Energy 283 (2023) 128436

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Identifying charging zones to allocate public charging stations for electric vehicles

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ARTICLE INFO

Handling editor: Neven Duic

Keywords:
charging infrastructure planning
Location-allocation
Optimization
Power distribution system planning
Public charging station

ABSTRACT

In recent years, several techniques have been presented in the specialized literature to identify the best location for installing public charging stations, considering the demand for charging the batteries of electric vehicles that travel along the main roads in urban areas. However, in cities with different travel patterns for electric vehicle drivers, such consideration may result in charging equipment serving few electric vehicles during high recharging demand. Thus, planning by zone can determine more chargers per station with greater utilization during the operation of charging stations. For this, this work presents a methodology that uses the concept of a charging zone, defined as a circular geographic space with charging equipment that will satisfy the charging demand of electric vehicles in their surroundings. Identifying the centroids of these zones is formulated as a p-median problem, solved by the Teitz-Bart algorithm to provide more coverage to the demands for electric charging in large urban areas. The proposed methodology was applied in a Brazilian city with approximately 3 million inhabitants to find the spatial distribution of public charging zones, considering six scenarios of the global penetration of electric vehicles. Furthermore, we compared the allocation of the centroids in these zones with the solution determined by commercial geoprocessing software. This comparison shows that the proposal determines a spatial distribution of 10% more of these zones with a load factor closer to 0.5 than the results of the commercial geoprocessing software. More zones with this load factor value contribute to better use of the power distribution network installations. In addition, the proposed methodology finds an average reduction of 319 kW of peak demand in regions with a low flow of electric vehicles to meet their charging needs in each analyzed scenario. This peak-demand reduction may allow less investment in connecting future charging stations to the power distribution network. Therefore, the proposed methodology can help public and private agents to disseminate electric mobility, finding public charging areas with greater utilization of chargers per station during the operation of charging stations.

1. Introduction

In 2021, the number of electric vehicles (EVs) sold worldwide reached more than 16.5 million, representing a growth of 60,78% compared to 2010 [1]. Furthermore, sales forecast studies carried out by international agencies show that sales EV will grow exponentially, reaching values above 300 million in 2030, as shown in Ref. [2], and up to 1.11 billion in 2050 [3]. However, the high cost of acquiring EVs compared to conventional vehicles means that EV buyers are not evenly distributed in urban areas [4]. Additionally, the low availability of charging stations in cities can hinder EV diffusion due to drivers' anxiety. Such difficulty instills the driver the sensation that they may run out of power in the EV batteries before arriving at their intended destination [5]. Nonetheless, this difficulty tends to decrease as the recharging infrastructure in cities is improved [6].

Several studies have shown that EV owners prefer to recharge at public charging stations (PCS) during their travels in short time intervals through the fast-charging station (Fast-CS) [7]. This preference can be justified because the charging time is fewer hours than residential chargers [8]. However, this type of charger has high power, which can

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https://doi.org/10.1016/j.energy.2023.128436
Received 31 July 2022; Received in revised form 8 July 2023; Accepted 13 July 2023
Available online 17 July 2023
0360-5442/

impact the power distribution network [9]. From the viewpoint of electricity grid planning, the connections of the new Fast-CS are to be made at the level of medium voltage distribution networks [10]. Therefore, distribution companies should plan as high maximum demand levels may require a reinforced network [11]. In some cases, this demand may occur at specific times of the day, resulting in high rates for recharging EVs and low utilization factors.

On the other hand, determining the best places to meet the demand for recharge arises must consider the stakeholders' objectives, enabling the transportation and electricity sectors to meet their quality goals in providing services [12]. In this sense, the most used approach is through the allocation-location problem, which makes it possible to identify the most suitable streets and avenues. However, more EVs and candidate installation sites increase the complexity of solving this problem [13].

1.1. Contributions

In most specialized literature methodologies, the charging station allocation problem has sought to determine a point for installing charging equipment [14]. However, this determination could require many charging points to cover EV charging demands in large cities [15]. Therefore, this work uses the concept of a charging zone (CZs) to improve the coverage of recharge services for EVs, which is illustrated in Fig. 1. Thus, the CZ is a circular geographic region with a coverage radius and with one or more PCS that will meet the demand for charging electric vehicles circulating through it.

The proposed method intends a better use of recharge infrastructures so that the investment made in the first years of EV penetration can meet future scenarios with greater EV penetration. A case study was conducted in a metropolis with approximately 3 million inhabitants in northeastern Brazil. The results were compared with ArcGIS software's optimized allocation to six prospective EV penetration scenarios [16]. This comparison shows that the proposed method determines the spatial distribution of Fast-CS with higher utilization factors and lower values of maximum demand can decrease investments related to Fast-CS connection. The main contributions of the methodology are listed below.

1) The proposed method introduces the concept of charging zones that can help planners in sustainable planning in large cities, looking for the higher coverage of recharging demands that arise from urban traffic patterns;
2) The proposal allocates more charging equipment with a high utilization factor during a typical day of urban traffic for each charging zone defined in the city under study when compared to the methodologies that seek to determine the allocation point of all charging infrastructures;
3) This work shows how to better use georeferenced information in most metropolises to assist in their sustainable planning and meet the new electrical demands that arise from electric mobility.

1.2. Paper structure

Section 1 presents an introduction to the work. Methods available in the specialized literature for installing charging stations are presented in Section 2. Section 3 describes the proposed methodology for determining the charging zones. Section 4 shows the tests, results obtained, and comparisons between the proposal and an allocation tool available in commercial software. Finally, the conclusions of the paper are presented in Section 5.

2. Literature review

The central issue of the PCS allocation problem is how to select appropriate locations considering the agents' objectives [6]. To successfully plan the CS installation, the planners must consider the legislation, the interrelationship between the transport and electrical networks, economic and financial viability, land use, and available geographical space.

Planners and involved agents can use many approaches to solve the

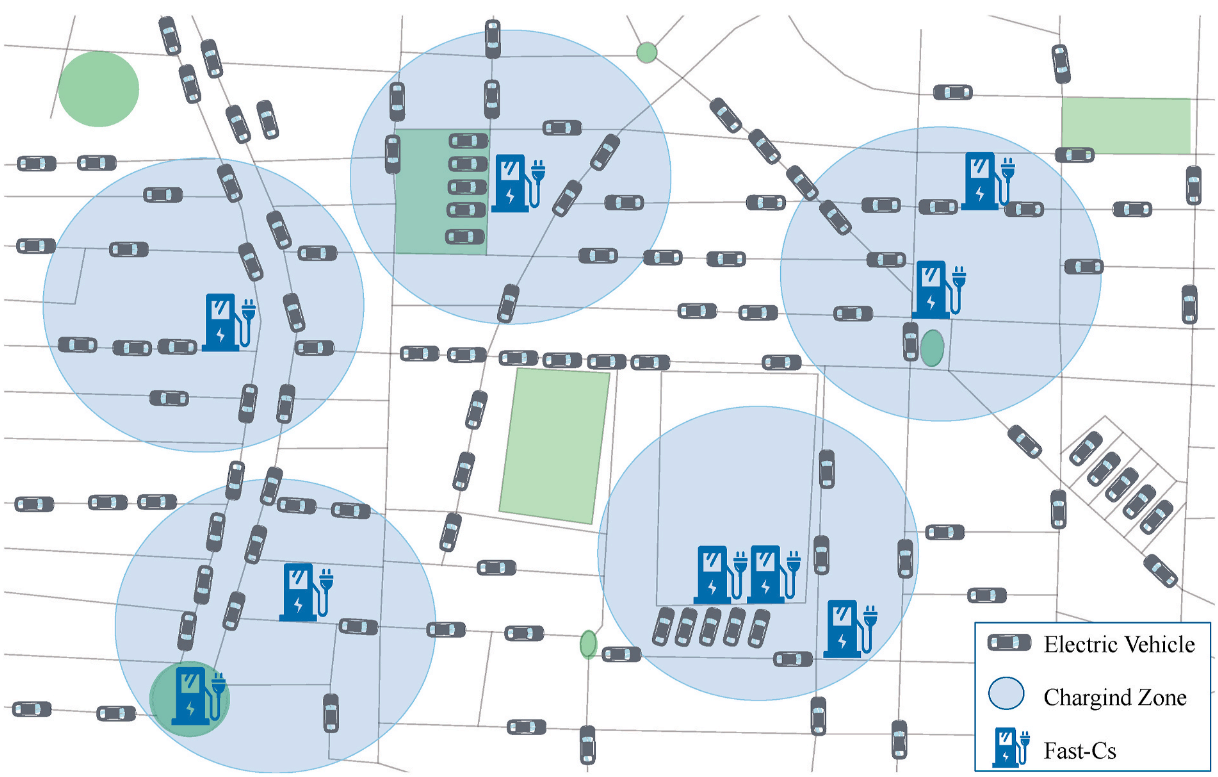


Fig. 1. Proposed planning concept: EV charging zones.

CS allocation problem [17]. For example, planners can use Hakimi's P-median graph-based approach to minimize the distance between EV drivers and the nearest CS [18]. In recent years, this approach has been used in several metropolises, considering the places where EVs are circulating (demand points) and the PCS (service points) available. Thus, a method based on graph theory with automorphic clustering is proposed by Ref. [19] to analyze transport networks containing EVs and charging stations, considering the impact on the urban road network. In Ref. [20], a graph with weights on the edges representing users' competitive and strategic behavior was presented to minimize the cost of EV charging.

On the other hand, there is a peculiar characteristic in the penetration of new technologies: the high price of an EV is not accepted by a large part of the population. Thus, EV buyers are spatially dispersed, as shown in Ref. [21]. In this context, the cost of installing CS is high, and the economic return on investment can take many years. Therefore, it is necessary to optimize the allocation of CS so that the amounts to be paid by EV drivers are viable, as explained in Refs. [22,23]. In Ref. [22], an optimized combination of chargers is proposed to manage the charging level and, at the same time, minimize the installation costs of charging stations.

