Fast Charging Stations Placement Methodology for Electric Taxis in Urban Zones

Igoor Morro-Mello[a,*], Antonio Padilha-Feltrin[a], Joel D. Melo [b], Aida Calviño[c]

[a] *Universidade Estadual Paulista (UNESP), Ilha Solteira, Brazil*
[b] *Universidade Federal do ABC (UFABC), Santo André, Brazil*
[c] *Dept. of Statistics and Data Science, Complutense University of Madrid, Spain*

Abstract

In recent years, as a policy to increase penetration of electric vehicles and reduce air pollution, the number of electric taxis has increased in the transportation networks. In contrast to private electric vehicles, electric taxis need to recharge in a short time due to their constant operation and different driving patterns. Therefore, fast charging stations are required to meet the demand for recharging electric taxis and should be located at strategic places. To improve the sustainable planning of urban infrastructures, this paper presents a methodology to help in decision making for installing fast charging stations, considering the criteria of all urban planners involved in the installation process. The result of the proposal is a spatial database that identifies locations for charging stations that meet the predefined criteria. Such database can be visualized in geographic information systems of the urban planning department or the electrical service concessionaire. The proposed methodology is tested in a Brazilian medium-sized city showing the importance of this information in decision making. The proposal is compared with another spatial methodology, showing that the proposed method creates a better spatial distribution of charging stations giving better options for the main agents interested in the city.

Keywords: Charging stations; Electric taxis; Geospatial analysis; Sustainable planning policies; Transportation networks; Urban infrastructures.

---

[*] corresponding author: igoormello718@gmail.com

Preprint submitted to Energy *April 17, 2019*

1. Introduction

The use of electric vehicles (EVs) has intensified recently and has become an alternative for the transportation network. EVs address an environmental concern by reducing local pollution and greenhouse gas emissions (when inserted with renewable energy) [1]. In addition, government incentives have been provided for the adoption of EVs in many countries [2]; [3]; [4]; [5]. Some countries have even created sustainable laws so that only EVs will be sold in the future [6]. With so many incentives in recent years, EVs have become popular in some developed and developing countries, with a significant increase in the EV fleet [7]; [8]; [9]; [10]; [11].

The insertion of EVs into urban zones can begin with the introduction of electric taxis (ETs) by means of tax incentives for taxi drivers to acquire them. Electric taxis (ETs) are not new in the literature and have been studied by the academic community mainly due to their different driving patterns. Traveling all day in the urban zone, ETs do not have time for slow recharges, and hence, require fast recharges in fast charging stations (Fast-CS) [8]. Several studies related to EVs, ETs and charging stations (CS) can be found in the literature with different objectives, such as recommendation systems for reducing waiting times at CSs [8] or the number of EVs in a CS [12], better use of slots for charging [13], cost optimization for route scheduling of EVs [14], better EV routes [2], optimal locations for CS [15]; [16]; [17], photovoltaic-wind design CS for EVs replacing a specific type of combustion vehicle by EV [18], coordinated charging of plug-in hybrid EVs allocating charging energy in low pricing periods [19], and an impact of photovoltaic systems and EVs in the urban distribution system [20]. However, as far as we know, none of these works consider the various agents involved in the installation of Fast-CS that have specific constraints and installation standards [21]; [22].

Many techniques proposed in the literature to find the location of Fast-CSs seek solutions without considering the stochasticity of the problem and/or do not consider the constraints of the various agents involved, which can cause problems to some agents participating as well in the Fast-CS allocation process. In addition, spatial information should be available to all agents to be incorporated in their GIS tools, and this is not always the case in these studies. To help in sustainable city planning, this paper proposes a methodology that allows to integrate and attend the planning requirements of interested agents in the installation process, as well as considering some sources of stochasticity.

The concern with urban smart buildings has led many public and private agencies to use planning systems and computational tools to make transportation, electric distribution and city planning studies. These studies are included in their plans and are shown as policies to improve the sustainability of vehicular traffic, energy systems and urban infrastructures. Studies related to vehicles comprise driving patterns, origin-destination (O-D) information, traffic congestion points, travel time and socioeconomic characteristics related to transportation and energy consumption [23]. However, these studies consider characteristics of the transportation network only at peak times of the day. In the case of ETs, obtaining the streets visited and other characteristics in other periods is necessary for the planning department of the electric power concessionaires that need to estimate the demand to be supplied by the recharge of these vehicles.

Therefore, this paper proposes a methodology that helps the various agents involved in the planning and installation process of Fast-CS. For the proposal, an hourly transport simulation tool is used to obtain the state of charge (SOC) variation during each ET trip and the Dijkstra algorithm [24] is applied to find routes for ETs[1]. This simulation, similar to a Monte-Carlo one [25], provides a spatial database with the streets visited by ETs and the SOC at each street during each realized trip. These results, along with other characteristics defined by planners (public agencies, traffic company, companies interested in the Fast-CS construction), promote a Fast-CS sustainable planning location.

Urban planning departments usually have computational tools to analyze spatially distributed information, as for example geographic information systems (GIS). These systems help utility planners to visualize and analyze geo-referenced data in order to obtain useful information for decision making [26]. The proposed method assists in the decision making of the location of Fast-CS. This work seeks to provide information to all agencies involved in the installation of Fast-CS: it helps in the planning of future transport networks and public policies; it assists ET users to recharge where they need it the most; and it provides information to the Fast-CS companies for the sustainable planning of urban infrastructures and distribution utilities in their distribution systems.

1.1. Contributions

The major contributions of this paper are as follows:

---

[1] Dijkstra algorithm is an optimization tool that aims at finding optimal routes, considering costs and weights, including an analysis of minimum paths, minimum travel times and congestion, among others.

- The proposed methodology determines the location of Fast-CS, taking into account all the criteria of the urban planners and other private or public agents involved in the sustainable planning of Fast-CS.

- The proposal considers stochastic factors, such as the SOC at the beginning of the simulations or the initial locations of taxi trips. Moreover, the proposal can be easily extended to consider more sources of stochasticity.

- The proposal creates maps of SOC and flows in each street visited by ETs. These maps are a byproduct that can be used by other agents interested in storing or selling batteries or create recharging points.

- The proposal characterizes, in a spatio-temporal manner, the requirements of the planners, providing, as a result, a spatial database that can be processed by any GIS of the public or private agent involved in the building process of Fast-CS.

1.2. Paper outline

The rest of this paper is organized as follows: Section 2 presents the most relevant models for the installation of CS available in the literature; Section 3 presents the proposed methodology including input data, simulation and definition of places to install Fast-CS. Section 4 presents the application of the proposal, showing different results and their comparison. Section 5 discusses the results and Section 6 concludes the paper.

2. Literature review for the installation of CS and EVs' model

Many studies can be found in the specialized literature devoted to determine the location of CS. Lam et al. [15] studied EV CS placement considering several human aspects in the long term with many social constraints like satisfaction, drivers' convenience, environmental impact, EV' accessibility. Due to this large number of constraint, the resulting problem is NP-hard[2]. The authors propose four CS placement methods, showing their own solution, as well as their pros and cons with respect to quality, algorithmic efficiency, problem size, nature of the algorithm, and existence of system prerequisites. Rajabi-Ghahnavieh et al. [1] determined optimal places and capacity of Fast-CS considering hourly urban traffic circulation and EV user preferences. Zhu et al. [16] developed a model for CS location for EVs and the number of chargers per station, minimizing installation costs. Asamer et al. [17] proposed a decision support system for

---

[2] NP-hard problem are a class of optimization problems whose solution can be verified in nondeterministic polynomial time. However, it is still an open question if they can be solved in polynomial time as well. Many NP-hard problems are related to graph theory [27] and can be solved in polynomial time through heuristics.

placing CS to satisfy the charging demand of ETs from operational O-D taxi data. Moreover, in [28] a methodology to calculate the number and position of CS in a road network is proposed, considering variables related to EVs' features, EVs' flows and CS technical characteristics.

However, in the above-mentioned studies, the identification of the places to install CS was carried out considering the objectives of a public or private agent in the city without considering the need to gather the specialists of these agencies for seeking the sustainable planning of the city. For example, in [1] and [15] the available physical space for CS installation is not considered, resulting in some geographic areas impacted by the installation of a Fast-CS. Such an impact can be avoided by the allocation of exclusive parking zones that prevent vehicular traffic. The calculation of SOC consumption in each street can help in the allocation of Fast-CS, as it will be shown in our proposal.

Policies to promote EVs are proposed in [29] by comparing the total cost of the ownership of EV and combustion vehicles. The results show that direct financial support, exemption of taxes and bonus systems can help to promote EVs. In our methodology, policies and financial support are considered for the replacement of combustion taxis by ETs. This proposal is based on Brazilian policies for replacing fossil fuel vehicles for ethanol in 1981. Such proposal reduced taxes for taxi drivers first [30]. A literature review showing the state-of-the-art of technologies and latest trends related to EVs, CS placement and their impacts can be found in [31] and [32]. After analyzing the state of the art, the authors state that the guidelines for the problem of Fast-CS placement should take into account multidisciplinary fields of knowledge, seeking solutions that satisfy the interests of the various agents involved in the installation of the stations. Following this line, this paper presents a methodology that considers important characteristics of the various agents involved.

In our proposal, the SOC along the streets is found through a model that considers several aspects of the transport system. Then, simulations for the movement of ETs in an urban zone are performed for a full weekday, considering, as random factors, the ETs' SOC and the initial locations of taxi trips, creating after the simulations a spatial database with a summary of the information provided by the simulations. This spatial database allows for the determination of the streets visited by ETs and ETs' SOC along the paths in heat maps. This information helps in the decision making of installing Fast-CS in locations with high ET flows with low state of charge. Therefore, this paper proposes a methodology for improving the planning of Fast-CS location attending the criteria of urban planners and other private or public agents involved in the installation of Fast-CS.

3. Proposed methodology

The use of transportation tools to model ETs' SOC and flow throughout the day can provide information for the detection of the most critical points, helping in the decision making for the allocation of Fast-CS. To attend the criteria of urban planners and other private or public agents involved in the installation of Fast-CS, a new methodology is proposed. The process is shown in Fig. 1 and explained in the following sections.

