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Electric vehicle charging stations' location in urban transportation networks: A heuristic methodology

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Abstract

The lack of public charging infrastructure has been one of the main barriers preventing the technological transition from traditional vehicles to electric vehicles. To accelerate this technological transition, it is necessary to elaborate optimal charging station location strategies to increase the user confidence, and maintain investment costs within acceptable levels. However, the existing works for this purpose are often based on multipath considerations or multi-objective functions, that result in taxing computational efforts for urban transportation networks. This article presents a heuristic methodology for urban transportation networks, that considers the deployment of the charging stations for coverage purposes, and the fulfilment of user preferences and constraints as two separated processes. In this methodology, a Reallocation Algorithm is formulated to prioritize the selection of Locations of Interest, and to reduce the number of stations with overlapping covering areas. The methodology results are compared to those drawn from a Greedy Algorithm based on a multipath consideration, in an extensive metropolitan transportation network. The results show that the proposed methodology significantly reduce the computational time required for solving the location problem, and furthermore, allows for similar results to those obtained when considering $k = 2$ and $k = 3$ deviation paths.

1 | INTRODUCTION

The continuous worldwide effort to reduce greenhouse gas emissions has translated into a large adoption of electric vehicles (EVs), reaching a fleet of over five million vehicles [1]. This growing tendency has enhanced the development of more reliable batteries and charging infrastructure to allow larger vehicle ranges and a faster charging process [2]. In fact, most EV users can charge their vehicles at home, and the range autonomy from most batteries are suffiencient to carry out practically any daily activity [3]. However, the lack of a fast public charging infrastructure is considered to be one of the main barriers for the adoption of EVs, as it causes 'range anxiety', especially when it comes to long-distance or inter-city trips [4, 5].

Based on the previous premise, it is essential to carry out a proper charging infrastructure location and quantification to allow a comfortable technological transition for users. However, as EVs can be charged at home, it is possible that the rate of use of these facilities will be marginal. Thus, it is not only necessary to satisfy the range requirements from users but also to avoid unfeasible investment costs [6].

There are various criteria to define the location of public charging infrastructure, among the most relevant ones are those that involve socioeconomic, environmental, technological, and urban aspects [7–9]. The local mobility patterns are a key feature to be taken into account in the aforementioned criteria. This means that in order to guarantee the financial sustainability of these facilities, their location has to consider the main subcentres of urban activities, and its accessibility for users [10, 11]. Moreover, user preferences for charging stations with higher charging power, connection points, charger compatibility, among other characteristics, have proven to substantially affect their use rate [5].

Multiple methodologies have been developed to properly locate EV charging stations, with a special focus on the development of mathematical optimization models [12]. However, from this point of view there are two important considerations: First, it is known that large transportation networks result in taxing computational efforts, and thus, often require heuristic methods or genetic algorithms for their solution. On the other hand, when optimization models include constraints related to the user preferences, they tend to result in multi-objective functions, making the problem more difficult to solve [13–16].

This paper presents a novel charging station location methodology, where the location of the facility, and the user preferences and constraints fulfilment are treated as decoupled processes. In this way, an initial location based on a given criterion is first proposed, and then refined to better match the user requirements in terms of charging power, comfort, and probability of connection. This process is carried out while maintaining distances deviations from the original solution within acceptable levels. The refinement process is carried out through a new heuristic algorithm called Reallocation Algorithm, which is aimed at prioritizing the selection of Locations of Interest that provide more suitable conditions for users, and also at reducing the number of overlapping coverage areas from stations.

This decoupled consideration avoids multi-objective formulations, and also reduces the computational effort experienced by classical k-deviation-paths considerations by allowing the problem to be formulated only through $k = 1$.

The methodology is applied in a case study of a real urban transportation network of a city with 7.2 million inhabitants, and 380 km^2 [17], where the subcentres of urban activities, such the main corridors, malls locations, exit routes, and high-income areas of the city are considered.

The results obtained from the proposed methodology using the Reallocation Algorithm are contrasted with the results drawn from an implemented Greedy Algorithm which is based on a classical k-deviation path consideration, comparing the computational time and the final number of planned charging stations. It is important to point out that in this paper the deviations paths are related only to distance, and not to the travelling time, as traffic flow conditions have been previously proposed to not have an influence on the charging station location [18].

In summary, the contributions of this paper are the following: (i) a Reallocation Algorithm that reduces the computational time needed to solve optimization problems with user constraints, (ii) a strategy for the location of fast public charging infrastructure on a city of 7.2 million inhabitants and 380 km^2, (iii) a sensitivity analyses that determines how selecting main subcentres of urban activity as fixed charging station locations affects the final location strategy.

The paper is organized as follows: in Section 2, a literature review on the topic of charging station location is presented. Section 3 introduces the proposed methodology to carry out the charging station location in urban environments, and the description of the proposed Reallocation Algorithm. Section 4 describes the urban transportation network used as case study, along with the study assumptions. In Section 5, the results from the proposed methodology in the case study application are drawn, and finally, Section 6 presents the conclusions and discussion on the key findings.

2 | LITERATURE REVIEW

The charging stations location problem has been studied widely in recent years. This problem can be classified as a subset of the facility location problem, and can be grouped into three main categories: the P-median problem, the P-centre problem, and the covering problem [19, 20]. The P-median problem tries to allocate p charging stations minimizing the average distance between demand nodes and the nearest charging stations [21], while the P-centre problem locates p charging stations to minimize the deviation distances for drivers [22]. Finally, the covering problem locates the charging stations to maximize the total population served within a maximum distance or time criterion [23, 24].

Regardless of the approach used for the location of electric chargers, it is necessary to model the behaviour of the agents related to these facilities, such as EV users, charging stations owners and the electric network operator. For instance, authors in [16] model the behaviour of EV users suggesting that their preference for a charging station can be affected by their location at a given moment due to traffic flow conditions. The previous authors suggest that the location and capacity of charging station have influence on EV users. However, authors in [18] assumed that the EV users always prefer the charging station destination and route that reduce their cost. Therefore, their charging station selection may not be influenced by traffic conditions.

Authors in [25] propose that the behaviour of charging station owners can be modelled depending on the market structure as independent companies pursuing economic benefits through their investment on charging stations or individual-owned service. In [26] the authors modelled the charging stations like ‘chain stores’, and in [25] the independent owners are considered as the main body of the charging station investment. These models can include some costs considerations regarding the construction, operation, and maintenance of the facility.

In [27], a charging station location model named Multipath Refuelling Location model is proposed and solved using Greedy algorithms to locate charging stations in the Sioux Falls network and in the state of South Carolina. The k-deviation paths considerations were used to reduce the number of required facilities, and consequently the investment cost. Other studies suggest that a multipath approach might not be a suitable technique for urban areas represented by large size graphs as routing complexity grows exponentially with the number of nodes [28]. Nonetheless, only considering a minimum path scenario can result in a significant number of contiguous stations whose proximity result in overlapped covering areas.

Other aspects to be considered for the charging station location problem are the objective function and the algorithm used to solve the optimization problem. In literature objective functions from linear to multi-objective functions can be found, in most cases to model cost functions [13–15]. These cost functions can be associated to the cost of EV users, cost of charging station owners, or cost of network operators [16].

Other works use classic optimization algorithms to solve this particular location problem, for example in [29, 30] it is formulated as a mixed-integer linear problem and solved by deterministic branch-and-bound method. However, the charging stations location problem is a NP-hard problem [13, 31], and thus, the use of heuristic methods and artificial intelligence algorithms have become some of the most recurrent solving techniques [27, 32]. In [16] the problem is formulated as MINLP and solved using genetic algorithm technique. In [25] a bi-level optimization model is transformed to a single-layer model using Karush-Kuhn-Tucker optimality conditions, and an improved dynamic differential evolution algorithm solved each layer.

Newer optimization models consider aspects such as the charging power demand, the public infrastructure requirements, and target market constraints [18, 33, 34]. Moreover, authors in [16] assumed aspects such as urban roads, city zones, and electric substation locations. To solve this problems the authors propose different approaches such as Bi-level problem, Multi-Objective function, Monte Carlo simulation, Nash Equilibrium, Chicken Swarm, Genetic Algorithm techniques, Chemical Reaction Optimization [15, 18, 26, 33, 35].