Additionality, the planning of CS should consider aspects related to the energy supply and transport network, as was explained in Ref. [24]. Thus, a model for planning charging stations was developed considering user convenience, economic benefits, and impact on distribution systems [25]. Likewise, the optimization model for sizing and allocating charging stations in a distribution network was presented in Ref. [26], using a probabilistic approach for demand recharging. Another example of a planning model for CSs with distributed photovoltaic generation units is proposed [27] considering simultaneity and aiming to reduce energy losses in distribution systems.

Additionally, in several works available in the specialized literature, the problem of locating CS has been formulated as a linear and mixed integer nonlinear optimization model. Thus, a model for optimizing the location of charging stations is proposed in Ref. [17], considering a real-time control to reduce queues and, consequently, the waiting time for a recharge. This model was approached through mixed integer linear programming (MILP). Likewise, a MILP-based CS allocation optimization model was shown in Ref. [28], using a set of charging stations from the candidate locations to minimize the fixed cost of charging stations and the cost of moving EVs.

Several studies for allocating charging stations have considered new communication technologies and market structures for billing electric vehicle charging in recent years. Thus, in Ref. [29] a framework for planning PCS infrastructure was proposed, especially for electric taxis, which are helpful for large urban areas. In the study [30] the feasibility and proposals of possible development agencies were examined, covering government policies, owners, real estate agencies, and users of electric vehicles. In Ref. [31] an optimization model was proposed to plan and develop mobile energy hubs based on optimization criteria and considering the temporal variability of EV recharge demands. In the proposal elaborated by Ref. [32], the Internet of Things (IoT) and big data techniques were used to examine the influence of the EV in the urban context to predict the vehicle's charge level when entering the parking lot, EV location, and periods of connection to charging stations.

From the literature review, we have identified that the locations chosen by planners for installing the PCS are as accessible as possible in central regions of cities, parking lots, malls, and commercial areas, among others [7]. Furthermore, the greater the charging infrastructure, the better it can meet the several patterns of recharging demands of EV drivers on the road network [11]. In this sense, the most used approach is through the allocation-location problem, always considering a set of previously selected locations for PCS, as shown in Ref. [33].

It is common for allocation-location proposals to be handled through geographic information systems (GIS) since it requires spatial modeling. In such an approach, it is possible to integrate location variables (coordinates) with any descriptive variable that shows location characteristics (such as the amount of energy consumed by an installation). For example, the charging station location using fuzzy multicriteria decision analysis based on GIS is presented in Ref. [34]. Furthermore, a holistic approach integrating GIS techniques, building energy modeling, and sensitivity analysis to categorize key urban planning factors in energy performance is explained in Ref. [35].

Unlike the cited works that determine an installation location of PCS, the proposed methodology uses the concept of CZs to improve the coverage of recharge services for EVs. These zones are circular geographic regions with one or more PCS that will meet the demand for charging electric vehicles circulating through them. Additionality, the results of the proposal are a georeferenced database. These results provide information for technical and economic feasibility studies of new undertakings' recharging equipment, showing regions where there can be high growth in recharging demand.

3. Proposed methodology

The proposed methodology has three modules, as illustrated in Fig. 2. The input data is inserted in the format of vector layers that represent the candidate locations for the CZs centroid and the transportation network location with the demand for recharging on the main urban transitways. Additionally, coincidence factors and the power of the types of chargers that will be installed must be reported. In Module 1 of the proposed methodology, a graph is constructed with two node sets: the transportation network demand points and the candidate locations for Fast-CS installation. The output of Module 1 is the CZ centroids determined by the Teitz-Bart algorithm, which are entered as input data in Module 2. Circular polygons are built in Module 2 using GIS tools to represent the coverage areas of each CZ. Additionality, Module 2 determines the number of EVs within each CZ's coverage radius. Finally, in Module 3, the coincidence factor curves are used to determine the maximum coincident electricity demands in each period of the day, considering the types of chargers available in the input database.

3.1. Input data

The input database must be organized into two distinguished sets. The first set consists of spatial layers with information on candidate locations for the CZs centroid and the demands of recharge in the main transitways. The other set should be formed by non-spatial information related to coincidence factors, nominal electric power values, and voltage of the chargers to be installed in the CSs.

3.1.1. State of charge and flow of electric vehicles

One of the premises of the proposal is that a candidate location for the installation of CZ is one with the high movement of EVs and a low state of charge (SOC) of their batteries. Transportation departments use traffic simulation software to identify vehicle movement patterns, as explained in Ref. [36]. In Ref. [11], a model was presented for creating georeferenced databases (Inp_1, illustrated in Fig. 2.) that show the flow and SOC value with which the EVs travel. This model could help to determine the charge demand points. These data are used as input, allowing the proposed methodology to identify the center for each CZ.

3.1.2. Candidate locations for the charging zones centroid

Urban planners have generally identified candidate sites for building charging infrastructure for large urban centers. These locations can have various features, such as convenient locations and easy access. Since planners have already identified these locations, a georeferenced database can be inserted as input data (Inp_2) in the proposed methodology, as shown in Fig. 2. If planners have not mapped such sites, then-candidate location can be found using the results of urban traffic simulations. In this case, a site that is a candidate location for PCS installation has a high movement of EVs and low SOC in their batteries [11].

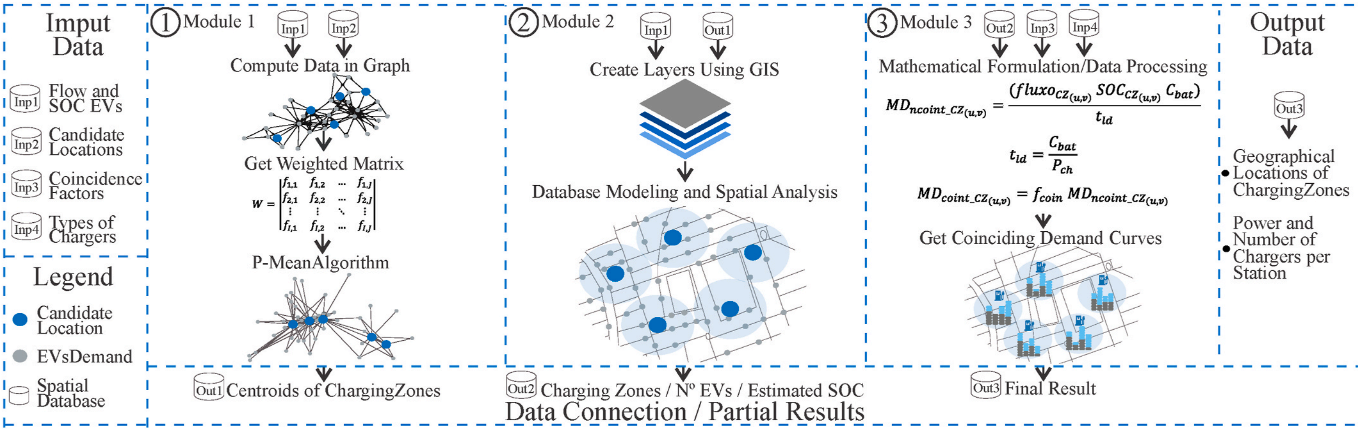


Fig. 2. Flowchart of the proposed methodology work routine.

3.1.3. Coincidence factors for electric vehicles charging

In general, distribution planners use coincidence factors to estimate maximum coincident electricity demands to calculate the power rating of distribution network facilities [37]. Moreover, these factors can be used to calculate the electric power of the charging stations [38]. The simulation tools available in traffic software can characterize EVs' movement and their SOC in a CZ, so it is possible to determine the coincidence factor and to insert as input data (Inp_3), as illustrated in Fig. 2.

3.1.4. Types of chargers for fast charging stations

In specialized literature, there are several classifications for Fast Charging [6]. Generally, this type of charging is performed by EV chargers with 43 kW, 50 kW, and 150 kW powers rating to reach about 80% of the EV battery in less than 30 min [5]. Therefore, the proposal considers this information input data (Inp_4), as illustrated in Fig. 2.

3.2. Module 1: allocation-location of charging zones centroids

It is undeniable that establishing a charging infrastructure is a complex problem [39]. The decision-making process involves multi-variable investment, a high initial cost, and countless technical/-economic restrictions [10]. For this reason, in the planning and market research stage, owners seek to define the best locations for the installation to minimize operating costs, maximize profits, provide a high level of service, and improve customer service quality considering all stakeholders' objectives and interests [5].

A highlight between the proposal and some methodologies available in the literature is the determination of favorable regions for recharge, that is, not just a point but an entire service zone. Within this zone, a suitable location can be chosen, paying attention to factors such as easy and safe access for the EV driver, price/availability of land, and proximity/possibility of connection to the electrical grid. This location is achieved through careful modeling that addresses traffic dynamics and the structure of the electricity distribution network.

3.2.1. Problem formulation

Generally, in an allocation problem, the intrinsic geographic elements must be considered [40]. Therefore, the proposed methodology uses georeferenced maps to characterize urban roads (streets, avenues, etc.) and their intersections. Furthermore, candidate sites (previously selected) and the location of EVs are considered input data.