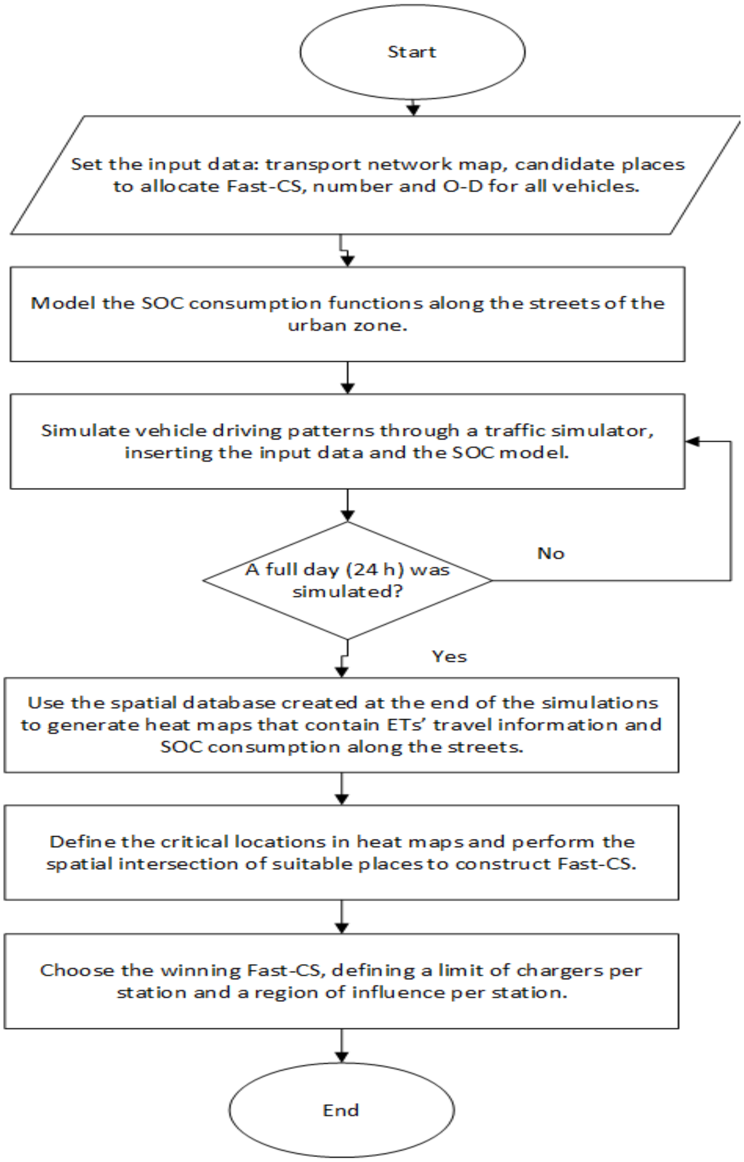

Fig. 1. Flowchart of the sequence of the method.

3.1. Input data required for the proposed methodology

3.1.1. Transportation Network Map

The transportation network map consists of georeferenced information of urban zones with their main and secondary roads and traffic lights. Other data should be georeferenced by the planner, such as the allowed speed limit of the roads and the different sectors of the city (residential, industrial and/or commercial). The transport network information can be found in the transportation department files or georeferenced maps with streets in specialized sites.

3.1.2. Initial location of candidate places to allocate Fast-CS

In several metropolises, there are areas that do not have available physical space or have some restrictions that impede building Fast-CS. In order to avoid the analysis of such places, the spatial distribution of initial candidate locations where it is possible to build them should be informed as input data. To find this spatial distribution of initial candidates, the planners can use the city zoning information and generate spatial point samples in places that do not have any restrictions to build using the tools in GIS [26].

3.1.3. Number of electric taxis and combustion vehicles

The number of ETs may vary according to the planning performed. Taxi owners can obtain ETs through granted incentives, possibly leading to full replacement of the taxi fleet. The replacement of combustion taxis by ETs may vary according to the planned project. The number of combustion taxis and vehicles that cross the urban zone can be obtained through reports in the transportation department of the analyzed city.

3.1.4. O-D for combustion vehicles

For the simulation of real traffic during the day, modeling combustion vehicles circulation in urban zones provides congestion points, speeds and travel times. Such information is necessary for the model of SOC and to obtain optimal routes for ETs.

Transportation departments often take field measurements and divide them in average estimates by hour. In each hour of the day, there are O-D characteristics described in the transport department database that can be used on transport modeling tools. The O-D information varies from home and/or work to places of leisure, education, health, etc. If the planner does not have complete information, database of cities with similar characteristics can assist in the decision making to allocate O-D data of combustion vehicles.

3.1.5. O-D for ETs

ETs driving patterns have different characteristics from those of combustion vehicles, which have similar intentions during the different periods of the day. To characterize ETs' O-Ds, the observation of combustion vehicles ones might be of help. Reports show that origins are a combination of random and fixed cabstands located in strategic places [33]. Destinations follow a combination of similar characteristics for combustion vehicles peak times (morning and afternoon peaks) and are modeled by a random distribution the rest of the day due to the varied destinations of ET users [34]. In addition, the following ETs characteristics should be considered and calibrated in the simulations according to the planner’s experience, the percentage of ET type (fixed origins or not) and available reports:

a) ETs that go from one origin to one destination and return to their origin to wait for the next trip (cabstand in strategic places already located in the urban zone obtained through study reports);

b) ETs that go from one origin to one destination and wait there for the next trip.

3.2. Simulations

ETs' SOC in the city streets is an important piece of information to evaluate the building of Fast-CS. Indicating locations where ETs will usually require recharging avoids Fast-CS allocation in regions with high SOC in ETs’ batteries. Furthermore, ETs always look for the shortest route and/or shortest travel time and a shortest path algorithm is required for this purpose.

The SOC consumption model in each street is simulated by the proposed methodology. For this modeling phase, tools are used in order to simulate the movements of each ET through a traffic simulator, such as AIMSUN [35], SUMO [36], or VISSIM [37]. In traffic simulators, the input data are the transport network map, the O-D information and the number of vehicles during each hour. Simulations must be performed for all hours of the day and a hybrid (microscopic and mesoscopic) traffic simulation is used. To characterize the behavior of each ET and its SOC consumption at each instant of the simulation, the microscopic simulation is used. To characterize O-Ds for combustion vehicles at each hour and zone, groups of vehicles with similar characteristics of O-D in each zone are placed together in clusters and the mesoscopic simulation is applied. During each hour, a percentage of vehicles in each cluster is assumed to leave and/or arrive the center of the different zones, such as industrial, educational, health, etc. (this information and the corresponding percentages should be available in the transport department files).

To determine ETs' SOC along the city's roads, Goeke and Schneider's [38] model of EVs' SOC is chosen due to the fact that it considers several characteristics related to vehicles, cities and travel times. This model is used to take into account the battery discharge due to traveling, as well as its potential recharge (due to the regenerative braking system) during the trip since almost all EVs currently produced have a regenerative braking system. The initial SOC of ETs is considered random, as it will be shown in the simulations setting, representing the stochasticity of the SOC for the first travel (first simulation at 00:00) and can be calibrated according to the planner needs. For the following trips, the SOC considered is the residual of the previous trips.

Initially, a mechanical power P_M model is presented to consider factors such as mass (m), speed (v), gradient, road surface, vehicle dimensions, and engine properties. With this information, P_M is then converted to electric power P_E using a homogeneous regression model[4], suitable for an ETs' P_M demand of up to 100 kW as seen in [38], and the latter is converted to battery power P_B considering the relationship between them.

$$P_M = \left(m * a + 0.5 * Cd * \ \rho a * Af * v^2 + m * g * sin(\alpha) + Cr * m * g * Cos(\alpha)\right) * v \qquad (1)$$

Where a is the acceleration, Cd is the aerodynamic drag coefficient, ρa is the air density, Af is the frontal area of the ET, g is the gravitational constant, α is the average gradient angle for the city obtained in transportation department files, and Cr is the rolling friction coefficient. $\emptyset_d$ and $\emptyset_r$ are the discharged and recuperated regression coefficients, respectively:

$$\emptyset_d = \frac{P_E^d}{P_M} \qquad \text{for} \qquad 0\ kW \leq P_M \leq 100\ kW \qquad (2)$$

$$\emptyset_r = \frac{P_E^r}{P_M} \qquad \text{for} \qquad -100\ \text{kW} \leq P_M < 0\ \text{kW} \qquad (3)$$

Here, P_E^d and P_E^r indicate the discharged and recuperated (recovered energy in the braking system) electric energy, respectively. After, the regression coefficients for the discharged φ_d and recuperated φ_r battery efficiency are modeled:

$$\varphi_d = \frac{P_B^d}{P_E} \qquad \text{for} \qquad P_E \geq 0\ \text{kW} \qquad (4)$$

---

[4] The homogeneous regression model is a kind of linear regression where the intercept is set to zero.

$$\varphi_r = \frac{P_B^r}{P_E} \qquad \text{for} \qquad P_E < 0\ \text{kW} \tag{5}$$

Here, P_B^d and P_B^r are the discharged and recuperated SOC, respectively. Then, the following function is used to compute energy consumption ($P_{O-D}(u_D)$):

$$P_{O-D}(u_D) = \left(0.5 * Cd * \rho a * Af * v^2 + m * g * \left(sin(\alpha) + Cr * cos(\alpha)\right)\right) * v \tag{6}$$

Here, u_D is the amount of SOC needed to make a trip. Finally, the battery discharged and recuperated during the ET trip associated with travel time t_{O-D} is

$$\mathrm{b}_{O-D}^d(u_D) = \emptyset_d * \varphi_d * P_{O-D}(u_D) * t_{O-D} \qquad \text{if} \qquad \mathrm{P}_{O-D}^d(u_D) \geq 0\ \text{kW} \tag{7}$$

$$\mathrm{b}_{O-D}^r(u_D) = \emptyset_r * \varphi_r * P_{O-D}(u_D) * t_{O-D} \qquad \text{if} \qquad \mathrm{P}_{O-D}^r(u_D) < 0\ \text{kW} \tag{8}$$

The proposed SOC model considers plug-in ETs with regenerative braking. For ETs without a regenerative brake, Eqs. (3), (5) and (8) should be disregarded.