3 | METHODOLOGY

This section presents the methodology used to optimally locate charging stations (CS) in urban environments. As a key part of this methodology, it is necessary to carry out a characterisation of the transportation network and user mobility patterns to identify aspects such as the network topology, expected vehicle ranges, an identification of the most common origin and destination locations, along with possible driving routes and potential charging stations. As shown in Figure 1 the Reallocation Algorithm is incorporated as the final step of the proposed methodology.

As first step, and to obtain a proper location strategy, an understanding of the urban transportation network is required. To this end, the key features that define the mobility patterns of the transportation network users should be characterised; this can be achieved by modelling the network as a graph of N nodes, with and identification of the common origins ($\widehat{O}$) and destinations ($\widehat{D}$) of the EV users, potential charging station locations ($\widehat{S}$), and the graph lines (δ) are clearly identified. This graph modelling allows to carry out an origin destination routing process (O-D routing), which should provide as result the k-deviation paths that connect each O-D pair ($\widehat{R_{od}}$).

The graph topology along with the set of O-D routes are used as input data for the implementation of a heuristic algorithm to draw a preliminary set of charging station locations ($\hat{I}$). Finally, the Reallocation Algorithm is applied to refine the solution in order to give a better match to user preferences, and to reduce the number of overlapping stations, obtaining the final set of $\widehat{T}$ selected charging stations.

The Origin-Destination routing (O-D routing) is carried out to identify the travelling route between an origin and a destination node, along with the cost of covering the route; it is essential to point that O-D travelling routes should be composed by potential charging stations [27]. This process can be considered as a k-shortest path problem, and thus, it can be addressed through different techniques such as Dijkra's, Bellman Ford's, Floyd-Warshall's, or Yen's algorithms [27].

The following sections describe the proposed methodology to carry out the preliminary selection of the required charging stations and the developed Reallocation Algorithm.

3.1 | Preliminary selection of charging stations

In the proposed methodology, the preliminary selection of charging stations is carried out through heuristic methods with the purpose of avoiding the high computational effort that results from traditional optimization models [32].

The selection of the heuristic method should be based on an optimization criterion (e.g. cost, coverage, charge duration, profit, etc.), a transportation network characterization, and a suitable O-D routing consideration depending on the number of nodes composing the graph. Particularly, in urban scenarios the characterization of the transportation network should also take into account a proper spatial zonification of the main corridors, and possible user preferences that could lead to a more realistic selection of O-D pairs [36]. Accordingly, the

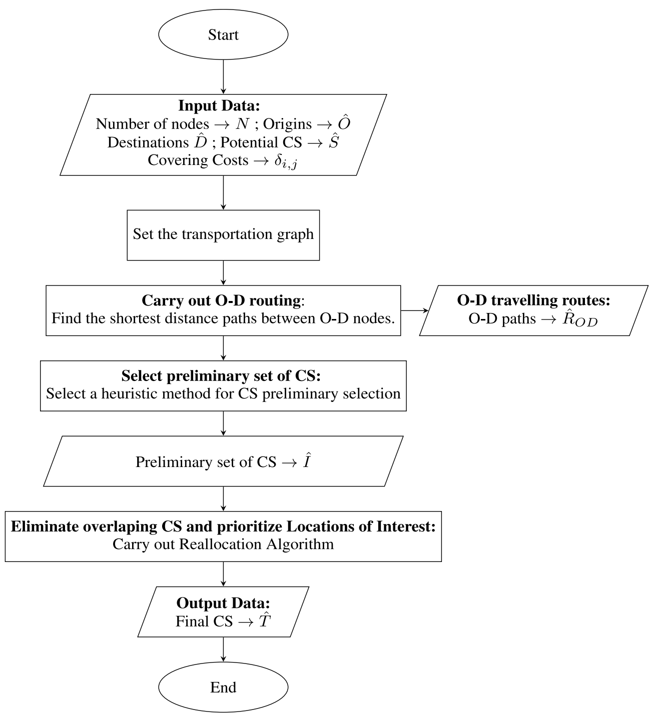


FIGURE 1 Methodological proposal to locate charging stations

summarized methodology proposed to carry out the selection of the heuristic method, and consequently, the preliminary location of the charging stations is depicted in Figure 2.

3.2 | Reallocation Algorithm

This section describes the proposed Reallocation Algorithm, which is formulated to reduce the number of overlapping charging stations by considering a coverage radius for each facility, and contemplating the possibility of reallocating some stations into Locations of Interest which might be better suited to fulfil the customers' requirements.

However, in order to do so, there are two critical steps to follow. First, it is necessary to characterize the level of relevance of the planned charging stations as this will ultimately dictate which stations remain after the reallocation process. This characterization should contemplate how the facility conditions match the user preferences. For example, stations with the higher charging power and number of available connection points, should be considered as the more relevant facilities as they allow a faster charging and connection.

On the other hand, it is necessary to carry out a proper coverage area assignation for each of the charging stations, mainly because this feature has a direct influence on the number of overlapping facilities.

To fulfil the previous requirements the Reallocation Algorithm was designed to follow the methodology depicted in Figure 3.

Note that the algorithm consists of three main blocks, which are the weight assignation block for the planned charging stations, the coverage radius computation block, and finally, the reallocation block. The previously mentioned blocks will be explained in detail in the following sections

3.2.1 | Weight assignation block

In this article the relevance level of the stations is assessed by proposing a weighted index that considers three key features of the user preferences. These are: the charging station power (which defines the length of the charge), the number of connection points (which increases the probability of a faster connection), and the facility comfort (which is associated to the activities that the user can carry out during charging periods). These parameters are used to define a Station Weight index as shown in Equation (1).

$$SW_i = \mu_{P,i} \times \omega_P + \mu_{S,i} \times \omega_S + \mu_{C,i} \times \omega_C \tag{1}$$

where SW_i is the Station Weight Index of the ith station, with a value comprehended in the range of 0 to 1. Terms $\mu_{P,i}$, $\mu_{S,i}$, and $\mu_{C,i}$ stand for the Power Index, the Size Index, and the Comfort Index, respectively; these terms describe a given charging station condition in each of its aspects in comparison to the best possible facilities. On the other hand, ω_P, ω_S, and ω_C are relative weights in the range from 0 to 1 for the facility Power Index, Size Index, and Comfort Index, respectively. These last terms indicate the relevance of factors μ_P, μ_S, and μ_C during SW computation.

The proposed calculation procedures for $\mu_{P,i}$ are shown in Equations (2) and (3), for $\mu_{S,i}$ in Equations (4) and (5), and for $\mu_{C,i}$ in Equations (6) and (7).