In graph theory, the elements of the study zone are modeled by a graph $G = \{V, E\}$ [41]. Vertices (points or nodes) are assigned to set $V \in G$, representing places of interest within the study region (an intersection or any point in the network topology), as illustrated in Fig. 3 [42]. In the allocation de CZ, set V is subdivided into two subsets: one to represent a candidate site for CZ (V_J) and another for the location of VEs (V_I). Similar to what was proposed by Refs. [40,43], the entire set V is geographically located according to its spatial points $\{x_n, y_n\}_{n=1}^{V}$. Set $E \in$

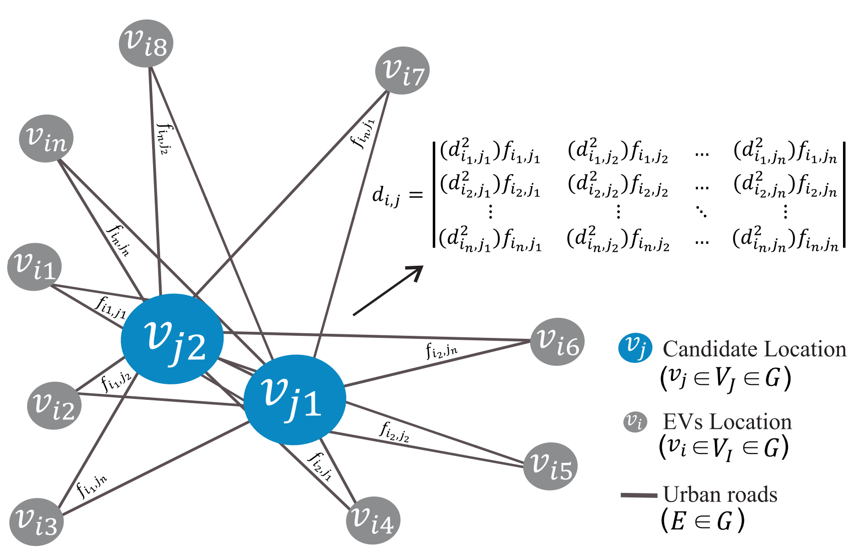


Fig. 3. Application of graph theory to the allocation problem.

G contains the edges (arcs, links, or segments), which represent all the roads of the region (streets, avenues, and similar) through which vehicles travel, as shown in Fig. 3. Therefore, in the proposal, set E represents the path that connects vehicles in the position $v_i \in V_I$ to a charging zone $v_j \in V_J$. It is common for a weight to be assigned to E, for example, the distance between a vehicle and a charging point. In the proposed methodology, it was decided to weigh the distance through a function $f : E \rightarrow \mathbb{R}^+$, which will be described in the next section. The result of this function shows weights for each edge, represented through a matrix.

In the proposed methodology is presumed that.

- A vertex can be connected to more than one urban via when that vertex is an intersection between two or more vias;
- V_I can be understood as a set of charging demand points, as each vehicle has a certain amount of energy in its battery and wants to reach a station to supplement it;
- All allocated CZs are presumed to meet and are capable of meeting the demand for recharge, whatever it may be, in its entirety;
- Function f allows correlation to the investment needed to meet the charging demand.

3.2.2. Weighting matrix

The proposed methodology seeks the graph with the lowest value for the sum of the weights of all edges. For this seeking, a weighting function per edge uses the distance between the demand and the candidate CZ centroid, the average flow of EVs, and their SOC crossing the site v_i. The results of this function are organized into a Weight Matrix (WM). In the formulation of WM, the graph is formed by V vertices where each vertex has given coordinates in a two-dimensional plane (Cartesian). The distance between two vertices is determined by (1) [39].

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

Where (x_i, y_i) are the coordinates of the demand location at the vertex v_i and (x_j, y_j) is the location of the candidate CZ centroid at the vertex v_j. Lastly, the weight assigned to the edges is calculated using (2), through which the candidate location for an installation is selected. The equation determines that a candidate site is in a region with a high flow of electric vehicles and where these vehicles have a low SOC.

$$f_{i,j} = \frac{\frac{d_{i,j}}{d_{i,j(max)}}}{\frac{F_i}{F_{j(max)}} + \frac{(80 - SOC_i)}{SOC_{j(max)}}} \tag{2}$$

Where $f_{i,j}$ is the weighting between demand v_i and the location of the candidate CZ centroid in vertex v_j; $d_{i,j(max)}$ is the maximum coverage distance of the CZ in vertex v_j; F_i is the average flow of EVs at the vertex v_i; $F_{j(max)}$ is the maximum flow that the CZ can cover at vertex V_j; SOC_i the EVs average state of charge at the vertex v_i; and $SOC_{j(max)}$ is maximum SOC to be supplied by CZ in vertex v_j. The term $80-$ SOC_i represents that EVs tend to charge their batteries up to 80% of SOC to maintain their physical integrity and battery longevity [17]. From (2), locations near the CZ vertex v_j with large flow EVs and with low SOC present lower weights.

To illustrate Equation (2), consider that the maximum values of distance and maximum flow, and maximum SOC are 10 km, 10 VE, and 80%, respectively, for two candidate recharge zones, A and B, which are located at a distance of 2 and 4 km from a demand location, respectively. At this demand location, 5 electric vehicles cross with an average SOC of 20%. The edge weighting values are 0.16 and 0.32 for candidate zone A and B, respectively, using the abovementioned parameters for such an equation. The value of the flow and SOC to be served by each candidate zone is the same as the proximity criterion of the smallest one weight for A. However, when it has a smaller group with 2 electric vehicles, an average SOC of 70%, and a distance of 2 km to each candidate zone, the weighting value would be 0.62. Therefore, it observes that locations near candidate zones with average SOC close to the maximum value and low vehicle flow have high weightings on the edges.

The graph that connects each demand to a candidate zone with the lowest possible weight is found by the p-median model.

3.2.3. The P-median model

A P-median Model (PMM) was used to find the graph that gathers only one v_i of demand with only one centroid v_j. Such a model, introduced by Hakimi [44], has been widely used when demands and candidate location installations p are known [28]. PMM allocates a number p of facilities, minimizing the sum of weights to meet all demands.

The set of graph vertices G that make the one demand v_i be supplied by only one centroid v_j is represented by V_P, as explained in Refs. [45, 46]. For the construction of this graph, it is considered that each demand at the vertex v_i is a Euclidean distance away V_{p*} which is regarded as a P-median of G. Therefore, the distance between a vertex v_i and the element v_{p*} $(d_{vi,vp*})$ times the weighting of $f_{i,p*}$ should be equal shorter than the distance between that vertex and another closer element $(d_{vi,vp})$ of V_P times the weighting of $f_{i,p}$. Thus, for each P-median of G the model is (3):

$$\sum_{i=1}^{V} (d_{vi,vp*}) f_{i,p*} \leq \sum_{i=1}^{V} (d_{vi,vp}) f_{i,p} \tag{3}$$

3.2.4. Teitz and Bart algorithm

The specialized literature classifies the resolution of PMM as an NP-hard problem [47], demanding high computational effort, especially when there are high numbers of vertices [48]. However, the algorithm of Teitz and Bart (TB) [49] finds solutions in large graphs, allowing a better characterization of the centers of the circular geographic region as a function of the weight of the edges [46]. Such characteristics are closely related to the definition of CZs since each zone must meet the demands of electric vehicles within its coverage radius in metropolises. The TB is known as the vertex replacement algorithm. At each iteration, it chooses a locally optimized solution, which can be replaced until reaching the optimal solution [17]. Furthermore, among the algorithms used to find the set of vertices (3), the TB stands out due to finding solutions in large graphs with minor computational effort compared to other techniques [50]. The following paragraphs describe the algorithm's operating logic, with further details available in Ref. [49].

TB Algorithm uses a binary variable to represent the vertex in which an installation is allocated. Thus, value 1 represents the installation at the vertex; otherwise, value 0 is used [46]. For the implementation of the algorithm that solves the PMM, a matrix A was defined with this variable class considering (4):

$$A_{i,j} = \begin{cases} 1, & \textit{if the demand at vertex } i \textit{ is allocated to} \\ & \textit{center of CZ at vertex } j \\ 0, & \textit{if no} \end{cases} \tag{4}$$

From the definition in (4), the optimization model minimizes the total sum of weighted distances and finds a set V_P is:

$$Z = Min \sum_{i,j}^{V} (w_{i,j}) A_{i,j} \tag{5}$$

Being subject to restrictions:

$$\sum_{j}^{V_J} A_{i,j} = 1, i \in V_I \; and \; j \in V_J \tag{6}$$

$$\sum_{i}^{V_I} \sum_{j}^{V_J} A_{i,j} \leq p, i \in V_I \; and \; j \in V_J \tag{7}$$

Constraint (6) ensures that demand at vertex v_i can only be supplied by the CZ, whose centroid is at the vertex v_j. This restriction ensures that all recharging needs are met. The expression (7) restricts the number of installations to a maximum amount of p. Unlike the methodologies available in the literature that consider equality in Equation (7), this present work considers that an inequality. In some urban areas, such inequality is justified because the whole set of candidates informed in the database could not be necessary for the demand-supply [51].

On the other hand, an appropriate criterion is defined in Ref. [46] for the optimization model solution defined by (5) to (7). For this reason, the TB algorithm performs in each iteration one vertex substitution [49], storing the lowest value of the objective function determined by (5) and using a transition strategy in each iteration [17]. Such a transition strategy avoids repeating the analysis of vertices that did not diminish the objective function, and it has participated as part of V_P in former iterations [46].

Algorithm 1 presents the step by step to find the set V_P for the allocation of the CZs centroids. On line 3, a set of V_p random initial solutions are assigned. Then, on line 4, a loop is implemented to analyze vertices. Next, on line 5, one vertex will be tested (v_k) to be part of the set of V_p. Then on line 6, the metric (Δ_{ik}) is calculated to help in seeking the minimum weighted distance between the edges of the graph, as shown in lines 7 to 9. Lastly, line 11 returns to the allocation solution. The allocation result is a spatial database with the geographical location of each of the CZ centroids, as illustrated in Fig. 2, output Out_1.

Algorithm 1. Allocation of p-centroids

Input: Inp_1 with average flow and SOC, Inp_2 with candidate location;
Output: Out_1 with solution allocation;
1 Implements graph: $G \leftarrow (V_{i,j}, E)$ where v_i is demand point of EVs set, v_j is candidate location set, E are urban streets, $f_{i,j}$ is a value of weight function between i demand and j candidate location;
2 Gets the weighted matrix $w_{i,j}$ from $f_{i,j}$;
3 Random selection within candidate vertices to be part of the solution set (V_P) of size equal to p-centroids. All vertices $v_p \in V_j$ are marked as analyzed vertices, and other vertices are marked as not analyzed vertices;
4 **while** there were not analyzed vertices in $\{V_J - V_P\}$ **do**:
5 Select $v_k \in \{V_J - V_P\}$ to be marked as the analyzed vertex;
6 Calculate $\Delta_{ik} = \sum_{i=1}^{I} w_{i,k}$
7 **if** $\Delta_{ik} < \min(\Delta_{i1}, \Delta_{i2}, \dots \Delta_{ip})$ **do**:
8 Replace v_k with the vertex of the value of $\min(\Delta_{i1}, \Delta_{i2}, \dots \Delta_{ip})$
9 Insert v_k in $\{V_P\}$;
10 **End while**;
11 **return** updated V_p as the set of p-centroids.