The shortest path algorithm used in the proposed model is based on a cost function for the movement of ETs. The algorithm, similar to mobile applications that determine the shortest path of an O-D, is a variation of Dijkstra's algorithm [35], resulting in a shortest path tree for each O-D pair. ET paths are defined according to the algorithm shown in *Fig. 2*.

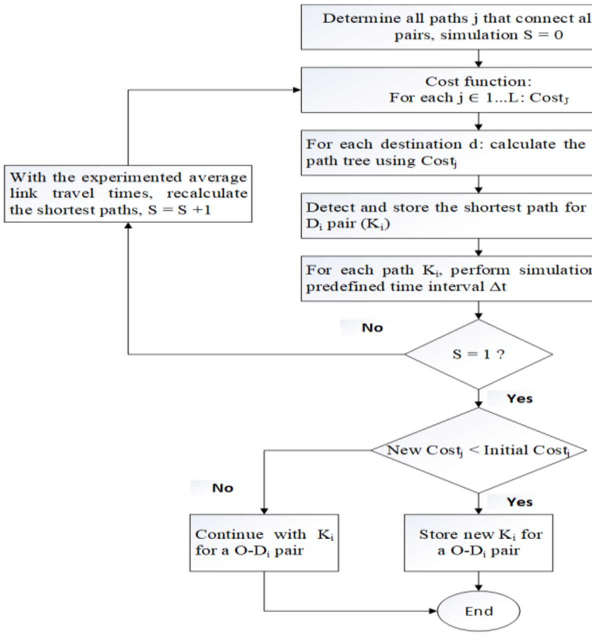

Fig. 2 ETs' shortest path algorithm.

With multiple first paths leading from the O-D structure, the algorithm will first store only the shortest path for each O-D pair. Later, an extra function is executed in order to update the costs (or equivalently, travel times) considering real-time congestion points and streets' speed limits. If equal costs are detected for an O-D pair when storing the data, the first one already stored remains, as costs are only updated if lower values are found.

Simulations should be performed storing in the traffic simulator the streets visited by ETs and their SOC consumption hour by hour. From these hourly records, the streets visited by ETs are summed up and the average and coefficient of variation (CV) of their SOCs are calculated for each simulation in every block. In order to work with a single (summary) value for the SOC, a weighted average is computed, with weights equal to 0.5 for values of SOC with high dispersion (without loss of generality, we assume CVs above 95%, as these values may be sporadic or wrong) and 1.0, otherwise. At the end of these calculations, a spatial database is obtained to create heat maps, where the hottest tonal colors show the most critical locations for the analysis of the Fast-CS installation.

3.3. Definition of Places to Build Fast-CS

To define the places to build Fast-CS, the proposed methodology seeks to meet several criteria in order to find a solution that can meet the needs of the planning agents in the city. Each agent (public, transport department, Fast-CS potential owners, etc.) can provide a spatial database with their conditions and restrictions for Fast-CS construction so heat maps can be created. These maps are superimposed one by one (as layers) pointing at the location of Fast-CSs where a spatial intersection of suitable locations in all layers is found. The spatial intersection is a Boolean intersection operation, using the logical "AND" applied to all regions that meet the criteria defined by the planner as explained in [39] and [40]. The layers used to define places for Fast-CS building are: i) the initial candidates to allocate the Fast-CS; ii) ETs' average SOC along the paths, and iii) the streets visited by ETs.

The proposal considers as main criteria: *highest ETs flow and lowest SOC*. Such criteria can be found in the layers according to the planner's studies and requirements. In the SOC layer, critical locations can be found by an average of hourly SOCs of all ETs that pass through each street. Critical locations are those with a percentage of the average SOC below a threshold defined by the planner. In the ETs flow layer, critical locations can be defined by the percentage of the total number of ETs trips. The candidate places to allocate Fast-CS must be selected considering these critical locations, subject to a minimum distance from each other (adjusted by the planner), preventing them from becoming idle in the case of being very close or overloaded when placed too far. In the literature, this minimum distance between stations is known as the region of influence and it varies depending on factors such as the number of simulated EVs, city size and other socio-economic factors [16].

The strategy for building Fast-CS from the previous layers is performed from a spatial intersection (using the operation "AND") of the critical locations of the SOC consumption and ETs flow layers, differentiating the most critical locations from *medium* critical ones (only SOC or flow location are very critical) and the least critical ones. With this result, a spatial intersection with the layer of initial candidates must be performed. Candidates are represented as points on a spatial map, corresponding to a specific location on the street where they would be placed and, therefore, the flow and SOC associated to them are the ones of the specific locations. For the selection of the winning candidates in the most critical locations to build Fast-CS, the number of chargers (the planner needs to define the number of chargers per station considering economic, technical or capacity constraints) and a region of influence (to exclude nearby candidates) needs to be defined. Finally, winning candidates for medium critical locations and for the least ones must be chosen. Note that if an intersection of a region of influence between two distinct critical zones is found, preference is given to the most critical one.

An example of the spatial intersection is shown in Fig. 3 with the hottest tonal colors representing the most critical locations. In this example, the spatial intersection of Maps 1 and 2, which represent flow and SOC, respectively, is performed. As a result, the most (red areas) and medium (orange areas) critical locations are found in Map 3. With the intersection of these results with Map 4, the Fast-CS allocation in a *most critical* location is found in Map 5 (point A), defining the number of chargers and a region of influence to exclude the nearby candidates. Note that, as shown in Map 5, none of the remaining candidates will be further considered because of this region of influence.

Please note that it is possible to get several locations that apparently have the same conditions to allocate Fast-CSs. However, due to the large number of simulations performed, although the locations might seem equal, if one checks the detailed records, they always have different values and, thus, it is always possible to select the most critical ones in terms of SOC and flow.

Finally, all Fast-CS are allocated in urban zones according to the planning requirements. The planner can vary the number of Fast-CS by varying the radius of the recharging zone and/or choosing to build the Fast-CS in the most critical locations initially and consider an expanding project for the future since the insertion of the ETs should serve as a basis for the subsequent insertion of EVs.

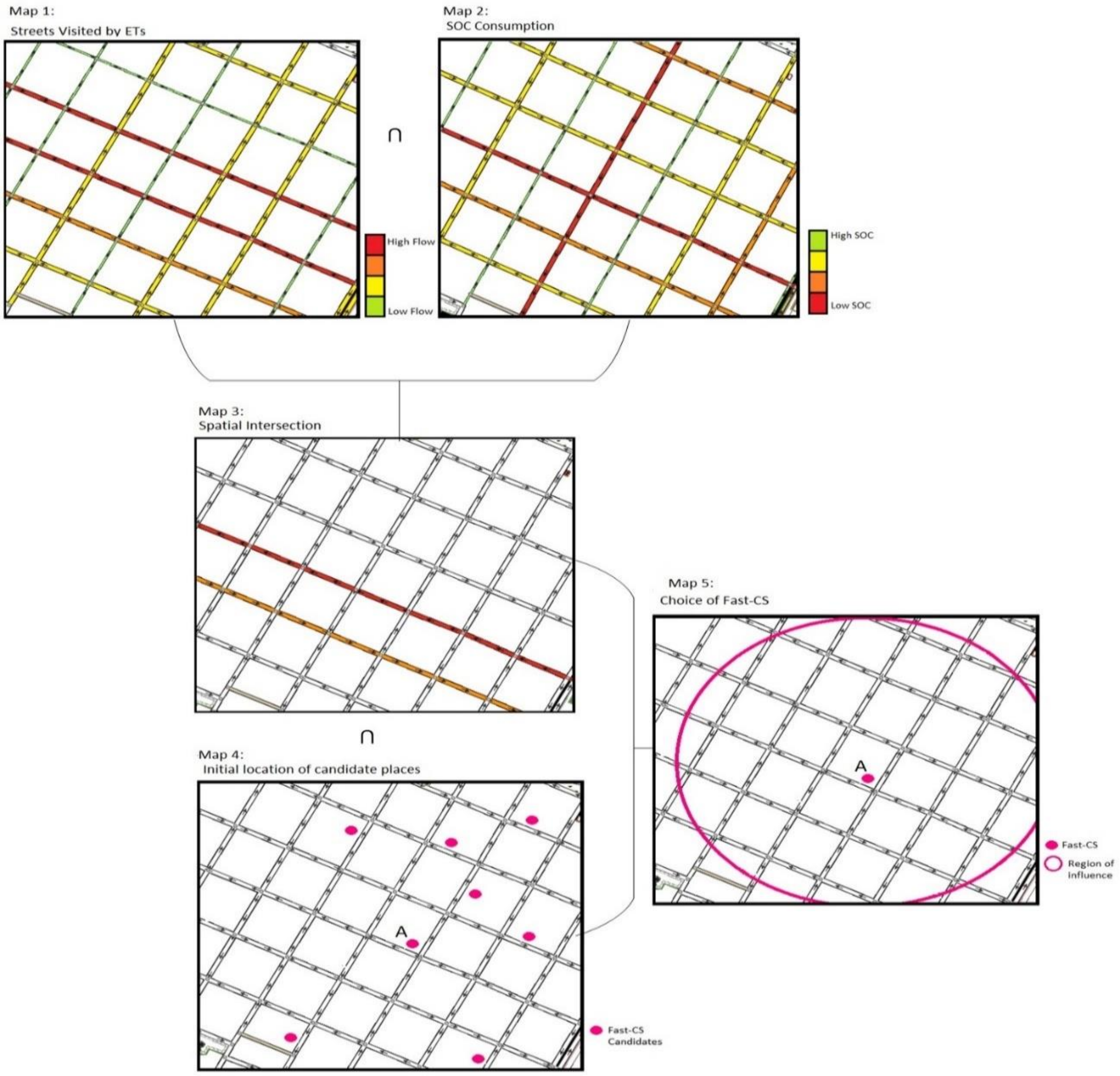

Fig. 3. Example of a spatial intersection.