$$\mu_{P,i} = \frac{CSP_i}{MSP} \tag{2}$$

$$MSP = max(CSP_1, CSP_2, \cdots CSP_n, \cdots) \tag{3}$$

$$\mu_{S,i} = \frac{NCP_i}{MCP} \tag{4}$$

$$MCP = max(NCP_1, NCP_2, \cdots NCP_N) \tag{5}$$

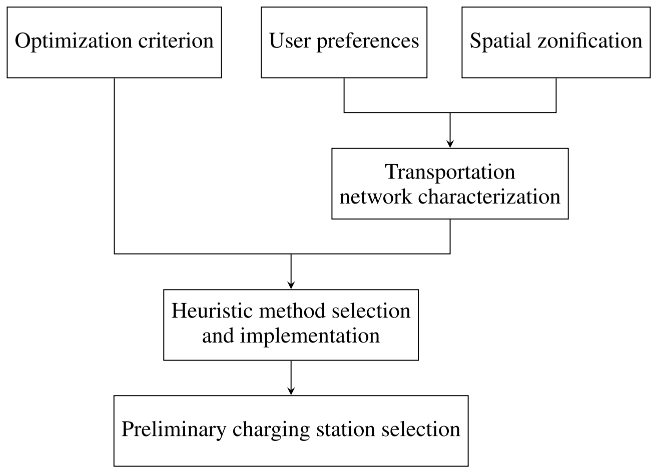


FIGURE 2 Preliminary deployment methodology

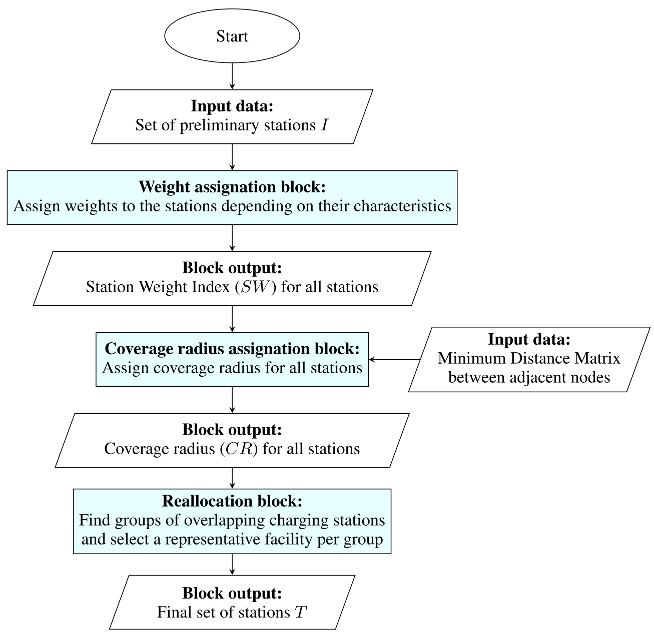


FIGURE 3 Reallocation Algorithm methodology

$$\mu_{C,i} = \frac{CC_i}{MSC} \tag{6}$$

$$MSC = max(SC_1, SC_2, \cdots SC_N) \tag{7}$$

where MSP is the maximum charging power connection from all chargers, MCP the highest number of connection points found in a facility, and MSC the highest comfort index from all subcentres of urban activity with a charging station. CSP_i represents the charging power of the ith station, NCP_i its number of connection points, and CC_i stands for its comfort index. Note that $\mu_{P,i}$, $\mu_{S,i}$, $\mu_{C,i}$ are also comprehended in the range from 0 to 1 since the reference patterns are the stations with the best respective conditions.

As for the Comfort Index ($\mu_{C,i}$), since it is a fully qualitative measure, a value of 1 is suggested for charging stations with barely any side activities offered, a value of 2 to locations with food courts or similar, and a value of 3 for facilities inside a mall parking spot.

It is important to point out that while the power, size and comfort indexes can variate for each station, the terms ω_P, ω_S, and ω_C remain constant for all facilities.

According to the previous indexes and terms description, the full weight assignation block works as follows:

Algorithm 1 *Weight assignation block*

1: Let I be the set of planned stations.
2: Set indexes ω_P, ω_S, and ω_C.
3: Set powers CSP_i, connection points NCP_i, and comfort condition CC_i $\forall i \in I$.
4: Compute MSP, MCP, and MSC using Equations (3), (5), and (7)
5: Compute $\mu_{P,i}$, $\mu_{S,i}$, and $\mu_{C,i}$ using Equations (2), (4), and (6) $\forall i \in I$.
6: Compute SW_i using Equation (1) $\forall i \in I$.

It is important to point out that since Locations of Interest are expected to provide conditions that better match to user preferences, the charging stations at these spots should have higher SW indexes than regular street stations.

3.2.2 | Coverage radius assignation block

The calculation of a proper coverage radius of the stations is a fundamental aspect to take into account [37], however, this matter requires two considerations. First, the reallocation will cause the facility to be moved from its original location. However, the distance a charging station is moved should not surpass the travel distance a user is willing to detour to charge in the new location.

This maximum detour distance can be related to the vehicle range; however, urban distances are often short in comparison to current EV ranges [3], and the coverage area of the charging stations would change depending on the EV regional park. Another option is to generate a Minimum Distance Matrix between the adjacent nodes of the network transportation graph, and carry out a percentile analyses. This last method would allow to set coverage areas that depend only on the transportation network characteristics regardless of the considered EVs.

Another aspect to consider is that similar to the SW index described in Section 3.2.1, the coverage radius assignation should contemplate features regarding the user preferences. Consequently, more relevant stations should have a greater coverage area than minor facilities. SW index is combined with the maximum detour distance to compute the coverage radius of a given station as it is shown in (8).

$$CR_i = mdd \times SW_i \tag{8}$$

Where CR_i is the coverage radius of the ith station, and mdd is the maximum detour distance. Note that even if a charging station matches ideal conditions for all indicators from Section 3.2.1, the maximum value that SW_i can take is 1. Thus, a driver will never detour further than mdd.

According to the previous indexes and terms description, the full weight assignation block works as follows:

Algorithm 2 *Radius coverage block*

1: Let I be the set of planned stations.
2: Generate Minimum Distance Matrix between connected nodes in the transportation graph.
3: Set mdd as the kth percentile of the Minimum Distance Matrix.
4: Compute CR_i using Equation (8) $\forall i \in I$.

3.2.3 | Reallocation block

The objective of the Reallocation Block is to eliminate stations with overlapping areas. A station is considered to be overlapped if it is located inside the coverage area of another facility. The general process consists in forming groups of overlapping charging stations and selecting the one with the highest weight to represent all the stations in the group; this process is to be repeated until there are no more overlapping stations.

Several considerations have to be taken during the previous process. Particularly, the station to which a group is reduced should not be considered for any further reallocation as this could result in distances greater than the maximum detour distances. On the other hand, it is possible that after applying the reallocation block there will be routes with less stations than needed to cover their energetic requirements; thus, to make the Reallocation Algorithm solution completely feasible, it is necessary to consider that the driver will take a deviation from its original path to charge the EV if the battery level reaches a certain threshold, and will not wait until a charging station is found on the route.

Based on the previous considerations the reallocation block works as follows:

Algorithm 3 *Reallocation block*

1: Let I be the preliminary set of stations.
2: Let T be the final set of stations.
3: Let MDA be the Minimum Distance Matrix between all nodes.
4: Let mmd be the maximum detour distance.
5: Let SW_i be the Station Weight Index $\forall i \in I$.
6: Let CR_i be the coverage radius $\forall i \in I$.
7: Set $V = \{\varnothing\}$.
8: Select the station k with the highest SW s.t $k \in I$ and add it in set V.
9: Compute distance from k to j as $MDA(k, j)$ $\forall j \in I$ s.t $j \neq k$.
10: Set distance from k to j as $MDA(k, j)$ $\forall j \in I$ s.t $j \neq k$.
11: Add j to V $\forall j$ s.t $MDA(k, j) \leq mmd$.
12: Select the station with the highest SW in V and add it on T. If multiple stations have the highest SW randomly select one.
13: Remove all stations in V from set I.
14: If $I = \varnothing$ then T is the final set of stations. Else go back to step 7.

Note that in the Reallocation Block the facility with the highest weight of each group is selected as part of the final set of charging stations, while all the stations on its cluster are eliminated from set I. On the other hand, the selected station is also eliminated from I to prevent it to be moved since it can still be part of another cluster.

4 | CASE STUDY

The methodology described in Section 3 was applied to propose a charging station deployment strategy in the city of Bogota, Colombia. In this case study the preliminary selection of charging stations was carried out by implementing the Greedy Algorithm presented in [27] to then use this results as input data in the Reallocation Algorithm depicted in Section 3.2. The following sections describe the procedure of the Greedy Algorithm implemented, and the urban transportation network topology of the case study.

4.1 | Transportation network description

According to a 2018 social regional census, the city of Bogota has a population of 7.2 million inhabitants distributed in 380 km^2 of built-up area. Moreover, the metropolitan area constitutes a total of 17 municipalities with different grades of integration.

The spatial distribution of the city activities in Bogota is in the influence area of the city main road corridors and matches the some of the areas with highest incomes [38]. In this study Bogotá is considered to be divided into Transportation Analyses Zones (TAZs) [39], which are territorial areas defined by economic and social conditions, connectivity with other zones, land use, size, among other characteristics. Particularly even though the social-economic condition of these TAZs does not consistently reflect the population income level, it does give a starting point to elaborate a residential classification [40].