3.3. Module 2: determining charging zones

From the CZ centroid solution set in Out_1 found by Algorithm 1 and the input data of the average flow and SOC of the EVs (Inp_1), Module 2 uses geoprocessing techniques to create a new vector layer. This layer represents the polygons of the CZs, aiming to reduce the overlap in the coverage areas. Technical criteria of the coverage areas employed by telecommunication companies were used for the construction of CZs polygons [28]. In this study, a CZ is defined as a geographic space with recharge infrastructures that will meet EV charging demand every hour during the day. Thus, GIS's spatial intercession and buffering tools were used to determine a circumference around each point found by the TB algorithm [34]. After using these tools, the spatial input database is aggregated by each CZ.

The coverage radius of each CZ may be determined depending on the distance EVs need to travel to a PCS in case recharging is required. The size of this radius may vary depending on the objectives of the PCS expansion planning, another service to be provided by PCS, and other criteria. For example, the larger this radius reduces the amount of PCS installed, thus reflecting lower cost in infrastructure. On the other hand, a larger radius can overload the connection feeder between the PCS and the electric power grid since the demand to be supplied by the electric power network could be high value [28].

After the CZs creation procedure, the number of stations initially obtained by the TB algorithm is readjusted, removing stations in coincident coverage zones. This removal results in a spatial database containing each CZ with its centroids, the number of EVs, and their SOC for every period of the day, as illustrated in Fig. 2, output Out_2.

3.4. Module 3: the maximum coincident electricity demands

After allocating the CZ, the number of EVs that travel through each zone and the SOC in their batteries are determined. Thus, from the new spatial database found in Module 2 (Out_2) and using input data set (Inp_3 and Inp_4), maximum coincident electricity demand in each CZ for every period of the day may be calculated. These demand values are information necessary to plan and operate electric power distribution networks [11].

In the electrical calculation for the coincident electrical demand, typical factors were used to characterize the maximum charge per period [37]. Thus, the maximum non-coincident demand in a CZ with centroid in (u, v) for the day ($MD_{ncoin\_CZ_{(u,v)}}$) is the product of EVs flow with a CZ ($\mathrm{flow}_{CZ_{(u,v)}}$), times the average SOC of EV flow ($SOC_{CZ_{(u,v)}}$) and battery capacity in kWh (C_{bat}) of EVs divided by charging time into hours (t_{ld}), as shown in (8):

$$MD_{ncoint\_CZ_{(u,v)}} = \frac{\left(flow_{CZ_{(u,v)}}\ SOC_{CZ_{(u,v)}}\ C_{bat}\right)}{t_{ld}} \tag{8}$$

Charging time t_{ld} varies according to battery capacity C_{bat} and the power of the charger type P_{ch} (kW) as formulated in (9):

$$t_{ld} = \frac{C_{bat}}{P_{ch}} \tag{9}$$

Maximum coincident demand for the period under analysis can be found from the result of (8) multiplied by the coincidence factor (f_{coin}), as explained in Ref. [37] and shown in (10):

$$MD_{coint\_CZ_{(u,v)}} = f_{coin}\ MD_{ncoint\_CZ_{(u,v)}} \tag{10}$$

Eventually, to determine the coincident demand curves for each period, the expressions (8) up to (10) are used for all available periods of the day under this study.

3.5. Output database: final results

A spatial database, Out_3, represents the results of the proposed methodology, as shown in Fig. 2, and they are:

- The geographical location of all CZs allocated;
- According to the technology available in the input database, the maximum demand and the number of chargers for each CZ.

4. Simulations and results

The proposed method was applied in Salvador, northeastern Brazil, which has an approximate area of 700,000 km^2, equivalent to twice the size of countries such as Germany, Italy, and England. It is the 4th largest Brazilian metropolis, with about 3 million inhabitants and a fleet of vehicles estimated at more than 1 million units [52]. In addition, urban mobility data from this metropolis are publicly accessible and can be used for further research or future comparisons of the proposed methodology. Thus, the city's size and availability of information were a motivation for choosing this city for the case study of the proposal.

As computational tools, the statistical software R [53] was used for Modules 1 and 3. The QGIS software [54] for Module 2 and, in addition, the comparisons proposed were carried out using the ArcGIS Software [16]. ArcGIS uses different techniques to optimize processing time and find satisfactory results for service coverage problems [55]. Thus, ArcGIS is used by various public and private bodies, as pointed out by Ref. [56], providing wide application in the provision of utilities [57].

4.1. Case study input information

As presented in Section 3.1, the application database consists of two datasets. The first set with vector layers will be used in Modules 1 and 2. The other set presents technical information about the coincidence factor and nominal values of chargers to be processed by Module 3.

4.1.1. Spatial database for geoprocessing

The city's urban traffic reports in this study show that there are 3 periods of higher urban traffic on days of typical flow. The peak morning period is from 6:00 to 8:00, the peak period of the afternoon is from 12:00 to 14:00, and the peak period of the night is from 17:00 to 19:00. In the application of the proposal, six scenarios of global EV penetration were considered, taking into account such peaks. Thus, the spatial input base for the proposal application contains a variety of EVs SOC in the main avenues, considering such urban traffic patterns, as presented in Ref. [6]. Penetration values for each scenario were 7%, 15%, 30%, 45%, 55%, and 65%.

In Fig. 4, the flow map and SOC are displayed from 6:00 to 8:00 for an EV penetration of 7%, respectively. In these maps, the color scales are composed of green, yellow, orange, and red to characterize the concentration in the flow and the SOC. In the flow map, the colors represent the highest and lowest EVs circulation places. The green color relates to the lowest recorded circulation, and the red to the most increased circulation. In the SOC map, where the variation from highest to lowest value is presented, the color scales are in reverse order. The green and red colors represent the highest and lowest SOC, respectively.

4.1.2. Database for electrical calculation

The values of coincidence factors used in this application are shown in Fig. 5, where the X-axis represents the total amount of EVs that travel through the CZ during a day of operation, and the Y-axis is the value of f_{coin} for each penetration scenario. These values were calculated using the results of a traffic simulation in AIMSUN presented in Ref. [11] to find the total EVs that travel to the CZs when their minimum SOC is around 25%.

Another input data used are the types of chargers and their technical information, which can be obtained from the manufacturers' data sheets. Table 1 shows the chargers consider in this case study. Such charges were chosen because they are currently being considered by charging station installation companies.

4.2. Module 1 results: spatial distribution of charging zones centroids

Module 1 results are a map showing the centroid of CZ for each global penetration scenario. To illustrate the locations found by this module, in Fig. 6 centroid of CZ is presented, considering the weighting determined by (2), for a penetration scenario of 7% EV in the study zone.

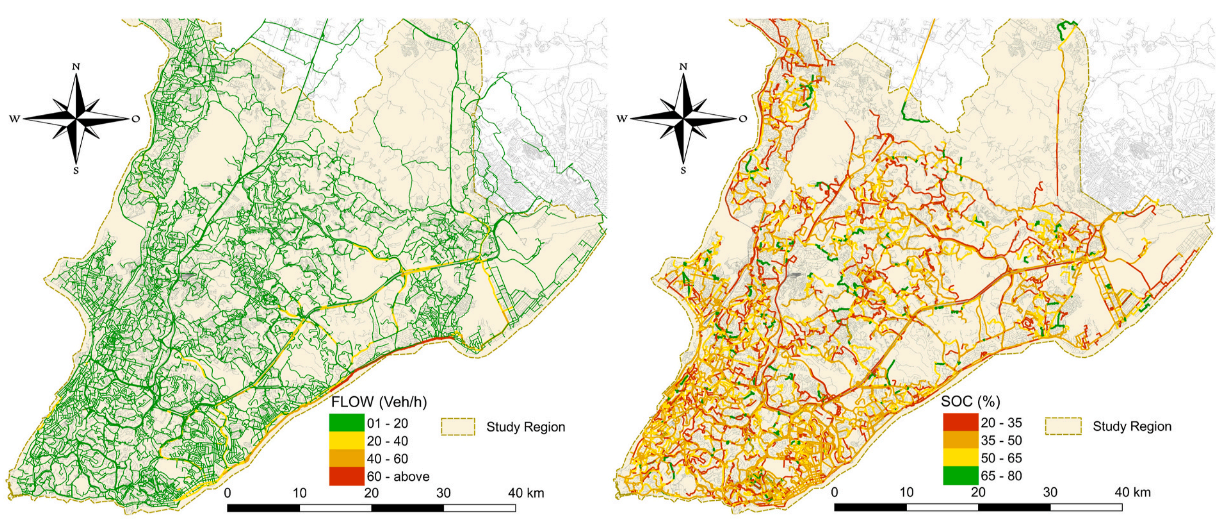
4.3. Module 2 results: charging zones creation

In Fig. 6 it is possible to observe several centroids in nearby CZs. Thus, to avoid overlap in the coverage areas, a spatial grouping technique, called density-based spatial clustering of applications with noise (DBSCAN) and available in GIS, was used [58]. This technique makes it possible to find groups of two CZ centroids located at a certain user-defined distance. Once these groups were identified, only one point belonging to each cluster was chosen. For the city in this study, CZ centroids should be at least 290 m apart. The selected distance allowed an EV to have three CZs available for charging within a 1 km range. Thus, this distance provides better coverage of the demands of EV owners, as illustrated in Fig. 7.