4. Results

4.1. Data for Simulations

The proposed method is applied to some case studies for a medium-sized Brazilian city with 200,000 inhabitants and 16.56 km². The transportation network is obtained from the internet [41] and modified in AIMSUN [35] for corrections and improvements such as road speed limits, traffic lights, imperfections and identification of the main sectors (residential, commercial, industrial and educational) of the city. The city roads have a total length of approximately 2,000 km with more than 26,000 sections of roads and more than 9,000 intersections. The input data are modeled for each hour of the day and simulations are performed for a full weekday (24 h) starting at 00:00. The choice in modeling the traffic on weekdays is based on other studies [23]; [42]; [43], considering that vehicular traffic must be performed on critical days. On weekends, there is a relief in traffic in every way due to lower vehicle flows.

The number of simulated ETs is 420 (assuming substitution of all combustion) and the fleet of combustion vehicles comprises just over 100,000 vehicles [44]. The percentage of vehicles traveling at each hour of the day is obtained in [45] and shown in Fig 4 (for the sake of simplicity, in this example we assume this quantities to be deterministic but, in the case of cities with *non-stable* percentages, this source of stochasticity can be easily incorporated). O-D pairs are created for combustion vehicles following the ideas shown in Fig. 5. ETs origins are allocated in fifty real cabstand strategic locations (five taxi points, one bus station, six universities, seven hospitals, twenty commercial points, two malls and nine in other locations) and in other points of the city (corresponding to ETs booked by phone/internet) generated randomly taking into account the information in Fig. 5. ETs destinations are allocated following again the information in Fig. 5 for each period of the day and covering the entire city.

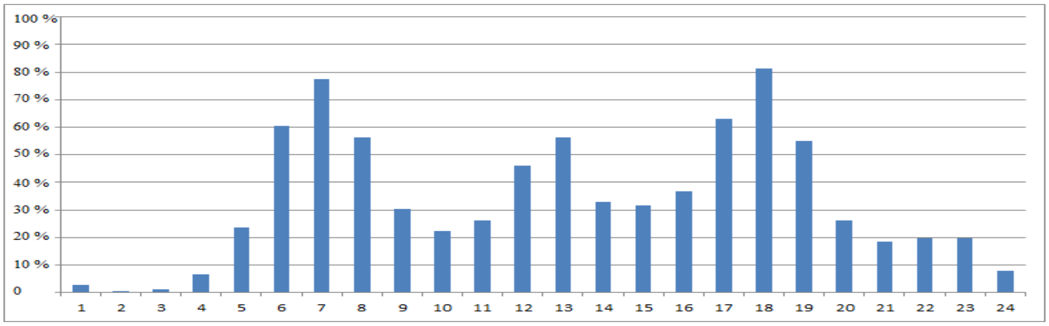

Fig 4. Percentages of vehicles traveling the city at each hour.

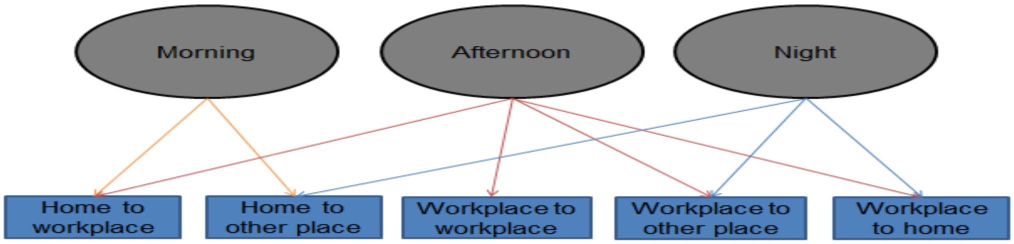

Fig. 5. Main O-D for conventional vehicles per period.

In the study city, about half of the taxis are owned by conventional taxi companies that use fixed origin points and these ETs are used throughout the day (with drivers switching). The remaining taxis belong to private owners who work during part of the day, with mobile services (Uber, 99 Taxi) and wait in the previous destination for the next origin. Thus, ETs take the O-D route and back to the origin in half of the trips. In the other half of the trips, ETs take the O-D route and wait for the next trip in the destination or in a place near it. ET's shortest cost path is used in the simulations to find the shortest paths of the O-D pair.

Maximum speeds are determined by the allowed speed limits and may vary with congestion and traffic lights. Our simulations obtain ETs travel times through ETs speed. ETs SOC for the first trip follows a normal random distribution (25% to 100%) to characterize the randomness of the SOC. Moreover, two different numbers of Fast-CS candidates, 100 and 200, with available physical space are allocated for further analysis with a required area of 25 m² per connector [46], as shown in Fig. 6 and 7. These real physical spaces are found based on suitable places for the construction of Fast-CS. ETs specifications in Table 1 are used to calculate the SOC on the city's roads. Only one type of ET taxi is used, with an average range of 200 km, due to the fact that other Brazilian cities have already used this ET model to replace the combustion taxis fleet [47].

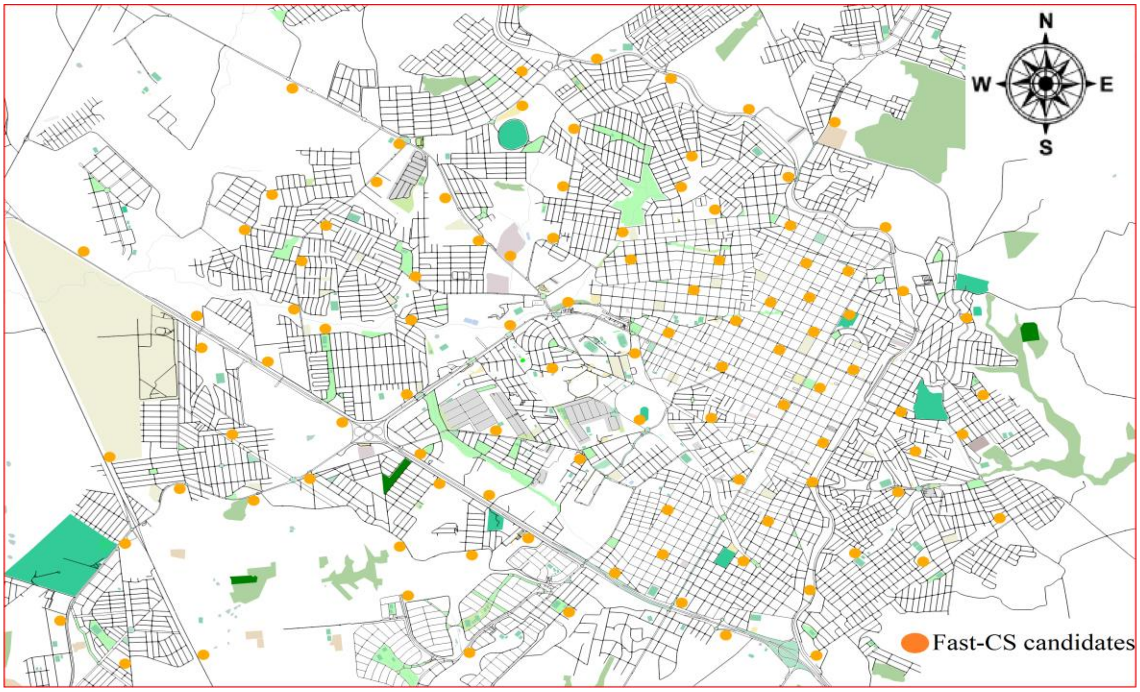

Fig. 6. 100 Fast-CS candidates.

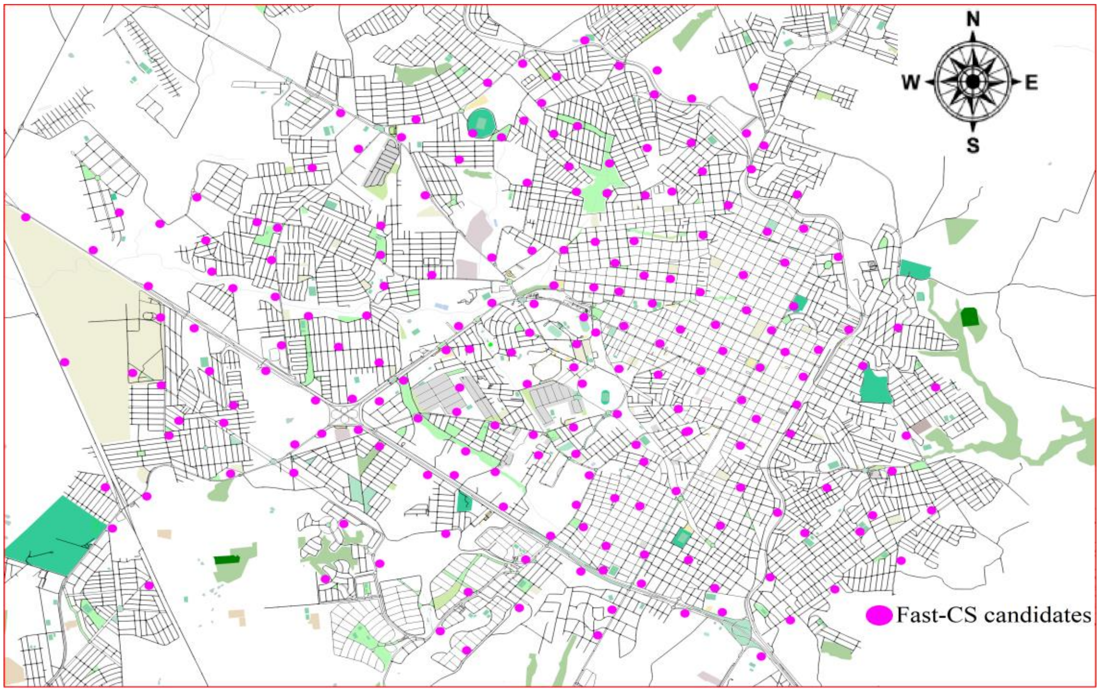

Fig. 7. 200 Fast-CS candidates.

Symbol	Description	Value
m	ET mass	1570 kg
Cd	aerodynamic drag coefficient	0.28
ρa	air density	1.2041 kg/m³
Af	vehicle frontal area	2.7435 m²
g	gravitational constant	9.81 m/s²
α	average gradient angle	2.25
Cr	rolling friction coefficient	0.01

Table 1 – Specifications for ET

4.2. Simulations

The total time taken by the simulations is almost 40 h, with AIMSUN [35] on a computer Intel® Core ™ i7 7700, 3.6 GHz, 16 GB RAM. A large number of simulations were performed to obtain the convergence in the O-D routes and in ETs' SOC along the paths.