The corridor network was modelled by representing the above mentioned TAZs as centroids using TRANSCAD software, obtaining a graph composed by 960 arcs and 601 nodes. The graph attributes are related to the topology of the main corridors, some secondary and tertiary corridors, and the intersections by which they are connected.

Based on criteria such as the TAZs social-economic level, industrialisation level, malls, and exit routes, the main sub-centres of urban activity were selected from the TAZs as potential origins and destinations, obtaining a total of 37 nodes, which generate 1330 O-D pairs combinations. From these 37 centroids, 12 were selected as Locations of Interest, based on criteria such as the EV users preferences for places of easy accessibility, and that can provide multiple services [38, 40].

Figure 4 presents the general TAZs distribution on the main road corridors, along with the selected O-D nodes represented by the blue shaded areas, and the Locations of Interest with the red areas.

The graph was set up to consider every TAZ as a possible charging station location, and the graph arcs values were related to the minimum distance between nodes. These distances were also generated using TRANSCAD software, and were organised

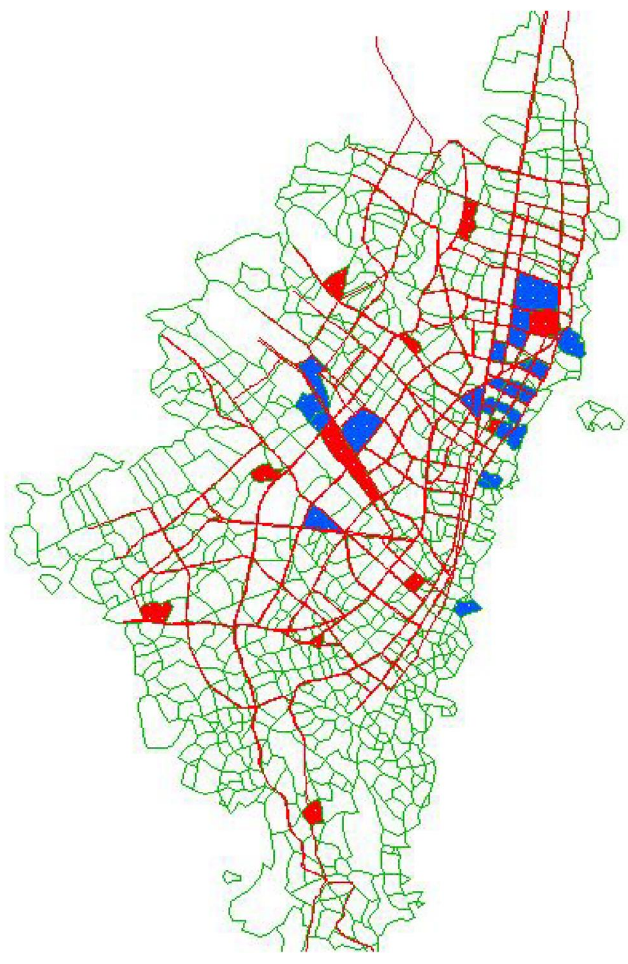


FIGURE 4 TAZs distribution on the main network mesh

in a Minimum Distance Matrix; the terms of this matrix take the value of the minimum distance between TAZs centroids ($\delta_{i,j}$) if these nodes are directly connected; otherwise they are assumed as a sufficient large number. It is important to clarify for sizing proposes, that the minimum distance between connected TAZs is 0.19 km, the average is 4.25 km, and the maximum is 39.47 km.

4.2 | Heuristic method selection and implementation

To carry out the preliminary selection of charging stations the Greedy Algorithm presented in [27] was implemented. This algorithm carries out an iterative weighted selection process by locating the minimum number of stations needed to cover the energetic expense of all the travelling routes considered. Weights are assigned to each potential station depending on how many times the facility is needed to cover different routes; a route is covered if the vehicle can reach its final destination by using some, or all of the deployed stations throughout the route in any of the considered k-shortest paths. The charging station with the highest weight is placed in the graph, and the process is repeated until every route is covered.

This heuristic method was designed to minimise the charging infrastructure investment. However, if no investment distinction is considered between the possible facilities, the objective becomes minimising the number of deployed stations, and consequently the investment cost. The process for this matter is shown in Figure 5, where $\widehat{I}$ represents the final set of selected charging stations, $\widehat{O}$ refers to the origin nodes, $\widehat{D}$ to the destination nodes, δ represents the value of the graph edges, C_B is used to represent the battery capacity of the vehicle, ℓ is the remaining capacity of the battery at a certain node, $R(O_i, D_j)$ is the optimal route between an origin node O_i, and a destination node D_j, which is stored in the set $\widehat{r}$. The term λ represents the battery level at which a station is needed, and P stands for the node where a charging station is required to cover the energy expense between an O-D pair, and μ is a charge level to which the EV reaches once it stops in a charging station.

4.3 | Assumptions

The case study was divided into two scenarios; in Scenario A the results obtained by combining the shortest path with the proposed Reallocation Algorithm are compared to the results drawn from considering $k = 2$ and $k = 3$ shortest paths computed through Yen's Algorithm [41]. In Scenario B, all the Locations of Interest were assumed to be obligatory charging station locations and only the shortest path was considered; since these locations match the main road corridors this consideration can be more convenient for users.

The assumed EV battery capacity corresponds to the specifications of the most sold EV in the Colombian market; this vehicle has a battery capacity of 30 kWh, which translates into an approximate 200 km range. Starting SoCs of 20%, 22.5%, and 25% of the selected vehicle battery capacity were considered. It will be shown in Section 5 that since the EV ranges are substantially higher than the average graph distances a small change in the initial SoC can drastically affect the charging station locations.

During the implementation of the Greedy Algorithm described in Section 4.2 it was assumed that a charging station will be located at a node if the EV remaining range is below 3 km. Also it was assumed that if an EV charges at a Location of Interest it will reach a 25% of the battery full capacity over its current SoC. Else, if it charges in an ordinary station it will charge an additional SoC of 10%; these values represent critical conditions as they are lower than those that would be expected from a usual charging process.

During the Reallocation Algorithm implementation the relative weight of the power index (ω_P) was set to 0.5, of the

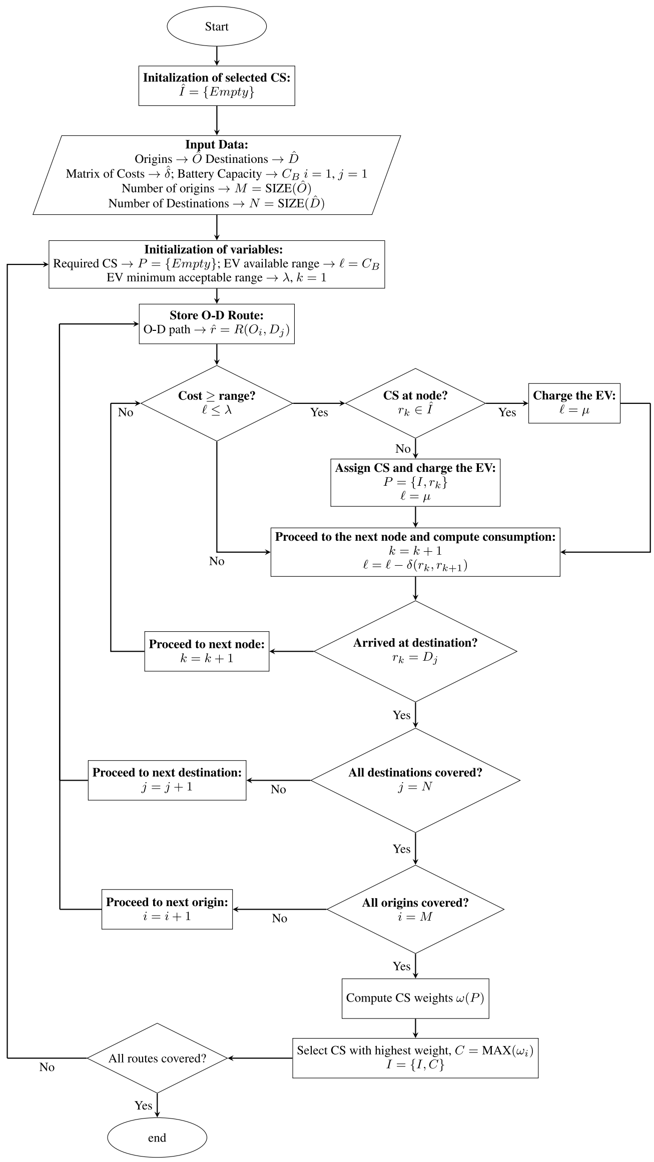


FIGURE 5 Greedy Algorithm implementation for the preliminary charging station location