In the application of Module 2, it is used as the computational buffer tool available in QGIS to create the coverage zones for each CZ. This tool makes polygons around spatial objects at a distance or coverage radius defined by the planner, as shown in Fig. 8. In specialized literature, it could be found that the minimum radius of coverage for CZ varies from 0 to 1 km, and in the present study, the value of 300 m was defined around each centroid. This criterion was adopted after several simulations, noting that the greater the coverage radius, the greater the coincident demand in the CZs, as explained in Ref. [28]. Moreover, according to Ref. [31], a long distance from the CZ will reflect a higher cost for Fast-CS connection because the electric power demand increases considerably, making it difficult to connect to the power grid. After constructing the polygons of the CZs, Module 2 determines the amount of EV that each CZ traverses in each scenario and the SOC values, creating a new spatial database.

4.4. Module 3 results: electrical calculations

The coincident maximum electrical demand is shown in Fig. 9 for one of the considered scenarios. Demand is calculated from the spatial



(a) Flow (b) SOC

Fig. 4. Input data of traffic simulation results: scenario 1 (7%), period 06–08h AM [11].

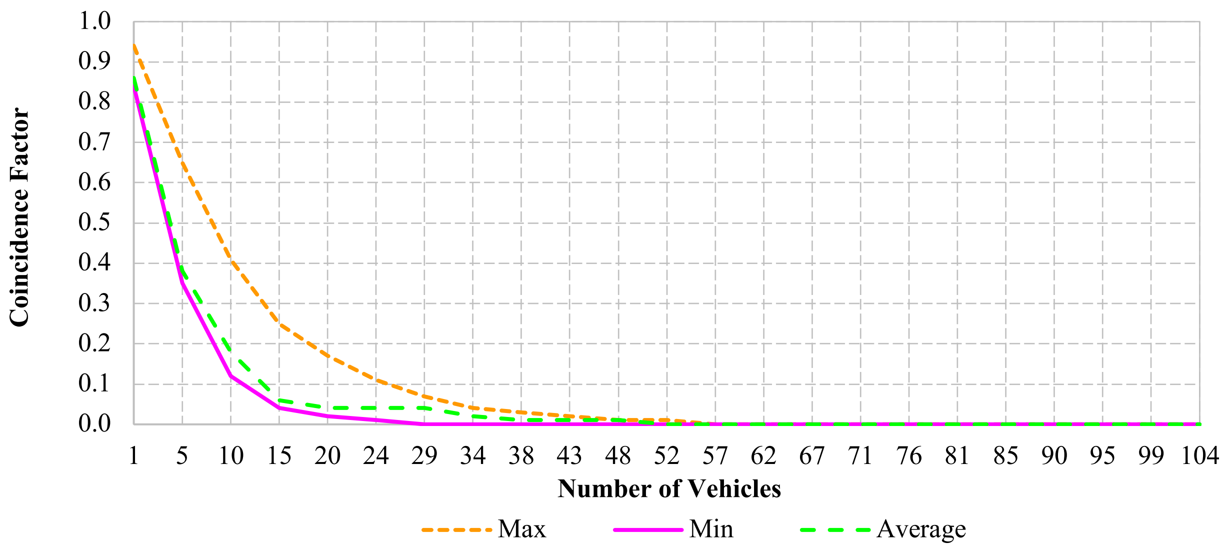


Fig. 5. Input data for coincidence factor.

Table 1
Chargers employed in analyzes.

Power (kW)	Current	Type	Time of Charge (min)
43	AC	Fast	37
50	DC	Fast	27
150	DC	Ultra-fast	18

database created in Module 2, the coincidence factors shown in Fig. 5, and technical data for chargers with a nominal power of 43 kW. For comparison purposes, the WM was built from function $f_{i,j}$ using Equation (2) and by the Euclidean distance, Equation (1), which is employed in most of the allocation-location models found in the specialized literature. The results were better when using Equation (2), Fig. 9a, since only 3 CZs with peak demand greater than 2 MW were determined against 26 by Equation (1), Fig. 9b. The low peak demand possible that there is no need to reinforce the electrical network when connecting the PCS to the distribution feeder.

In calculating the coincident demand, it was considered that drivers assume the following behavior: at the beginning of each trip, the SOC is close to 100%, so they drive to a particular destination, whether work, school, or leisure, among others. Then, drivers park their EVs for a few hours and return to their origins. Therefore, the charging may occur on one-way and return trips, considering the energy consumption during travel to the destination. This analysis was performed for the morning, afternoon, and evening peak periods and extrapolated to the other times,

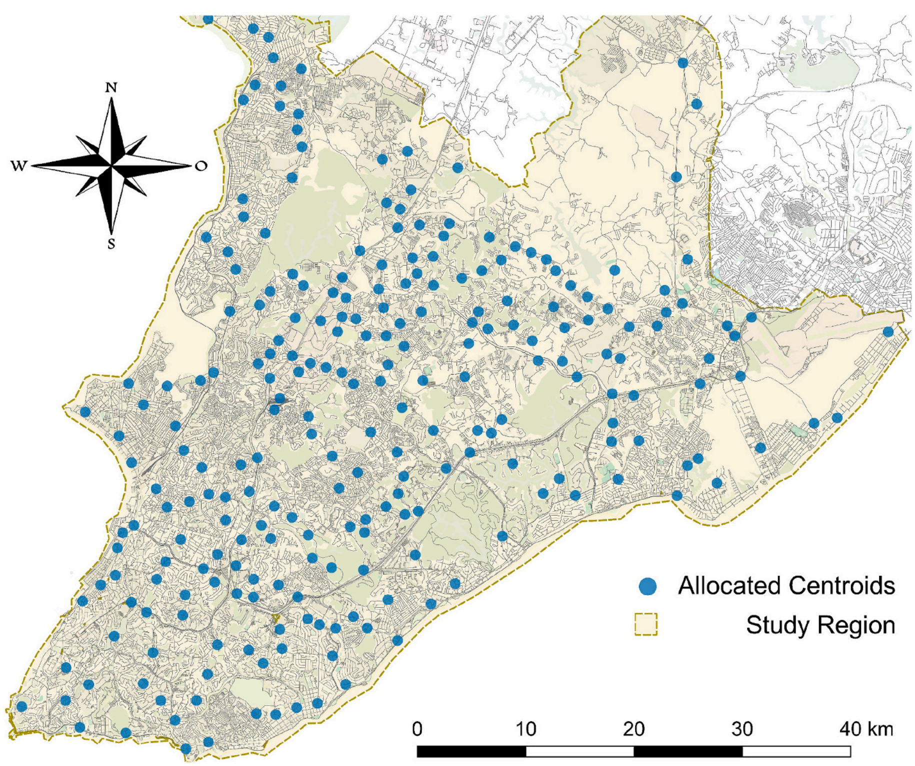


Fig. 6. Centroids allocated by the proposed methodology for scenario 1.

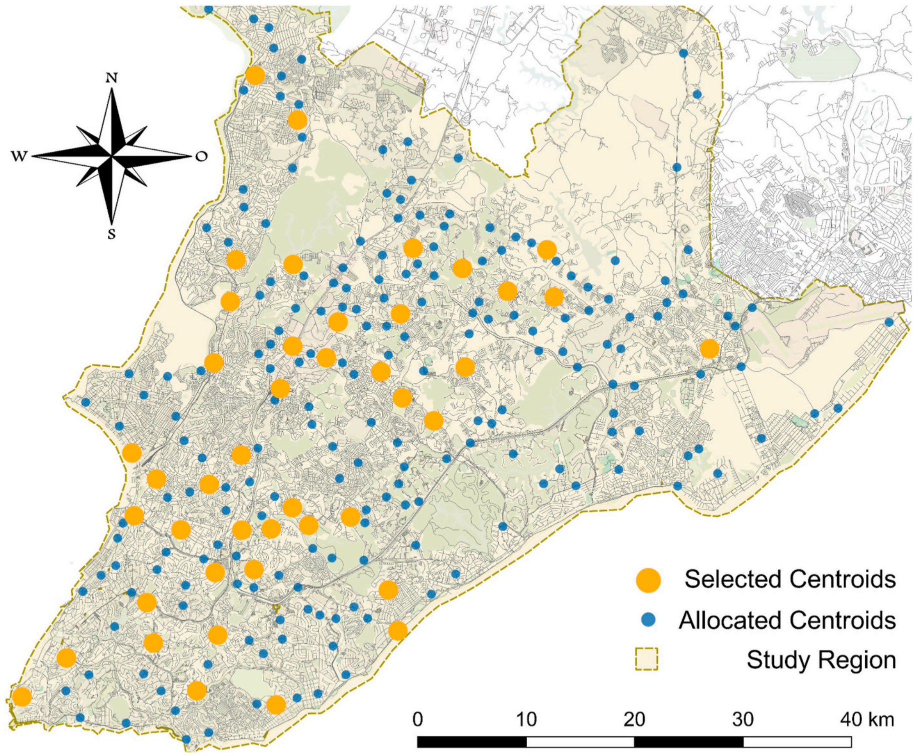


Fig. 7. Centroids selected after use the DBSCAN technique for scenario 1.