Fig. 8 and 9 show the streets visited by ETs and SOC heat maps for a full day respectively, following the simulations. These maps can be made for each hour of the day as well. However, for the sake of brevity, in this paper, 24 hours maps with the sum of all streets visited by ETs and the average SOC consumption are chosen. In the main avenues that connect the center to the periphery, there is a greater flow of ETs due to their driving patterns. The SOC along paths, however, varies more and not always a region with large flows has low SOC levels. In this paper, total flow above 100 ETs and SOC less than 60% are considered as critical, but these criteria can be adapted according to the planners. Due to the high cost of fast charging equipment [48] and taking into account other studies [49] that relate the number of chargers to the number of daily trips; the number of chargers per station is limited to three and follows the rules expressed in *Table 2*.

Chargers per station	State of charge (SOC)	Streets visited by ETs (Flow – number of ETs)
0	SOC > 60 %	Flow < 100
1	20 % < SOC < 60 %	100 < Flow < 200
2	20 % < SOC < 60 %	Flow > 200
2	SOC < 20 %	100 < Flow < 200
3	SOC < 20 %	Flow > 200

Table 2 – Number of chargers per station

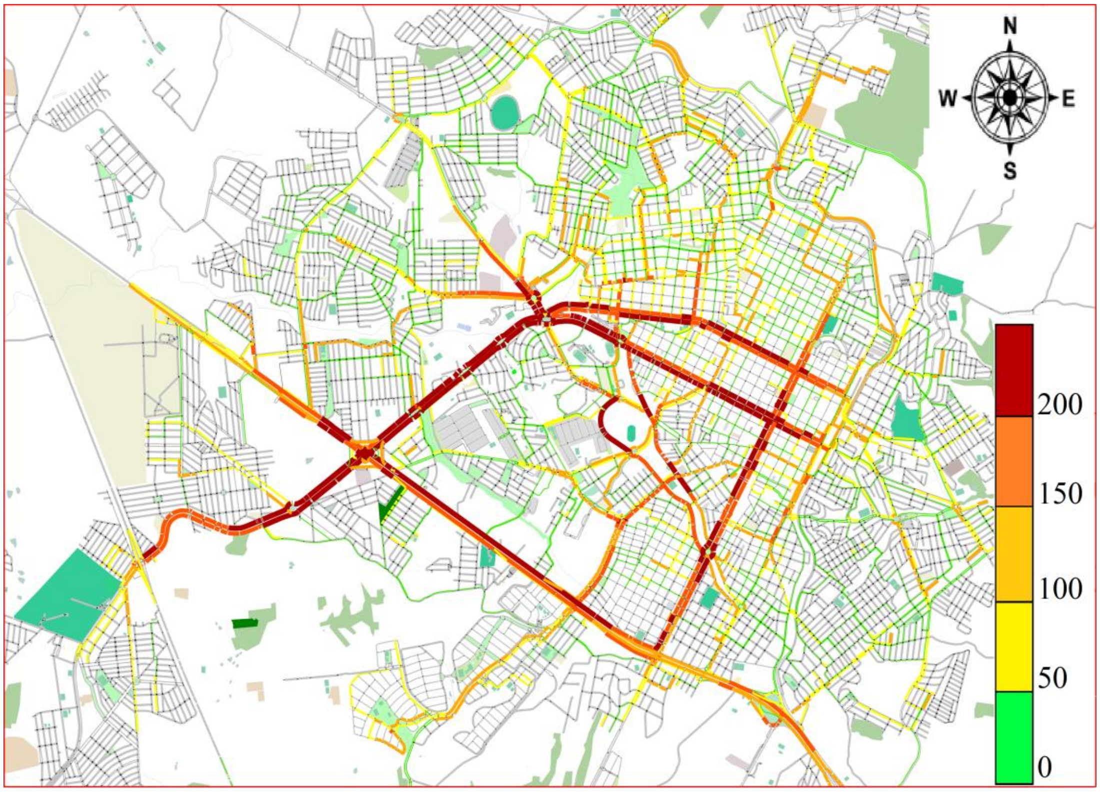

Fig. 8. Streets visited by ETs.

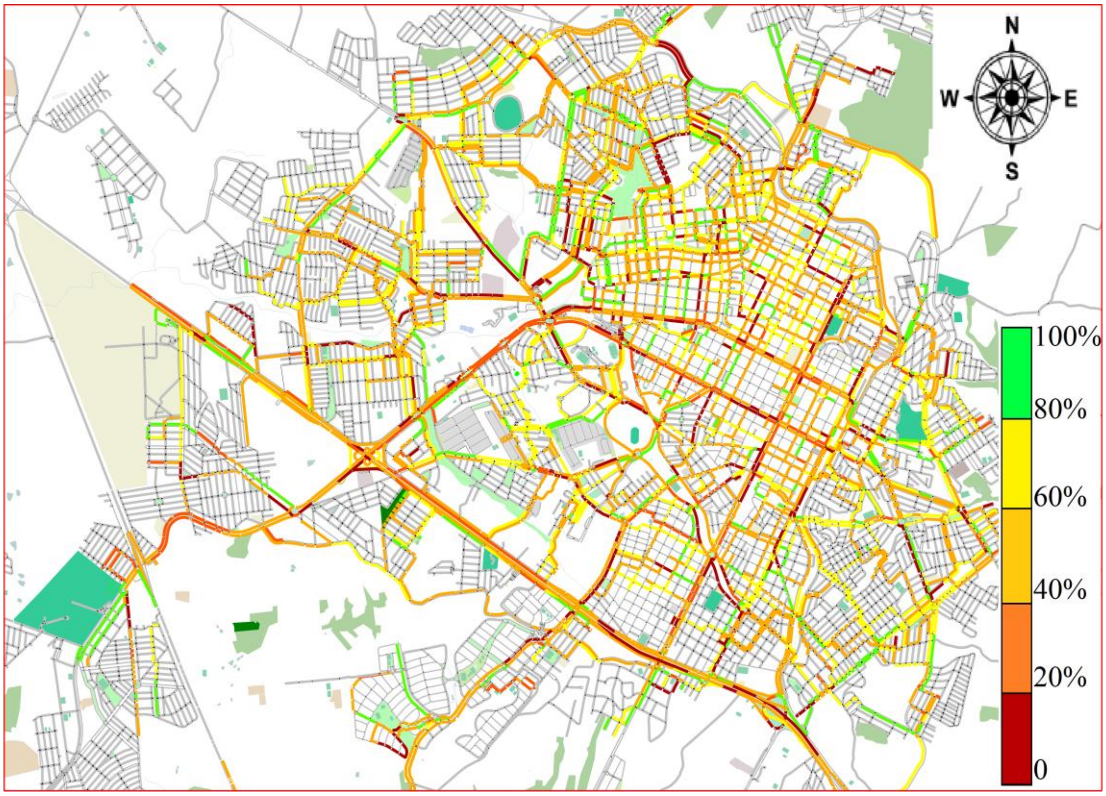

Fig. 9. ETs' average SOC along the paths.

The power of each fast charger is 55 kW [50] and the average time for charging is 20 minutes for SOCs above 20% and 30 minutes for SOCs below 20% [51]. The proposed model allows the creation of several scenarios. Four scenarios are presented in order to exemplify the utility of the proposal. These scenarios were created from the expected goals of Fast-CS growth in the city with a minimum distance from one station to another depending on the number of chargers [46]. Fig. 10 – 13 show the Fast-CS placement for the four cases specified in Table 3. Fast-CS candidates with 3 chargers are initially allocated and its region of influence is determined. If the regions of influence of two or more candidates overlap, some of them should be discarded according to the planners' criteria. Afterwards, Fast-CS candidates with 2 chargers (which lay outside the previous regions of influence) are considered following the same previous ideas. Finally, the process is repeated with Fast-CS candidates with 1 charger. The allocation ends, thus, when there are no more candidates available or all regions of influence overlap when attempting to allocate a new station.

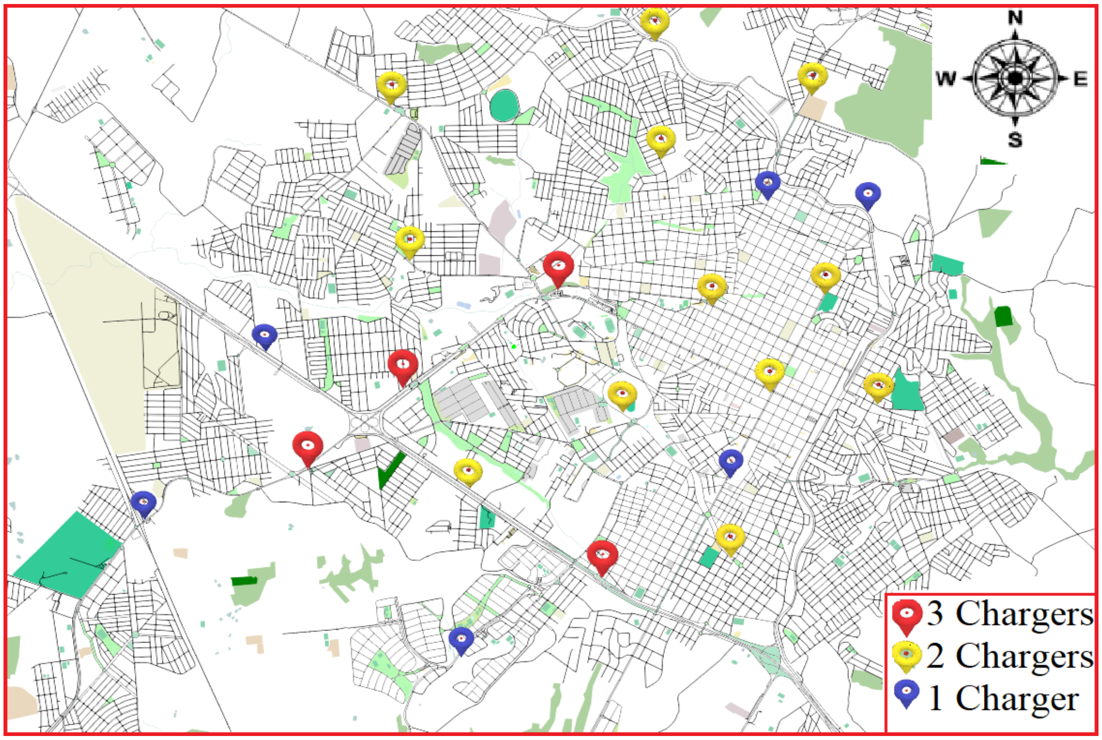

Fig. 10. Fast-CS placement for case I.

