline promising pathways for future research. Currently, the model operates under a conservative, worst-case assumption of simultaneous charging demand, and restricts users to a single primary preference. To further enhance the realism and applicability of this framework, future work will focus on: (i) developing high-performance local search algorithms with polynomial complexity strictly below $O(n^4)$ to accelerate large-scale real-time optimization; (ii) modeling multi-criteria user preferences using multi-attribute utility theory; (iii) integrating physical charging constraints, such as non-linear battery rates and dynamic electricity pricing; and (iv) incorporating stochastic vehicle arrival and queuing models to capture transient grid behaviors. In addition, although the study relies on real-world infrastructure and locations in Greater Vitória Metropolitan Region, full validation incorporating sensitive user-related data is beyond the scope of this paper and is left for future work. These advancements will continue to support the scalable and cost-effective expansion of global EV charging infrastructure.

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Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle
CS	Charging Station
IEA	International Energy Agency
BEV	Battery Electric Vehicles
PHEV	Plug-in Hybrid Electric Vehicles
FCEV	Fuel Cell Electric Vehicles
AC	Alternating Current
DC	Direct Current
UPSR	User Preference Success Rate
NN	Nearest Neighbor
LS	Local Search
OFC	Objective Function Cost
BEST	Best Objective Function Cost
UTM	Universal Transverse Mercator
AVtoCSCapacity	Algorithm assigns Vehicles to Charging Stations while respecting the Capacity
AVtoCSNN	Algorithm assigns Vehicles to Charging Stations using a NN strategy
AVtoCSRandom	Algorithm assigns Vehicles to Charging Stations using a Random strategy
AVtoCSMainRandom	Algorithm was run 10 times with AVtoCSRandom input
AVtoCSLSearch	Algorithm assigns Vehicles to Charging Stations performing the Local Search

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