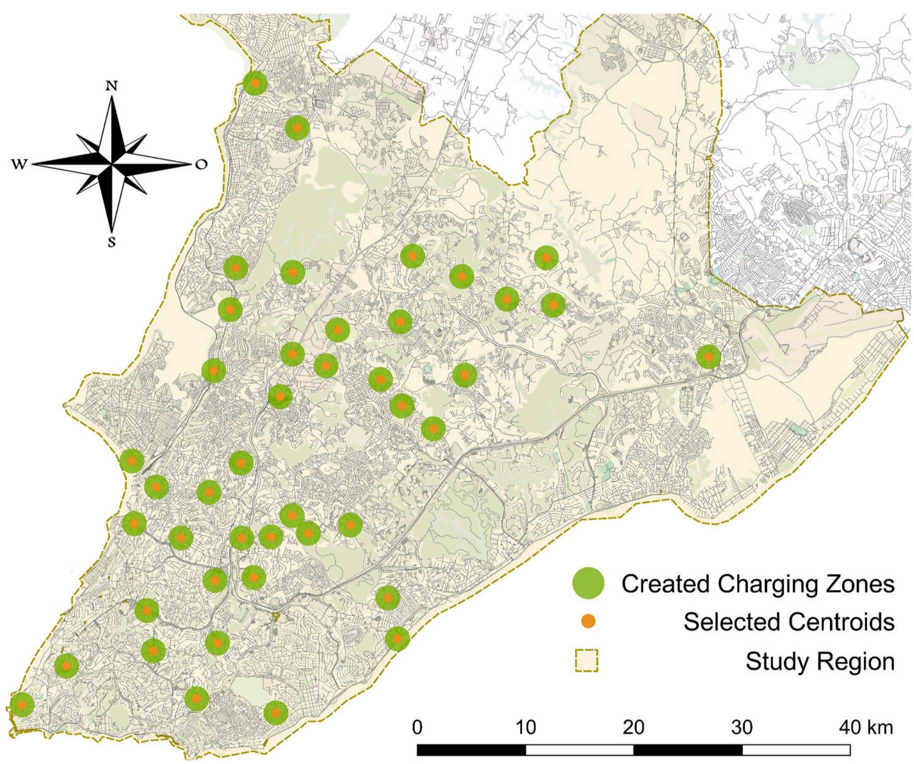
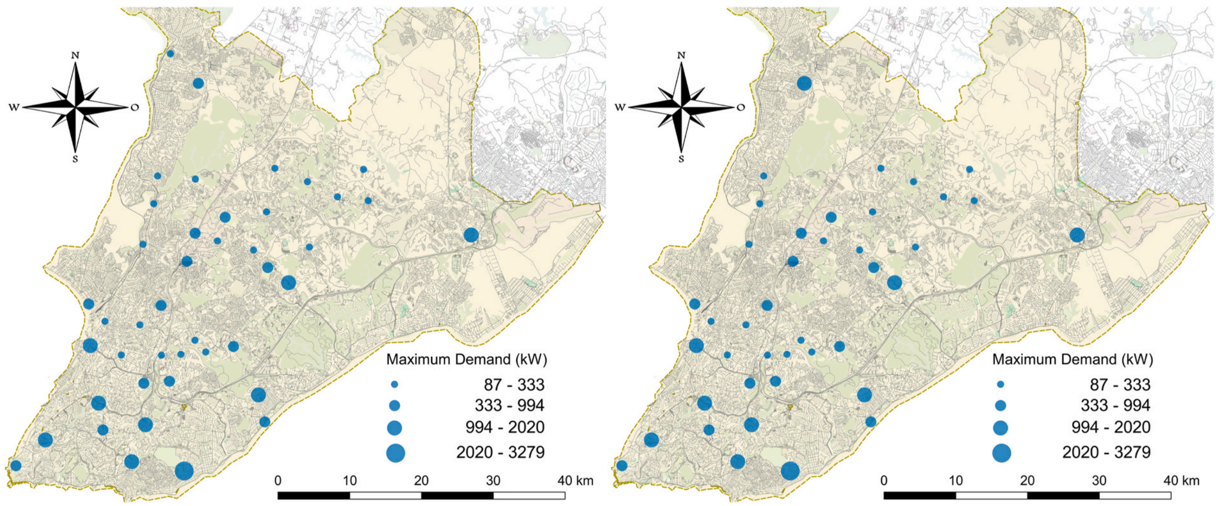


Fig. 8. Charging station zones created by the prosed methodology for scenario 1.

as explained in Ref. [11].

Figs. 10 and 11 show the spatial distributions of maximum demand in each CZ for the first and last penetration scenario, considering 50 kW DC chargers. In applying the methodology, it was evaluated that only one type of charger can be installed, varying from 43 kW AC and 50 kW DC power range, seeking to find the maximum rated power of the charger so that the EV recharge time is shorter. The chargers of 50 kW DC do not exceed 50% of the maximum capacity of the feeder, this capacity being 6 MW. In the first 7% penetration scenario, there are 45 CZs to serve a total of 4833 EVs. The CZs with a demand value of 3279 kW



(a) Weighting: by Equation (2)

(b) Weighting: by Euclidian distance

Fig. 9. Maximum demand: comparison of calculation options in each CZ for scenario 1 with 50 kW chargers.

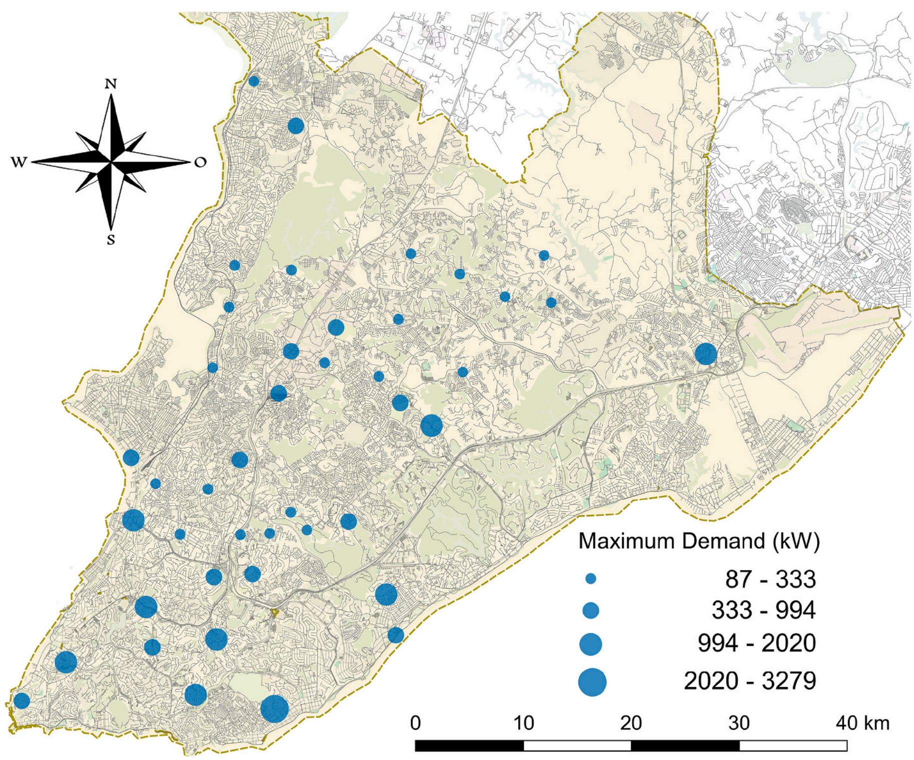


Fig. 10. Maximum demand in each CZ for scenario 1 with 50 kW chargers.

receive 271 vehicles. The largest circles represent the areas of higher demand. There are habitants with greater purchasing power in these circles, resulting in more early EV adopters, which may explain the peak demand in this area. The maximum coincident demand of the CZ exceeds a quarter of the rated power of the feeder used in the study area, which can change the utilization factors of the distributor's facilities. For example, in the case of connecting one of the high maximum demands, as in Fig. 10, the load factor of the feeder will be increased by 25% so that the feeder may have less capacity available to connect other loads in situations of restoration of the electrical network voltage. Typically, feeders operate at less than 50% of rated power to have available load recovery capability. In scenario 6, there are 44509 EVs, with the highest peak recorded in a region of increased circulation.

However, in Figs. 12 and 13 the most representative charge curves are presented for this study's first and last penetration scenarios. In such curves, it is considered that the charging is carried out preferably at home. Thus, EV owners look for a Fast-CS to complement the recharge needed to continue their journey.

4.5. *Confronting results using geoprocessing software*

In this section, it contrasts the allocation performed by the proposed methodology and the other considering the commercial software ArcGIS [16]. Module 2 provides the spatial distribution of CZ to meet the demand for EV recharging. Such distribution is possible to compare with one other determined by commercial GIS. For example, ArcGIS has a

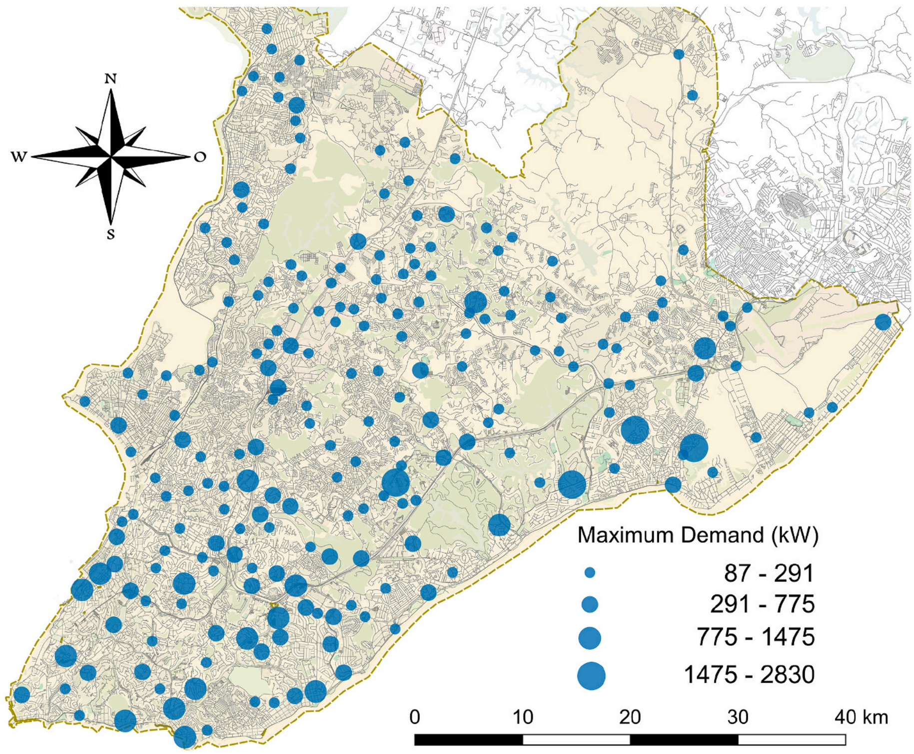


Fig. 11. Maximum demand in each CZ for scenario 6 with 50 kW chargers.