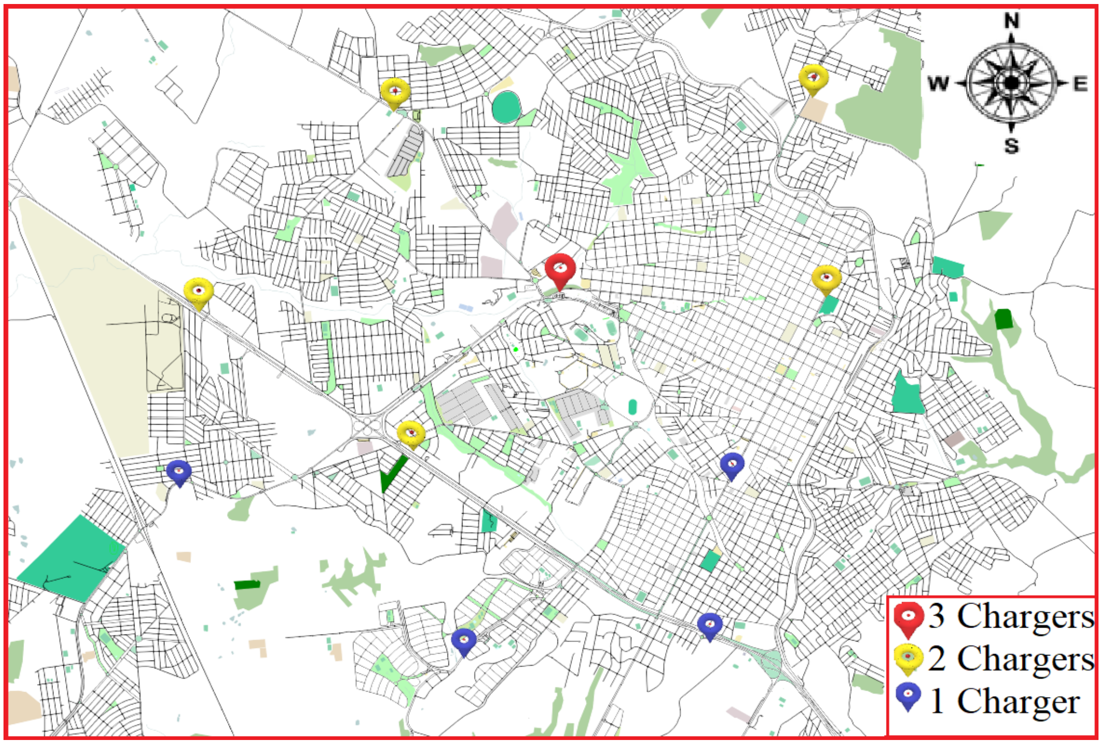

Fig. 11. Fast-CS placement for case II.

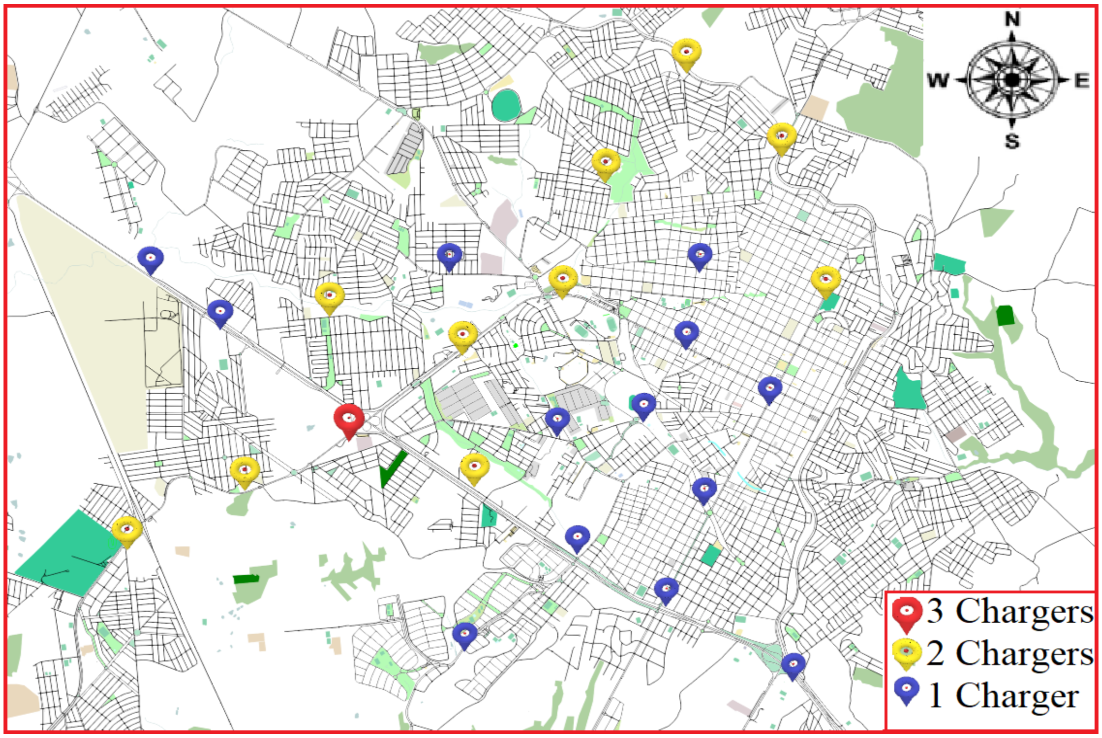

Fig. 12. Fast-CS placement for case III.

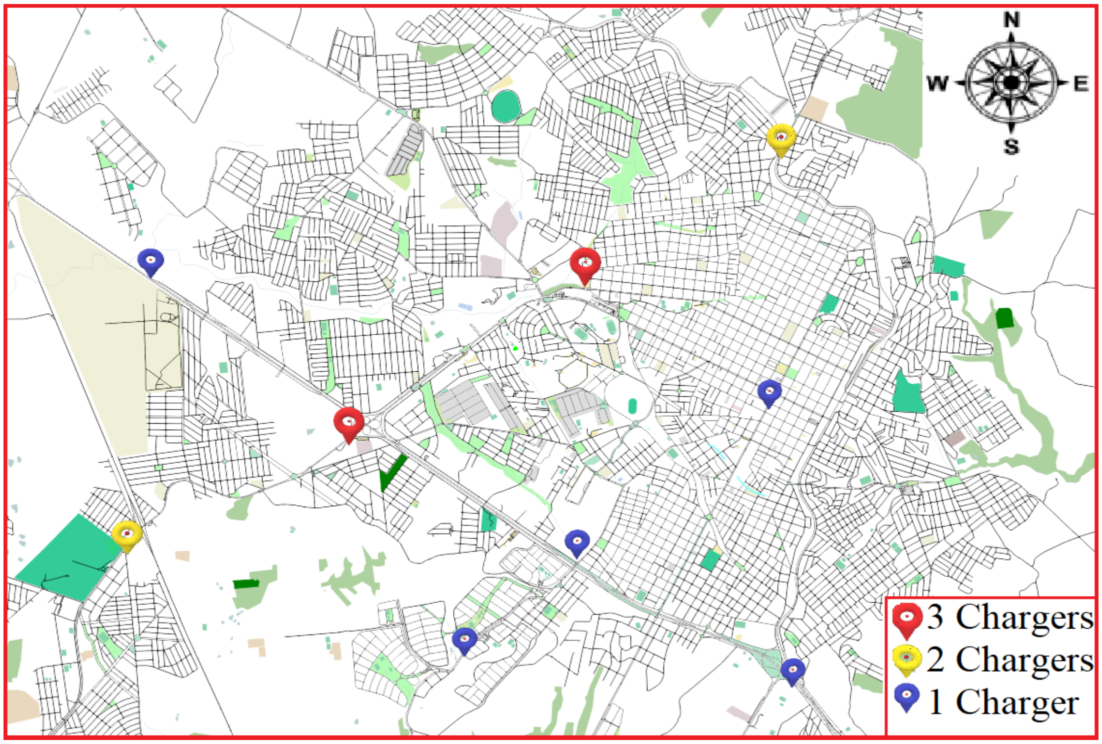

Fig. 13. Fast-CS placement for case IV.

Case	Candidates	Region of influence with 1 charger (km)	Region of influence with 2 chargers (km)	Region of influence with 3 chargers (km)
I	100	0.4	0.5	0.6
II	100	0.8	1.0	1.2
III	200	0.4	0.5	0.6
IV	200	0.8	1.0	1.2

Table 3 – Cases of study

Cases I and III allocate 22 and 24 Fast-CS, respectively. As the region of influence for the recharging zone considered is smaller, more stations are allocated than those in cases II and IV, with 10 and 9 Fast-CS, respectively. Fast-CS in the four cases are located in the main avenues of the city, where the ETs most need recharging (such as shopping malls, gas stations, public squares, commercial centers, etc.). In all cases, the number of stations allocated is sufficient to meet the demand of the ETs throughout the day since there is an availability of chargers for all ETs with less than 20% of SOC at each hour of the day. With more stations, ET will not travel too much to recharge and waiting time will be shorter, but the installation costs will increase. The planner may choose to build fewer Fast-CS, as in cases II and IV, performing an economic analysis and considering a project horizon to build more Fast-CS as more ETs and EVs are introduced in the urban zone.

4.3. Comparison of results

The methodology proposed in this paper is compared with a spatial allocation method of Fast-CS described by Lindblad [52]. The rationale behind the choice of this model for comparison is that the data is also presented in a spatial manner and, thus, is compatible with our data. This spatial allocation method uses the road grid, potential charging places (parking areas, shopping malls, gas stations) and traffic density as input data. The method finds suitable places for EVs to have access to Fast-CS considering spatial factors for the allocation, resulting in a spatial database.