TABLE 1 Charging power, number of connections, and comfort index assignation

	Charging Power	Connection Points	Comfort Index
Locations of Interest	Random selection between 50 kW, 75 kW, and 100 kW	Random selection between 6 and 10	Fixed value of 3
Remaining locations	Random selection between 50 and 75 kW	Random selection between 3 and 5	Random selection between 1 and 2

TABLE 2 Routing computational time for each shortest as percentage of $k = 1$

	Shortest Path		
	$k = 1$	$k = 2$	$k = 3$
Computational time (% of $k = 1$)	100	1100	2000

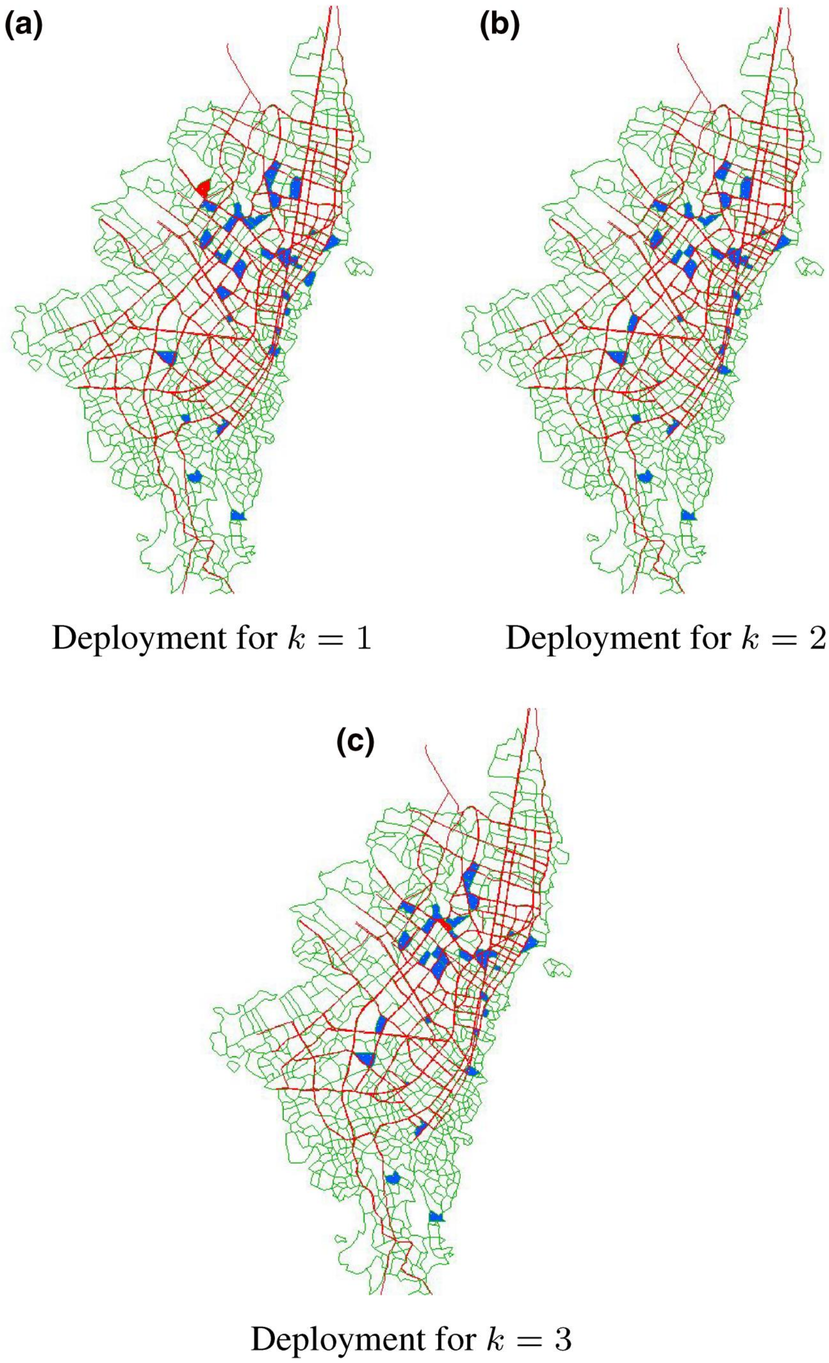


FIGURE 6 Charging station spatial location for starting SoC of 20%

size index (ω_S) to 0.3, and of the comfort index (ω_C) to 0.2. In the radius assignation block was assumed as the 50th percentile of the distances between connected TAZs, which correspond to 2.2 km. The power, number of connection and comfort index assignation for the charging stations is shown in Table 1.

Finally, in order to validate if the deployment obtained from the algorithm implementation still represents a feasible solution to cover the energy route expenses, it was assumed that the vehicle owner will search for a nearby station once the EV SoC reaches a SoC level of 20%, equivalent to a remaining EV range of 40 km; after the EV is charged the user will return to the original route.

5 | RESULTS

To study the k-shortest path consideration effect on the O-D routing complexity, the computational time of the first three shortest paths ($k = 1$, $k = 2$, and $k = 3$) between OD nodes were compared as a percentage value of the time of $k = 1$. As shown in Table 2 for this feature the time expended for $k = 2$ and $k = 3$ were approximately 11 and 20 times the value of $k = 1$.

The preliminary charging station location was obtained by applying the Greedy Algorithm from Section 4.2 to the case study network transportation graph, resulting in the spatial distribution depicted in Figures 6–8. It is important to recall