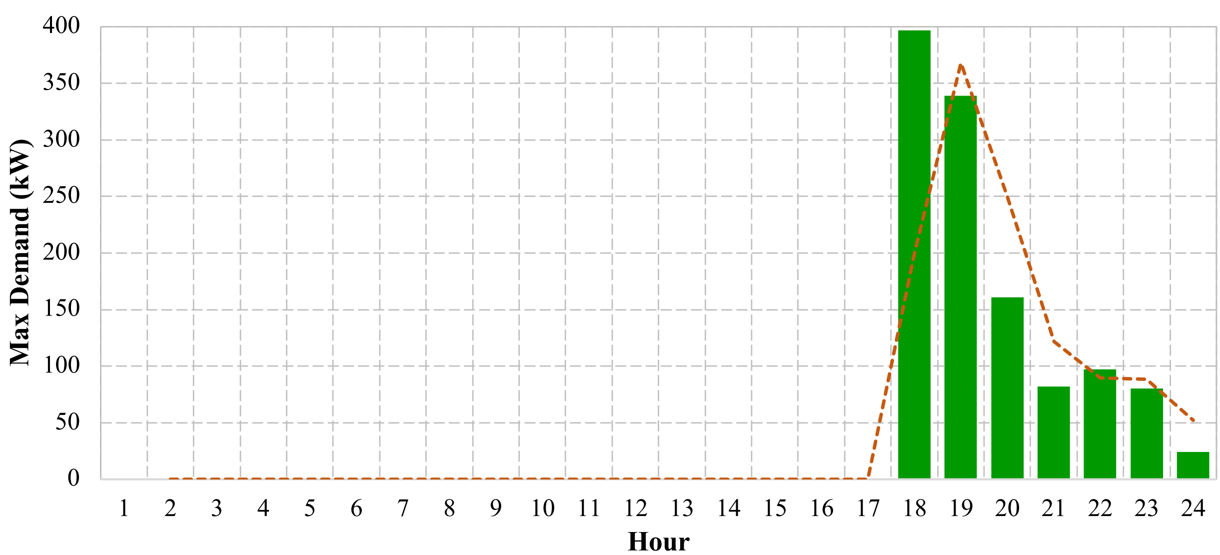


Fig. 12. Hourly demand curve for one of the CZs for scenario 1 with 50 kW chargers.

toolbox capable of performing the spatial allocation of utilities from different methods, such as Dijkstra's shortest path algorithm and other heuristic techniques widely used academically and commercially.

Table 2 presents the number of CZs allocated by the proposed methodology and ArcGIS software. This table shows that the proposed method determines more CZs than ArcGIS for most scenarios. This difference is because the proposed approach aims at higher coverage without minimizing the number of CZs. On the other hand, ArcGIS minimizes the number of installations needed to cover all points of demand. Additionally, we observed that the average number of new CZ for attending the EV charging of the global penetration during the entire study period is around 34 considering the zones found by the proposed methodology and ArcGIS. Although the ArcGIS method takes less computational time to find the allocation in each scenario, when we analyze the value of the maximum coincident demand for each allocation result presented in Table 2, the demand values are different, as will discuss in the following paragraphs.

In this section, the comparisons will consider the spatial distribution of the values presented in Table 2 and analyze the maximum coincident demand in the CZs. Figs. 14 and 15 illustrate the distribution of allocated CZs using each technique for scenarios 2 and 5. Each CZ is represented by a blue circle whose size depends on its maximum coincident demand value. The CZs with higher maximum demand values have a higher circle than others with minor demand. These figures show that the spatial distribution obtained by the methods is very similar, differing only in a few city areas. For example, the proposed method allocates CZs

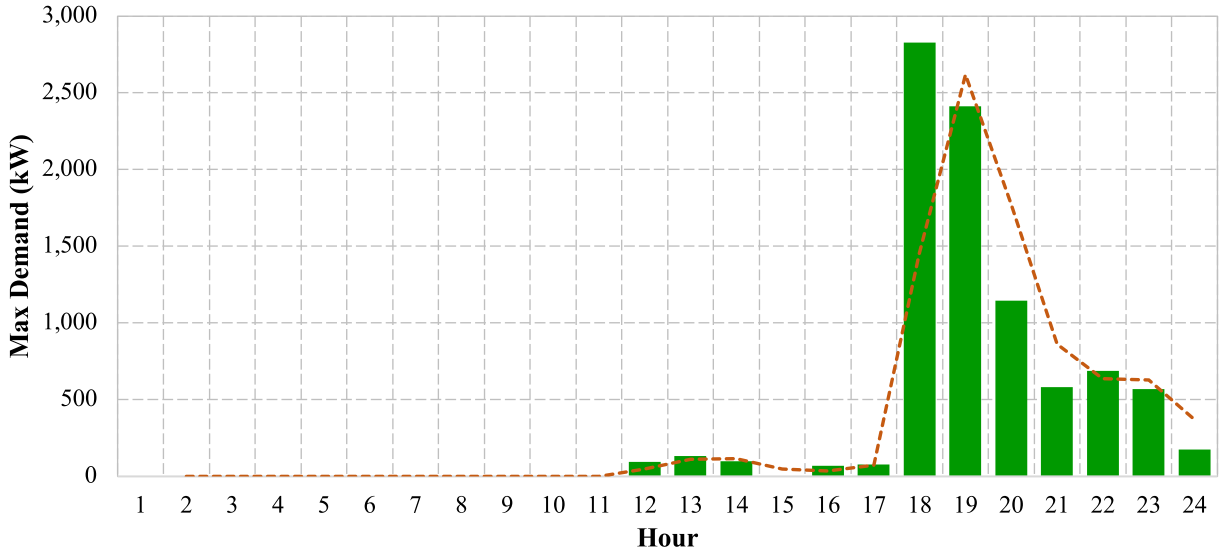


Fig. 13. Hourly demand curve for one of the CZs for scenario 6 with 50 kW chargers.

Table 2
Comparison of Allocated CZ: Proposed methodology and ArcGIS.

Prospect Scenario	Global Penetration	Proposed Methodology	ArcGIS Software
1	07%	45	42
2	15%	69	78
3	30%	125	121
4	45%	158	157
5	55%	188	187
6	65%	217	215

in the west and northwest of the city with an average of 319 kW peak reduction in the maximum coincident demand in regions with a low flow of electric vehicles, as shown in Fig. 14. Such allocation behavior can be observed in all other scenarios.

Fig. 16 shows the frequency distribution of the utilization factor values for all chargers in each CZ determined by the proposed methodology and ArcGIS software for scenario 3. This factor is the division between the maximum demand and the nominal power of all chargers in each CZ. Both methods find many zones with charging equipment with utilization factor values in the interval of 0.75–1, meaning that the chargers in these CZs will operate close to their nominal value. This operation can encourage investors to install public Fast-CS since the closer the power supplied by the chargers is to their nominal value, the greater the economic return will be, as explained in Ref. [10]. Additionally, we observe that some chargers in CZs would operate with a utilization factor greater than 1.1, which can be practiced as long as these utilization values occur in short periods and do not exceed the thermal capacities of the installations [38]. Thus, the load factor must be calculated to analyze how well-distributed the use of the chargers in one-day operation, as explained in Ref. [37].

The load factor is the relationship between the mean value and the maximum demand. There are low load factors when the maximum demand happens only for a few hours of the day. As illustrated in Fig. 17, the determined CS by the proposed methodology and ArcGIS presents lower load factors when considering 24 h of operation. In this case study, the load factors will be low because it is assumed that recharging takes place mainly in homes, and fast recharging happens to complete the charge of EVs until they reach their final destination. On the other hand, when we consider the hours in which the CZ is receiving EVs for

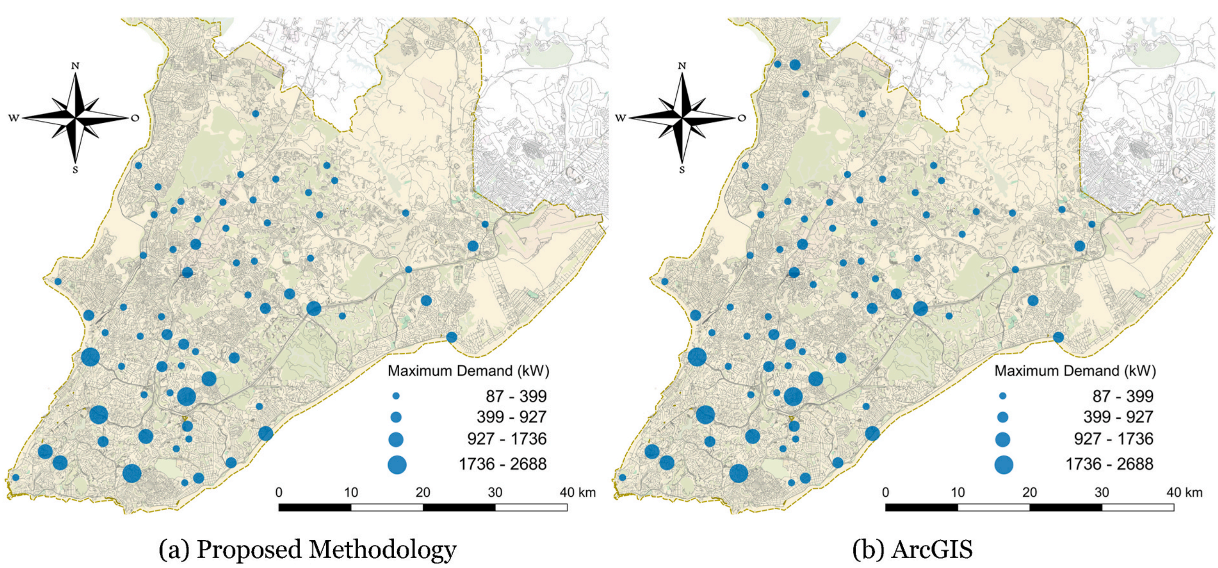
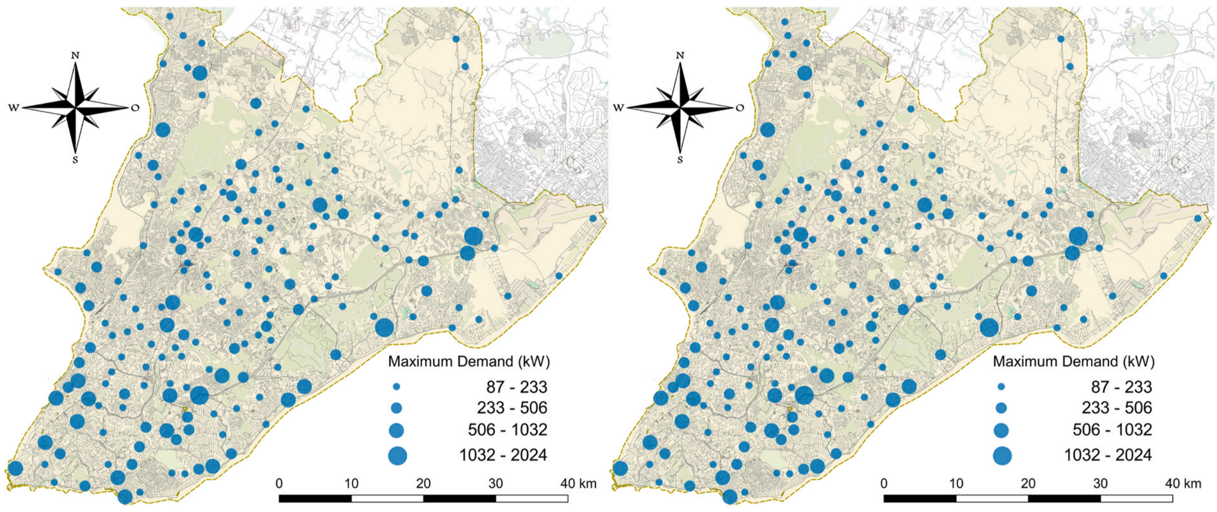
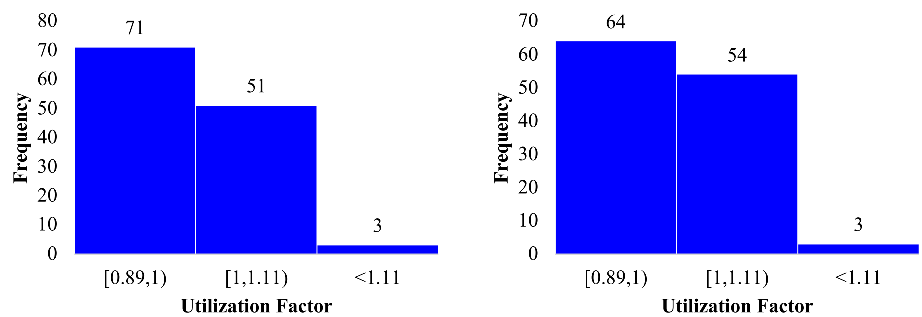