First, using ArcGIS Network Analyst Location Allocation tool [53] to compare the proposals, potential charging places are identified. Then, a series of tools are proposed and the planner uses the most suitable ones for Fast-CS allocation. The tools used include maximizing coverage, minimizing facilities, maximizing market share and target market size. Such tools help the planner find the locations for Fast-CS allocations based on vehicular traffic.

The method is implemented in the same medium-sized Brazilian city with the ArcGIS toolboxes, such as network analyst location allocation and spatial analyst. As a result, 19 places are found for Fast-CS installation, as shown in Fig. 14.

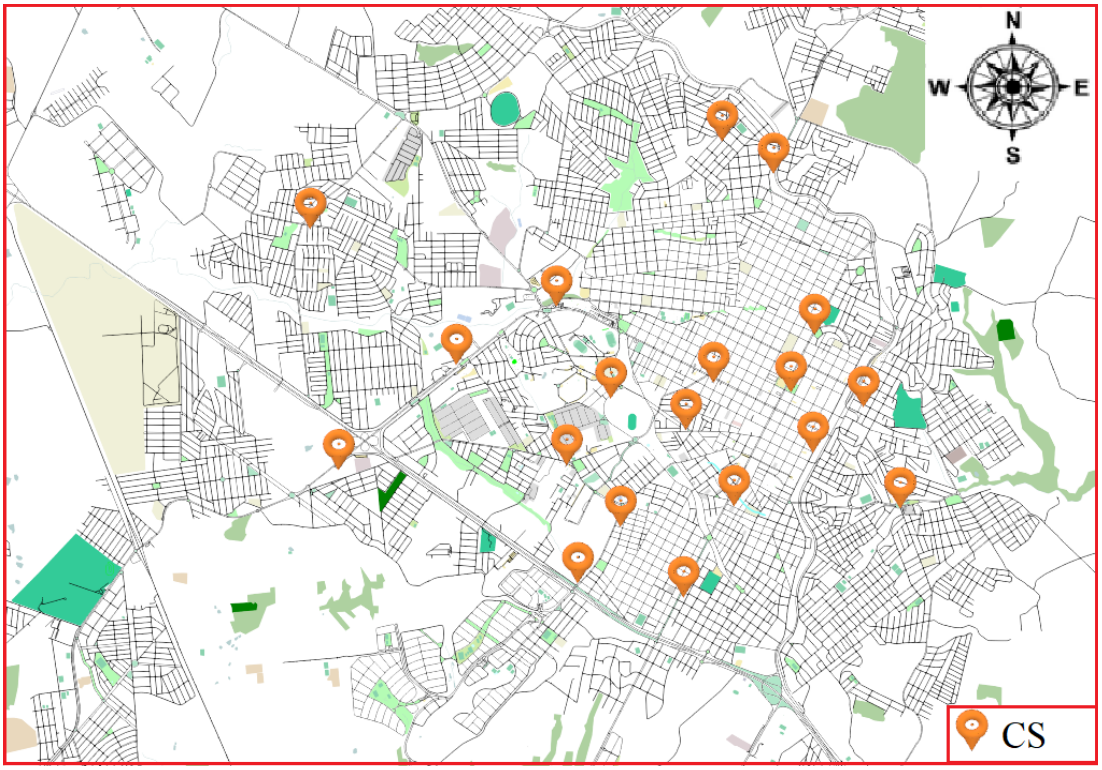

Fig. 14. Method for spatial allocation of Fast-CS proposed in [52].

Comparing the methodology of Lindblad [52] with our work; in the first one, Fast-CS are located mainly in the central zone, leaving them saturated. In addition, Fast-CS are very close to each other (with distances between them of less than 400 meters in some cases), increasing the investment needed (infrastructure, electric expansion, regulations). In our *Case I*, Fast-CS are allocated in higher-flow and lower-SOC places throughout the city, covering all the zones where ETs would need recharging (only 16% of Fast-CS proposed by Lindblad [52] are in residential zones while 32% are in that area in case I). For cases II, III and IV this percentage is 30%, 29% and 33%, respectively. In addition, in our work Fast-CS have different number of chargers depending on the SOC and the streets visited by ETs.

The methodology of Lindblad [52] can cause problems for the sustainable planning of cities because they do not consider important characteristics, being able to allocate Fast-CS in places with high SOC, which can lead to stations very close to each other saturating some regions. The main advantages of our proposal are: a) ETs' SOC along the paths is considered; b) different numbers of chargers in the stations is allowed; and c) simulations for a full day characterized hour by hour are given, thus showing that Fast-CS are distributed in all regions where ETs need to charge.

5. Discussion

The Fast-CS in Fig. 10 – 13 are located mainly in the city avenues, such as shopping malls and commercial areas, but also taking into account the entire urban zone (about a third of Fast-CS in all cases are allocated in residential zones). The analysis of different regions of influence for recharging zones and the number of chargers per station allows the planner to increase the distance between the stations if the Fast-CS is idle or decrease if it is overloaded. The regions of influence also depend on the city. For big cities, the region may be larger depending on the number of ETs circulating. For medium-sized cities, considering radius larger than 1200m can lead to a few stations. Considering small regions of influence can lead to a large number of stations, which would elevate the already costly Fast-CS and overload the electric network.

The proposed method contributes primarily by addressing a city that will carry out incentives for the introduction of ETs. Previous studies mostly consider cities already with EV penetration and treat CS expansion, but many cities in developing countries do not have EVs yet and incentive policies to introduce EVs can be used starting with ETs. The proposed methodology considers that ETs do not have enough time and need Fast-CS. Besides, the combination of real and estimated data to characterize the ETs driving patterns is important, since in most related studies, there is a lack of information on the transportation network. To calibrate the estimated data, the planner must know the city and, thus, the study of zones with similar characteristics can help. The information resulting from the simulations in heat maps helps in data visualization and the evaluation of available physical space must be performed beforehand to avoid indicating unavailable locations.

The proposed method helps in decision making for a company that wants to own a Fast-CS evaluating the places to build them. Moreover, it assists in the sustainable planning of urban infrastructures, the future of transportation network and helps the electricity distribution companies to evaluate the locations and making improvements (if necessary) to meet the demand of the stations.

Future studies can focus on simulating together ETs and EVs, aiming at future incentives for their inclusion with the building of semi-fast CSs (for EVs), considering the driving pattern of private users of EVs and connecting all CSs to the electric network. One of the challenges for electricity distribution companies planning their sustainable energy systems is to provide the necessary power to the stations. Additionally, as part of future work, we plan to include in the simulations the time required by EVs and ETs to recharge their batteries in CSs. Considering different types of CSs (fast, semi-fast, *classical*) in the simulations, will provide insight on the influence of this factor.

6. Conclusion

This paper proposes a methodology for a better allocation of ETs' Fast-CS in cities attending the planning requirements of urban planners and other agencies involved in the installation of Fast-CS, as well as considering some stochastic factors that influence this process.

The proposed method is applied in a medium-sized city, indicating locations to build Fast-CS in from traffic simulations that provide a spatial database of ETs' visited records and the SOC along the streets. This database is visualized in heat maps, which is one of the main contributions of the proposed methodology, allowing the analysis of the candidates and the regions of influence for parking zones. An evaluation of the proposed methodology is performed using an alternative model previously proposed in the literature and the differences and contributions of the methodology proposed in this paper are developed.

Fast-CS allocation is carried out considering criteria to improve their location, helping ETs that will need to go through the urban zone to recharge. The database and heat maps help public and/or private agencies involved in the building process of Fast-CS, the planning of transport network, sustainable planning of urban infrastructures and assist energy distribution companies in electric power planning.

Acknowledgements

This study was financed by CAPES - Finance Code 1806727; by São Paulo Research Foundation (FAPESP) under grants: 2015/21972-6, 2017/01909-3, 2017/22577-9, by CNPq under grant: 307281/2016-7.

The authors gratefully acknowledge Professor Dr. Humberto de Paiva Junior for his support with traffic simulation methods.

References

[1] A. Rajabi-Ghahnavieh, P. Sadeghi-Barzani, Optimal Zonal Fast-Charging Station Placement Considering Urban Traffic Circulation. IEEE Trans Veh Technol 2017;66:45–56. doi:10.1109/TVT.2016.2555083.

[2] H. Yang, Y. Deng, J. Qiu, M. Li, M. Lai, Z.Y. Dong, Electric Vehicle Route Selection and Charging Navigation Strategy Based on Crowd Sensing. IEEE Trans Ind Informatics 2017;13:2214–26. doi:10.1109/TII.2017.2682960.

[3] O. Hafez, K. Bhattacharya, Optimal design of electric vehicle charging stations considering various energy resources, Renew. Energy. 107 (2017) 576–589. doi:10.1016/j.renene.2017.01.066.

[4] V. Gass, J. Schmidt, E. Schmid, Analysis of alternative policy instruments to promote electric vehicles in Austria, RENE. 61 (2014) 96–101. doi:10.1016/j.renene.2012.08.012.

[5] J. Liu, T. Zhang, J. Zhu, T. Ma, Allocation optimization of electric vehicle charging station (EVCS) considering with charging satisfaction and distributed renewables integration, Energy. 164 (2018) 560–574. doi:10.1016/j.energy.2018.09.028.

[6] E.O. Lawrence, All Electric Passenger Vehicle Sales in India by 2030: Value proposition to Electric Utilities, Government, and Vehicle Owners Nikit Abhyankar Anand Gopal Won Young Park Amol Phadke Energy Analysis and Environmental Impacts Division 2017.

[7] Volvo Car Group, Sustainability Report, Gothenburg, Sweden, 2015.

[8] Z. Tian, T. Jung, Y. Wang, F. Zhang, L. Tu, C. Xu, Real-Time Charging Station Recommendation System for Electric-Vehicle Taxis. IEEE Trans Intell Transp Syst 2016;17:3098–109. doi:10.1109/TITS.2016.2539201.