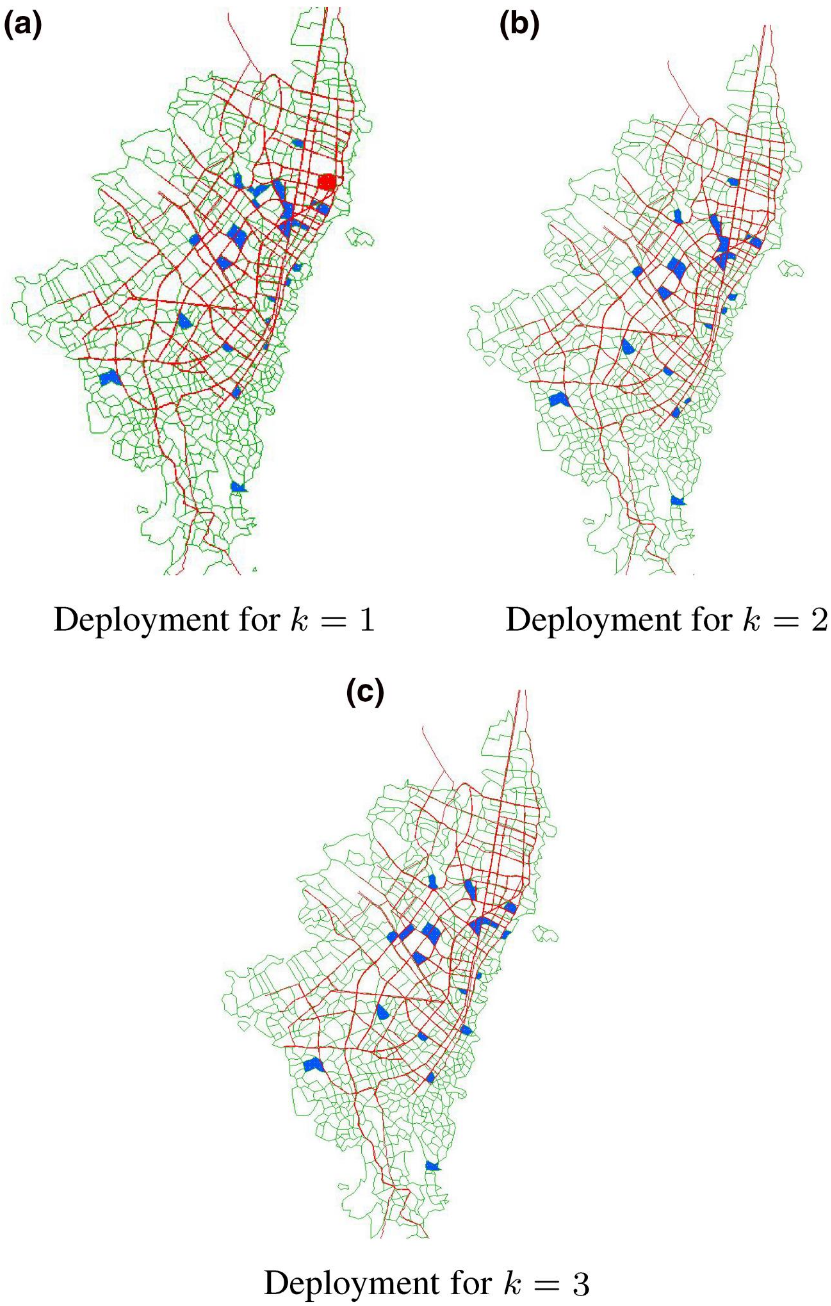


FIGURE 7 Charging station spatial location for starting SoC of 20%

that these deployment strategies constitute the input data for the Reallocation Algorithm.

Note from Figure 6 that considering $k = 2$ and $k = 3$ cause a slight reduce the number of required charging stations for a starting SoC of 20%. However, this is not the case for higher SoC values; as shown in Figures 7 and 8, the deployment strategy for $k = 1$ and $k = 2$ becomes even more similar when considering a starting SoC of 22.5%, and becomes identical for $k = 1$, $k = 2$, and $k = 3$ for a starting SoC of 25%

The similarity of the deployment strategies for higher SoC values is explained by the thoroughly transportation network modelling, which resulted in a graph where no significant routes deviations appear between $k = 1$, $k = 2$, or $k = 3$. Moreover, the paths have common nodes in the early stages of their O-D routes. Due to the low starting SoC consideration, charging stations tend to be deployed in these early route nodes; after a charging event at this spots it is feasible to cover an O-D pair without further charges.

Table 3 presents the results summary for the number of required facilities for each SoC level, along with the number of locations of interest selected as part of the deployment strategy. It can be noted that a slight increment on the starting SoC caused a significant reduction on the number of charging stations required.

The previous deployment strategies with $k = 1$ for each level were used as input data for the Reallocation algorithm implementation. Figure 9 depicts the algorithm results in terms of the spatial distribution for each SoC level, and Table 4 compares the original deployment strategies to those obtained from the algorithm implementation.

Figure 9 shows that the Reallocation Algorithm substantially reduced the number of overlapping stations in Figures 6–8 with $k = 1$, which is quantified as a 18%, 11%, and 19% for starting SoCs of 20%, 22.5%, and 25%, respectively, reaching a similar number of planned stations to the one considered with $k = 3$. Also, the Locations of Interest selected as part of the initial deployment strategy remained after the algorithm application due to their high initial weight assignation.

To validate the Reallocation Algorithm results it was evaluated if the driver can reach his travel destination after taking the required deviation to charge the EV. Table 5 presents the number of routes on which the driver was required to take deviations, along with the statistics related to the minimum, mean and maximum additional travelled distance.

Note from Table 5 that all routes with deviations were covered for all starting SoCs. It is important to point out that the additional travelled distance corresponds to the totality of the round trip. As the values are below the maximum detour distance this shows that a proper coverage radius selection can limit the number and distance of deviation routes that the user has to take to reach the new location of the charging stations.

In Scenario B, a sensitivity analyses is carried out by assuming all Locations of Interest as fixed locations for charging stations. These new locations were added to the set of selected facilities from Scenario A when only $k = 1$ was considered. This scenario allows to verify how fixed selections of charging stations might affect the original solution.

The spatial distribution of the new charging station locations is depicted in Figure 10 for each SoC considered.

The statistical results of the previous results are presented in Tables 6 and 7.

Table 7 shows that considering the Locations of Interest as part of the deployed stations did not affect the number of required deviations, and neither caused significant increments on the minimum, mean, and maximum detour distance.

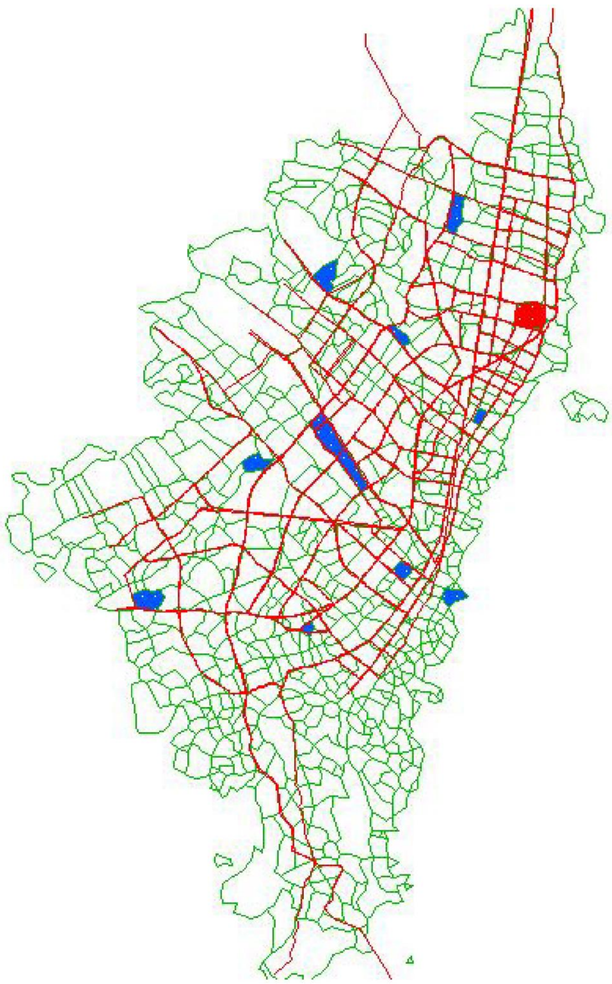


FIGURE 8 Charging station spatial location for starting SoC of 25% for $k = 1$, $k = 2$, and $k = 3$

TABLE 3 Preliminary number of charging stations for all SoC levels

	Number of CS			CS at LoI		
Starting SoC (%)	$k = 1$	$k = 2$	$k = 3$	$k = 1$	$k = 2$	$k = 3$
20	34	32	32	1	0	1
22.5	26	22	22	1	0	0
25	16	16	16	1	1	1