Fig. 14. The maximum demand in kW: comparison between proposal and commercial GIS for scenario 2.



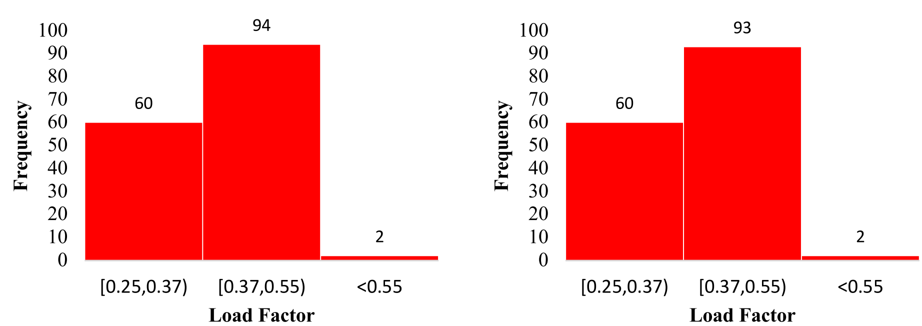
(a) Proposed Methodology (b) ArcGIS

Fig. 15. The maximum demand in kW: comparison between proposal and commercial GIS for scenario 5.



(a) Proposed Methodology (b) ArcGIS

Fig. 16. Utilization factor: comparison of the frequency distribution of the CZ infrastructure for scenario 3.



(a) Proposed Methodology (b) ArcGIS

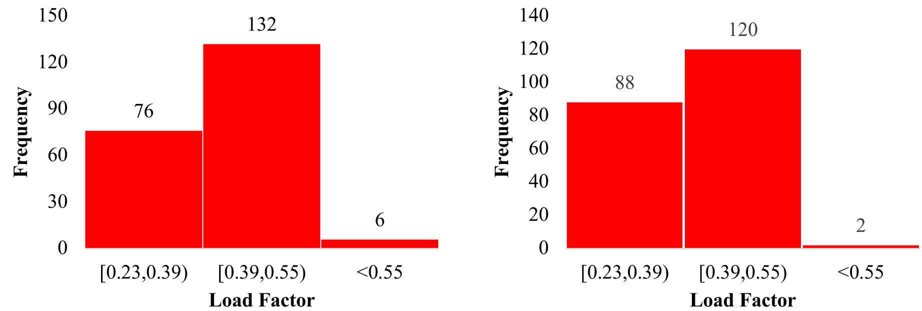
Fig. 17. Load factor: comparison of the frequency distribution of the CZ infrastructure for scenario 4.

charging, the proposal presents a higher amount of CZ with a load factor close to 0.5, as shown in Fig. 18. In Scenario 6 and considering the 24 h or hours of service to EVs, the proposed methodology presents 10% more CZs with a load factor closer to 0.5 than the results found by ArcGIS. Within the planning of distribution networks, consumers with a load factor close to 0.5 make better use of the electrical infrastructure [38].

Thus, from the analysis of charging and utilization factors, it may assume that the proposed methodology finds a spatial distribution that meets the dispersed demands proving a better usage of the installed chargers per each CZ.

5. Conclusions

This work presented an allocation-location methodology to identify sites for creating CZs, considering the spatial dispersion of EV penetration and circulation patterns in the urban area. Furthermore, the proposed method determines the maximum coincident demand in each CZ



(a) Proposed Methodology (b) ArcGIS

Fig. 18. Load factor: comparison of the frequency distribution of the CZ infrastructure for scenario 6.

for different EV penetration scenarios and the number of chargers that will be installed. The distribution of these values within the study area determined by the proposed methodology can help planners to identify areas with high growth in loading density.

One contribution of the proposed methodology is the weighting technique to determine the number of CZs needed to meet the EV charging demands in urban areas. When comparing the maximum demand of CZs obtained by the proposed method with a model that aims to minimize the number of CZs, we observed an average reduction of 319 kW of peak demand in regions with a low flow of electric vehicles to meet their charging needs in each analyzed scenario. Additionality, we observed that the chargers allocated in each CZ by the proposed methodology could meet the recharge demands for any penetration scenario with higher load factor values compared to the model that minimizes the number of CZs. Therefore, identifying CZ through a weighting technique that considers the distance, the EV flow, and SOC allows for better coverage of EV charging demands with a lower coincident demand value, enabling its connection to the electric network.

Finally, as an additional result, the proposed methodology allowed for evaluating which areas fast charging can bring high reinforcements to the electricity distribution network. In this sense, comparing results, the proposed method showed a better distribution of CZs with high utilization rate and load factors close to 0.5 for EV chargers that will be installed in all EV penetration scenarios analyzed.

Author statement

Joel D. Melo: Conceptualization, Methodology, Supervision, Writing- Reviewing and Editing. Fausta J. Faustino: Conceptualization, Methodology, Writing- Original draft preparation. José Calixto Lopes: Data curation, Writing- Original draft preparation, Writing- Reviewing and Editing. Thales Sousa: Writing- Reviewing and Editing, Supervision, Antonio Padilha-Feltrin: Writing- Reviewing and Editing, Supervision, José A. S. Brito: Editing and Supervision, Claudio O. Garcia: Editing and Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The authors would like to thank ANEEL, and the NEOENERGIA group for the financial and technical support provided in the scope of the ANEEL P&D project “Green Corridor and Charging Stations for Performance Evaluation of Hybrid and Electric Vehicles.” Process: 23006.001802/2019–09.

Nomenclature

Abbreviations

CZ	Charging Zone
EV	Electric Vehicle
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
Fast-CS	Fast-Charging Station
GIS	Geographic Information System
MILP	Mixed-Integer Linear Program
PCS	Public Charging Stations
PMM	P-median Model
SOC	State of Charge
TB	Teitz and Bart
WM	Weight Matrix

Symbols

V_J	Set of location/demand points of electric vehicles
V_I	Set of candidate site for charging station
v_i	Electric vehicles point

v_j Charging zone point
$d_{i,j}$ Weight matrix
x_i, y_i Coordinates of the demand location at the vertex v_i
x_j, y_j Coordinates of the candidate CZ centroid at the vertex v_j
$f_{i,j}$ Weighting between demand v_i and the location of the candidate CZ in v_j
$d_{i,j(max)}$ Maximum coverage distance of the CZ in vertex v_j
F_i Average flow of EVs at the vertex v_i
$F_{j(max)}$ Maximum flow that the CZ can cover at vertex V_j
SOC_i EVs average state of charge at the vertex v_i
$SOC_{j(max)}$ Maximum SOC to be supplied by CZ in vertex v_j
V_P P-median model set
$d_{vi,vp*}$ distance between a vertex v_i and the element v_{p*}
$f_{i,p*}$ Function in the P-median model
$A_{i,j}$ Matrix in the P-median model
Z Objective function in the P-median model
v_k Solution tested in Teitz and Bart's algorithm
Δ_{ik} Teitz and Bart Algorithm metric
$MD_{ncoin\_CZ_{(u,v)}}$ Maximum non-coincident demand in a CZ with centroid in (u, v)
$flow_{CZ_{(u,v)}}$ The flow of electric vehicles in a charging zone
$SOC_{CZ_{(u,v)}}$ SOC of electric vehicles flow
C_{bat} Battery capacity
t_{ld} Charging time
P_{ch} Power of the charger type
$MD_{coint\_CZ_{(u,v)}}$ Maximum coincident demand
f_{coin} Coincidence factor

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