[9] P.Z. Levay, Y. Drossinos, C. Thiel, The effect of fiscal incentives on market penetration of electric vehicles: A pairwise comparison of total cost of ownership. Energy Policy 2017;105:524–33. doi:10.1016/j.enpol.2017.02.054.

[10] A. Awasthi, K. Venkitusamy, S. Padmanaban, R. Selvamuthukumaran, F. Blaabjerg, A.K. Singh. Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm. Energy 2017;133:70–8. doi:10.1016/j.energy.2017.05.094.

[11] C. Çetinkaya, Optimal siting of electric vehicle charging stations : A GIS-based fuzzy Multi-Criteria Decision Analysis, 163 (2018). doi:10.1016/j.energy.2018.08.140.

[12] T. Conway, On the Effects of a Routing and Reservation System on the Electric Vehicle Public Charging Network. IEEE Trans Intell Transp Syst 2017:1–8. doi:10.1109/TITS.2016.2641981.

[13] Z. Yang, L. Sun, J. Chen, Q. Yang, X. Chen, K. Xing, Profit maximization for plug-in electric taxi with uncertain future electricity prices. IEEE Trans Power Syst 2014;29:3058–68. doi:10.1109/TPWRS.2014.2311120.

[14] F.V. Cerna, M. Pourakbhari-Kasmaei, R. Romero, M.J. Rider, Optimal Delivery Scheduling and Charging of EVs in the Navigation of a City Map. IEEE Trans Smart Grid 2017;3053:1–1. doi:10.1109/TSG.2017.2672801.

[15] A.Y.S. Lam, Y.W. Leung, X. Chu, Electric vehicle charging station placement: Formulation, complexity, and solutions. IEEE Trans Smart Grid 2014;5:2846–56. doi:10.1109/TSG.2014.2344684.

[16] Z.H. Zhu, Z.Y. Gao, J.F. Zheng, H.M. Du, Charging station location problem of plug-in electric vehicles. J Transp Geogr 2016;52:11–22. doi:10.1016/j.jtrangeo.2016.02.002.

[17] J. Asamer, M. Reinthaler, M. Ruthmair, M. Straub, J. Puchinger, Optimizing charging station locations for urban taxi providers. Transp Res Part A Policy Pract 2016;85:233–46. doi:10.1016/j.tra.2016.01.014.

[18] H.J. Vermaak, K. Kusakana, Design of a photovoltaic-wind charging station for small electric Tuk-tuk in D.R.Congo, Renew. Energy. 67 (2014) 40–45. doi:10.1016/j.renene.2013.11.019.

[19] M.F. Shaaban, A.A. Eajal, E.F. El-Saadany, Coordinated charging of plug-in hybrid electric vehicles in smart hybrid AC/DC distribution systems, Renew. Energy. 82 (2015) 92–99. doi:10.1016/j.renene.2014.08.012.

[20] D.M. Tovilović, N.L.J. Rajaković, The simultaneous impact of photovoltaic systems and plug-in electric vehicles on the daily load and voltage profiles and the harmonic voltage distortions in urban distribution systems, Renew. Energy. 76 (2015) 454–464. doi:10.1016/j.renene.2014.11.065.

[21] H. Abdi, B. Mohammadi-ivatloo, S. Javadi, A.R. Khodaei, E. Dehnavi, Energy Storage Systems. Distrib Gener Syst 2017;31:333–68. doi:10.1016/B978-0-12-804208-3.00007-8.

[22] F. Malandrino, C. Casetti, C.F. Chiasserini, A Holistic View of ITS-Enhanced Charging Markets. IEEE Trans Intell Transp Syst 2015;16:1736–45. doi:10.1109/TITS.2014.2371478.

[23] M.M. De Weerdt, S. Stein, E.H. Gerding, V. Robu, N.R. Jennings. Intention-Aware Routing of Electric Vehicles. IEEE Trans Intell Transp Syst 2016;17:1472–82. doi:10.1109/TITS.2015.2506900.

[24] TSS – Transport Simulation Systems. Aimsun7 Dynamic Simulators User's manual, 2012.

[25] S.G. Fishman, Monte Carlo Concepts, Algorithms, and Applications. New York, USA: Springer, 1996.

[26] K. Vincent, R.E. Roth, Q. Huang, N. Lally, S.A. Moore, H. Rosenfeld, improving spatial decision making using interactive maps: An empirical study on interface complexity and decision complexity in the North American hazardous waste trade, (2018). doi:10.1177/2399808318764122.

[27] V.E. Alekseev, R. Boliac, D.V. Korobitsyn, V.V. Lozin, NP-hard graph problems and boundary classes of graphs. Theor Comput Sci 2007;389:219–36. doi:10.1016/j.tcs.2007.09.013.

[28] S. Micari, A. Polimeni, G. Napoli, L. Andaloro, V. Antonucci, Electric vehicle charging infrastructure planning in a road network, Renew. Sustain. Energy Rev. 80 (2017) 98–108. doi:10.1016/j.rser.2017.05.022.

[29] V. Gass, J. Schmidt, E. Schmid, Analysis of alternative policy instruments to promote electric vehicles in Austria, RENE. 61 (2014) 96–101. doi:10.1016/j.renene.2012.08.012.

[30] A. Hira, L. Guilherme, D. Oliveira, No substitute for oil ? How Brazil developed its ethanol industry $, 37 (2009) 2450–2456. doi:10.1016/j.enpol.2009.02.037.

[31] I. Rahman, P.M. Vasant, B.S.M. Singh, M. Abdullah-Al-Wadud, N. Adnan, Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle

charging infrastructures, Renew. Sustain. Energy Rev. 58 (2016) 1039–1047. doi:10.1016/j.rser.2015.12.353.

[32] H. Shareef, M.M. Islam, A. Mohamed, A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles, Renew. Sustain. Energy Rev. 64 (2016) 403–420. doi:10.1016/j.rser.2016.06.033.

[33] J. Jung, J.Y.J. Chow, R. Jayakrishnan, J. Young, Stochastic dynamic itinerary interception refueling location problem with queue delay for electric taxi charging stations, Transp. Res. Part C. 40 (2014) 123–142. doi:10.1016/j.trc.2014.01.008.

[34] Y. Zou, S. Wei, F. Sun, X. Hu, Y. Shiao, Large-scale deployment of electric taxis in Beijing : A real-world analysis, Energy. 100 (2016) 25–39. doi:10.1016/j.energy.2016.01.062.

[35] Transport Simulation Systems—TSS, Trial Version, v. 8.2, Barcelona, Spain, 2017. Available: http://www.aimsun.com/

[36] Q. Ge, B. Ciuffo, M. Menendez, An exploratory study of two efficient approaches for the sensitivity analysis of computationally expensive traffic simulation models. IEEE Trans Intell Transp Syst 2014;15:1288–97. doi:10.1109/TITS.2014.2311161.

[37] W.M. Griggs, R.H. Ordonez-Hurtado, E. Crisostomi, F. Hausler, K. Massow, R.N. Shorten, A Large-Scale SUMO-Based Emulation Platform. IEEE Trans Intell Transp Syst 2015;16:3050–9. doi:10.1109/TITS.2015.2426056.

[38] D. Goeke, M. Schneider, Routing a mixed fleet of electric and conventional vehicles. Eur J Oper Res 2015;245:81–99. doi:10.1016/j.ejor.2015.01.049.

[39] D. Latinopoulos, K. Kechagia, A GIS-based multi-criteria evaluation for wind farm site selection. A regional scale application in Greece, Renew. Energy. 78 (2015) 550–560. doi:10.1016/j.renene.2015.01.041.

[40] Y. Zhang, Q. Zhang, A. Farnoosh, S. Chen, Y. Li, GIS-Based Multi-Objective Particle Swarm Optimization of charging stations for electric vehicles, Energy. 169 (2020) 844–853. doi:10.1016/j.energy.2018.12.062.

[41] Open Street Map, Open Data Commons Open Database License, 2018. Available: https://www.openstreetmap.org/

[42] J. Rominger, C. Farkas, Electrical Power and Energy Systems Public charging infrastructure in Japan – A stochastic modelling analysis, Int. J. Electr. Power Energy Syst. 90 (2017) 134–146. doi:10.1016/j.ijepes.2017.01.022.

[43] G.S. Bauer, B.F. Gerke, Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan, Renewable and Sustainable Energy Reviews, 2018. doi:10.1021/acs.est.7b04732.

[44] P.S.S Matsumoto, E.F. Flores, Spatial Statistics in Geography: A Study of Traffic Accidents in Presidente Prudente –SP. Geografia em Atos – GEOATOS, 2012.

[45] Synthesis of information, Mobility Research, 2013. Available: https://www.mobilize.org.br/midias/pesquisas/pesquisa-de-mobilidade-da-rmsp-20121.pdf

[46] P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh, H. Kazemi-Karegar, Optimal fast charging station placing and sizing. Appl Energy 2014;125:289–99. doi:10.1016/j.apenergy.2014.03.077.

[47] A.C.R. Teixeira, J.R. Sodré, Simulation of the impacts on carbon dioxide emissions from replacement of a conventional Brazilian taxi fleet by electric vehicles, Energy. 115 (2016) 1617–1622. doi:10.1016/j.energy.2016.07.095.

[48] R.J. Flores, B.P. Shaffer, J. Brouwer, Electricity costs for an electric vehicle fueling station with Level 3 charging. Appl Energy 2016;169:813–30. doi:10.1016/j.apenergy.2016.02.071.

[49] J. Rominger, C. Farkas, Electrical Power and Energy Systems Public charging infrastructure in Japan – A stochastic modelling analysis, Int. J. Electr. Power Energy Syst. 90 (2017) 134–146. doi:10.1016/j.ijepes.2017.01.022.

[50] Magnum Cap, MCR63 Charger - Electric Vehicle Charging for service stations, parks and workshops fleets of electric vehicles, 2013.

[51] D. McPhail, Evaluation of ground energy storage assisted electric vehicle DC fast charger for demand charge reduction and providing demand response, Renew. Energy. 67 (2014) 103–1408. doi:10.1016/j.renene.2013.11.023.

[52] L. Lindblad, Deployment Methods for Electric Vehicle Infrastructure 2012.

[53] ESRI, ArcGIS Desktop 10.5, 2017.