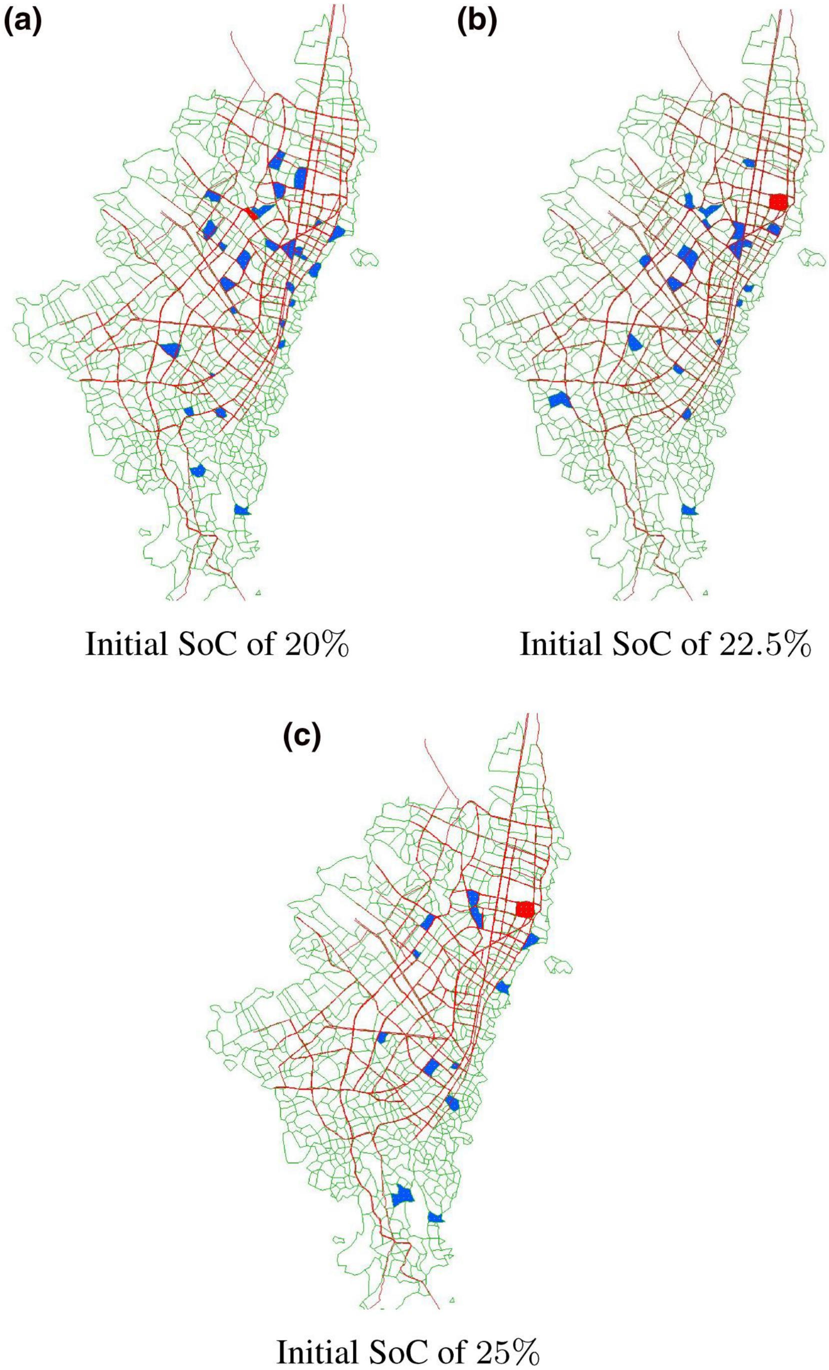


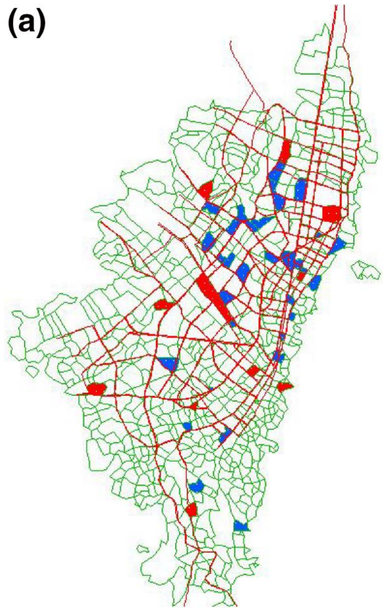
FIGURE 9 Reallocation Algorithm results in Scenario A

TABLE 4 Deployment strategy for all SoC levels after RA application -–Scenario A

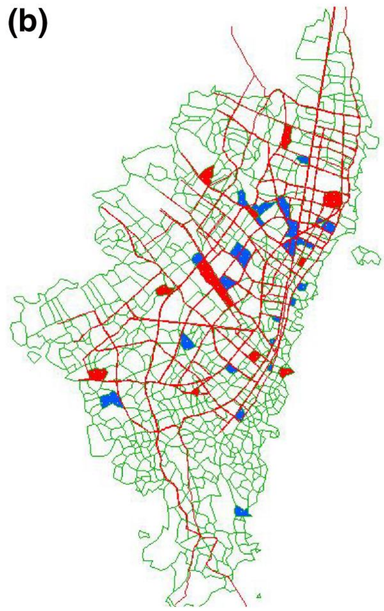
	Results before RA		Results after RA		
Starting SoC (%)	Number of CS	CS at LoI	Number of CS	CS at LoI	CS Reduction (%)
20	34	1	28	1	18
22.5	26	1	23	1	11
25	16	1	13	1	19

TABLE 5 RA validation in Scenario A – covered routes and required deviations

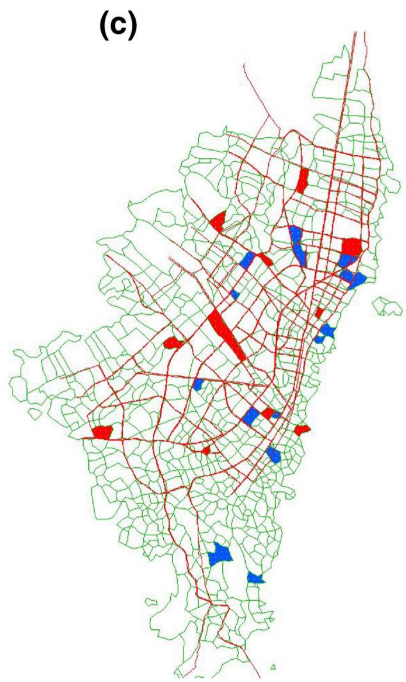
Starting SoC (%)	Routes with Deviations	Routes Covered	Total Number of Deviations	Min/Mean/Max Additional Distance (km)
20	3	3	3	2.4/1.6/3.1
22.5	5	5	5	2.8/2.6/3.2
25	2	2	2	2.8/2.8/2.7



Deployment for starting SoC of 20 % and $k = 1$



Deployment for starting SoC of 22.5 % and $k = 1$



Deployment for starting SoC of 25 % and $k = 1$

FIGURE 10 Reallocation Algorithm results in Scenario B

TABLE 6 Deployment strategy for all SoC levels after RA application – Scenario B

	Results before RA		Results after RA		
Starting SoC (%)	Number of CS	CS at LoI	Number of CS	CS at LoI	CS Reduction (%)
15	47	13	40	13	15
20	39	13	34	13	13
25	29	13	24	13	17

TABLE 7 RA validation in Scenario B – covered routes and required deviations

Starting SoC (%)	Routes with Deviations	Routes Covered	Total Number of Deviations	Min/Mean/Max Additional Distance (km)
20	20	20	20	1.7/3.1/4.34
22.5	12	12	12	3.0/3.1/3.24
25	11	11	11	1.7/2.8/3.4

6 | CONCLUSIONS

An Optimal EV charging station location methodology was proposed in this article to carry out a charging station infrastructure deployment in urban transportation networks by decoupling the covering problem from the user preferences and constraints. A developed Reallocation Algorithm was proposed to reduce the number of overlapping stations and to give priority to the selection of Locations of Interest as part of the deployment strategy based on preferences from users.

The Reallocation Algorithm allowed a reduction of the required number of charging stations in the range of 11%–19% when only considering the charging stations required to cover the energetic expense of the route, and 13%–17% when considering that all locations of interest are selected as charging stations. This was achieved while maintaining deviation travelling distances within an acceptable range. It is important to point out that the reduction could have been taken further with a higher coverage radius, nonetheless, this would have resulted in a significant increase in the additional distance a driver is required to travel to find a charging station. Thus, this could not reduce range anxiety in users.

The case study results showed that considering only the shortest path ($k = 1$) reduced the elapsed time for the routing process in the rate of 91%–95% in comparison to $k = 2$ and $k = 3$ considerations respectively. Moreover, the proposed Reallocation Algorithm proved to obtain similar strategies as those that could result from multipath considerations.

On the other hand, the case study results shown that an increment of 5% on the starting SoC led to a reduction of 53% in the number of stations needed to cover the O-D route's energetic expenses. Thus, high starting SoC considerations do not contribute to the public charging stations' deployment objective of reducing range anxiety in users.

REFERENCES

1. International Energy Agency: Global EV outlook 2018 (2018). https://www.iea.org/reports/global-ev-outlook-2018
2. Landi, M.M., Mohammadi, M., Rastegar, M.: Simultaneous determination of optimal capacity and charging profile of plug-in electric vehicle parking lots in distribution systems. Energy. 158, 504–511 (2018)
3. Alhazmi, Y.A., Mostafa, H.A., Salama, M.M.: Optimal allocation for electric vehicle charging stations using trip success ratio. Int. J. Electr. Power Energy Syst. 91, 101–116 (2017)
4. Noel, L., de Rubens, G.Z., Sovacool, B.K., Kester, J.: Fear and loathing of electric vehicles: the reactionary rhetoric of range anxiety. Energy Res. Social Sci. 48, 96–107 (2019)
5. Bonges, H.A., Lusk, A.C.: Addressing electric vehicle (EV) sales and range anxiety through parking layout, policy and regulation. Transport. Res. Pol. Pract. 83, 63–73 (2016)
6. Matteo, M.: Impact of uncoordinated plug-in electric vehicle charging on residential power demand. Nat. Energy. 3, 193–201 (2018)
7. Zhao, H., Li, N.: Optimal siting of charging stations for electric vehicles based on fuzzy delphi and hybrid multi-criteria decision making approaches from an extended sustainability perspective. Energies. 9(4), 1–22 (2016)
8. He, S.Y., Kuo, Y., Wua, D.: Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: a case study of Beijing, China. Transport. Res. Part C. 67, 131–148 (2016)
9. Wirges, J., Linder, S., Kessler, A.: Modelling the development of a regional charging infrastructure for electric vehicles in time and space. EJTIR. 12(4), 391–416 (2012)
10. Sechilariu, M., Molines, N., Richard, G., Martell-Flores, H., Locment, F., Baert, J.: Electromobility framework study: infrastructure and urban planning for EV charging station empowered by PV-based microgrid. IET Electr. Syst. Transp. 9(4), 176–185 (2019)
11. Budde, T., Wells, P., Cipcigan, L.: Can innovative business models overcome resistance to electric vehicles? Better place and battery electric cars in Denmark. Energy Policy. 48, 498–505 (2012)
12. Zhang, H., Hu, Z., Xu, Z., Song, Y.: An integrated planning framework for different types of PEV charging facilities in urban area. IEEE Trans. Smart Grid. 7(5), 2273–2284 (2016)
13. Lam, A.Y.S., Leung, Y., Chu, X.: Electric vehicle charging station placement: formulation, complexity, and solutions. IEEE Trans. Smart Grid. 5(6), 2846–2856 (2014)
14. Deb, S., Tammi, K., Kalita, K., Mahanta, P.: Review of recent trends in charging infrastructure planning for electric vehicles. WIREs Energy Environ. 7(6), 1–26 (2018)
15. Shukla, A., Verma, K., Kumar, R.: Multi-objective synergistic planning of EV fast-charging stations in the distribution system coupled with the transportation network,IET Generat. Transm. Distrib. 13(15), 3421–3432 (2019)
16. Rajabi-Ghahnavieh, A., Sadeghi-Barzani, P.: Optimal zonal fast-charging station placement considering urban traffic circulation. IEEE Trans. Veh. Technol. 66(1), 45–56 (2017)
17. Censo Nacional de PoblaciónVivienda y Explorador de datos (2018). https://sitios.dane.gov.co/cnpv/#!/ November 2019. Colombia. accessed
18. Xiong Gan, Y.J., An, B., Miao, C., Bazzan, A.L.C.: Optimal electric vehicle fast charging station placement based on game theoretical

framework. IEEE Trans. Intell. Transport. Syst. 19(8), 2493–2504 (2018)
19. Zhang, Y., Liu, X., Zhang, T., Gu, Z.: Review of the electric vehicle charging station location problem, Dependability Sens. Cloud Big Data Syst. Appl. DependSys. 1123, 435–445 (2019)
20. Ko, J., Kim, D., Nam, D., Lee, T.: Determining locations of charging stations for electric taxis using taxi operation data. Transport. Plan. Technol. 40, 420–433 (2017)
21. Daskin, M.S., Maass, K.L.: The p-Median Problem. In: Location Science, pp. 21–45. Springer (2015). https://doi.org/10.1007/978-3-319-13111-5_2
22. Lin, C., Lin, C.: The p-center flow-refueling facility location problem. Transport. Res. Part B. 118, 124—142 (2018)
23. Daskin, M.S.: A maximum expected covering location model: formulation, properties and heuristic solution. Transport. Sci. 17(1), 712–716 (1983)
24. Davidov, S., Pantoš, M.: Planning of electric vehicle infrastructure based on charging reliability and quality of service. Energy. 118(1), 1156–1167 (2017)
25. Liu, Y., Xiang, Y., Tan, Y., Wang, B., Liu, J., Yang, Z.: Optimal allocation model for EV charging stations coordinating investor and user benefits. IEEE Access. 6, 36039–36049 (2018)
26. Luo, C., Huang, Y., Gupta, V.: 'Placement of EV charging stations—balancing benefits among multiple entities. IEEE Trans. Smart Grid. 8(2), 759–768 (2018)
27. Li, S., Huang, Y.: Heuristic approaches for the flow-based set covering problem with deviation paths. Transport. Res. E Logist. Transport. Rev. 72, 144–158 (2014)
28. Liu, H., Jin, C., Yang, B., Zhou, A.: Finding top-k shortest paths with diversity. IEEE Trans. Knowl. Data Eng. 30(3), 488–502 (2018)
29. Zhang, H., Moura, S.J., Hu, Z., Song, Y.: PEV fast-charging station siting and sizing on coupled transportation and power networks. IEEE Trans. Smart Grid. 9(4), 2595–2605 (2018)
30. Aljaidi, M., Aslam, N., Chen, X., Kaiwartya, O., Khalid, M.: Proc. 11th International Conference on Information and Communication Systems (ICICS), pp. 161–166 (2020). An energy efficient strategy for assignment of electric vehicles to charging stations in urban environments
31. Mao, D., Wang, J., Tan, J., Liu, G., Xu, Y., Li, J.: Location planning of fast charging station considering its impact on the power grid assets. Proc. IEEE Transportation Electrification Conference and Expo (ITEC), 1–5 (2019)
32. Bi, R., Xiao, J., Pelzer, D., Ciechanowicz, D., Eckhoff, D., Knoll, A., pp. 1–7. Proc. 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC) (2017). A simulation-based heuristic for city-scale electric vehicle charging station placement
33. Andrade, J., Ochoa, L.F., Freitas, W.: Regional-scale allocation of fast charging stations: travel times and distribution system reinforcements. IET Gen. Transm. Distrib. 14(19), 4225–4233 (2020)
34. Giménez-Gaydou, D.A., Ribeiro, A.S.N., Gutiérrez, J., Antunes, A.P.: Optimal location of battery electric vehicle charging stations in urban areas: a new approach. Int. J. Sustainable Transport. 10(5), 393–405 (2016)
35. Deb, S., Tammi, K., Gao, X., Kalita, K., Mahanta, P.: A hybrid multi-objective chicken swarm optimization and teaching learning based algorithm for charging station placement problem. IEEE Access. 8, 92573–92590 (2020)
36. Zhang, Y., Liu, X., Zhang, T., Gu, Z.: 'Review of the electric vehicle charging station location problem. Proc. 5th International Conference on Dependability in Sensor, Cloud, and Big Data Systems and Applications. DependSys. 1123, 435–445 (2019)
37. Melaina, M., Bremson, J.: Refueling availability for alternative fuel vehicle markets: sufficient urban station coverage. Energy Pol. 36, 3233–3241 (2008)
38. Ruiz Estupiñán, N.H.: Estudio de la estructura urbana e identificación y análisis del impacto de la localización de la actividad económica sobre las dinámicas territoriales: El caso de Bogotá, Colombia, Ph.D. thesis, Universitat Politecnica de Catalunya (2016)
39. 'Zonas de Análisis de Transporte 2016, https://bogota-laburbano.opendatasoft.com/explore/dataset/zat/information/?location=10,4.5997,-74.02519&basemap=jawg.streets, Accessed November 2019
40. Avendaño, J.: Three essays on urban spatial structure in Bogotá D.C. Ph. D. thesis, Universitat Autonoma de Barcelona (2012)
41. Yen, J.Y.: Finding the K shortest loopless paths in a network. Manag. Sci. 17(11), 712–716 (2019)

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