Efficient Allocation of Electric Vehicles Charging Stations: Optimization Model and Application to a Dense Urban Network

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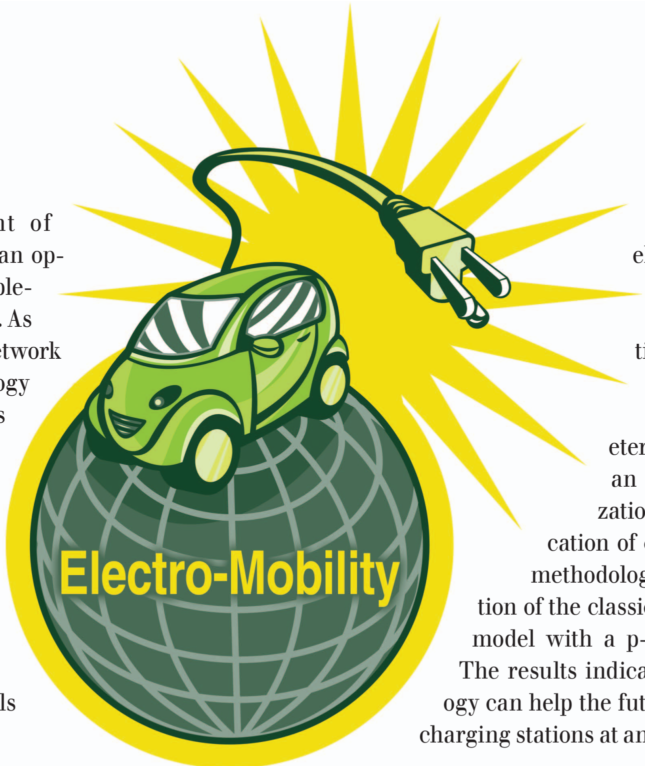

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Abstract—The deployment of Electric Vehicles (EVs) needs an optimized and cost-effective implementation of charging stations. As a decision support tool for network design, we define a methodology to allocate charging stations in a real network. This study uses trip OD matrix information from household travel survey coupled with a dynamic vehicle model to evaluate EVs consumption based on realistic trips (urban drive cycles). These trips are computed based on routing tools and supplied with elevation information. This enables an accurate characterization of energy needs in the Lyon Metropolitan Area. All these parameters are used as inputs of an integer linear optimization program for the location of charging stations. The methodology is based on an adaptation of the classic fixed charge location model with a p-dispersion constraint. The results indicate that this methodology can help the future implementation of charging stations at an urban scale.

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I. Introduction

In response to the European Economic Recovery Plan [1], the French authorities launched in 2009 a national plan for the deployment of charging infrastructure in order to promote the electro-mobility. This plan emphasizes that "Developing clean technologies for cars and construction" is one of the key objective to be addressed in order to recover from the environmental and economic crisis. Key stakeholders were encouraged to design and set up a network of charging stations (CS). These installations should include all types of configurations in terms of type of CS and location such as: public roads, parking, and workplace. In its latest report [2], the French Environmental and Energy Management Agency (ADEME) set standards and norms for the allocation of charging stations while drawing the roadmap to the expansion of these infrastructures. The latter incorporates the main elements of the "Roadmap to a Single European Transport Areas" [3] and included three key parameters for the establishment of a national charging network, which are:

1) *Standardization of the charging infrastructure*: this includes all the issues such as the interoperability of charging structures, security, infrastructure competitiveness, user comfort and convenience, and an optimized management of the energy consumption.
2) *Regulatory framework and a viable business model to ensure the integration and success of the EV*. This includes incentives of EV's ownership and smart grid using recycling battery technology.
3) *Trade-off between the deployment of the charging stations and the capacity of the electric vehicle battery in order to ensure resilience of the whole system*. Achieving a balance between these interactions is a key parameter to be taken into account in the strategy for the deployment of the charging infrastructure.

In this paper, one of the main points that should be emphasized is the standard that must be applied when designing a charging infrastructure. Concerning the type of charger, three types of terminals are identified: (i) slow charging points to be implemented in residential areas or long stay parking, (ii) semi-rapid charging points mainly at public park and (iii) fast charging stations along major urban motorways and dense road traffic. The charging standards are presented in Table 1.

Table 1. Charging station terminal type and cost.

Level	Type	Power (kW)	Usage	Server and Link Cost (k €)
I	Slow charging terminal	3.6	Home, parking…	1
II	Semi-rapid charging terminal	22	Office, public, park.	5~7
III	Fast charging terminal	43-AC / 50-DC	Motorway, large urban area	50

The goal of this paper is to present a methodology for the optimal location of charging stations. The proposed methodology is based on an adaptation of the Fixed Charge Location [4] with the p-Dispersion constraint [5]. More specifically, we adapt a linear model based on these two classical location models. Instead of fixing the charging stations in specified demand zones, our model focuses on minimizing the total travel cost from these demand zones to the charging station location together with the server investment cost. The energy demand was derived from a vehicle consumption model developed as part of the VEHLIB model library [6] [7]. The energy consumption was assessed by VEHLIB based on realistic trips generated from routing tools and enriched with elevation profile. This effort allowed us to accurately approximate the real energy needs in addition to the trip demand derived from the OD matrix household travel survey of the Rhône region. For the validation, a case study covering the Lyon Metropolitan Area was set and various configurations of the EVs market penetration rate were introduced.

The article is organized as follows. In section 2, we present a state of the art of the allocation problem with a special focus on the electric vehicle charging station assignment. The modeling approach and the VEHLIB library are presented in section 3. The study case and results of the simulation are presented in section 4. Conclusions and prospects for future work are presented in section 5.

II. Review of Location Models

The advent of electro-mobility brings new challenges and research issues. Indeed, several challenges came up with this e-mobility, including those related to charging stations. Many researchers and stakeholders tackled the issue of design and standardization of charging points. With respect to the allocation of charging stations, several subtopics have been identified including the choice of the type of charging stations, the size effect (number of points), etc.

The problem of the allocation of charging stations has attracted many research efforts in the last five years [8]–[16]. Most of the proposed methods and models are derived from the resources/work sites location and Emergency Medical Services (EMS).

Seminal work on location problems was based on the traditional set-covering problem. Set covering describes the minimum number of facilities required to meet all the system demand. A population is considered covered when a facility is located within the maximal coverage distance. Church and Revelle [17] presented the Maximal Covering Location Problem (MCLP) to maximize the total amount of served population within a maximal service distance, given a fixed number of facilities.

The class of discrete models is one of the most studied problems and considered among the easiest ones. However, the resolution is quite difficult due to their complexity. This class includes the Maximum Distance Models (MDM), its general form is known to be NP-hard [18]. However, the use of linear relaxation often gives integer solutions. It can also be solved efficiently with heuristic methods, and some authors recommend the use of a Lagrangian relaxation coupled with a branch and bound algorithm [19]–[21].

Many variants of this problem are discussed in the literature that covers many applications such as emergency services (ambulances or/and firefighting vehicles), petrol stations and cell-phone antennas. The most cited algorithm in the literature to solve this problem is the "greedy-set-cover" which takes a greedy approach [22]. The objective is to minimize the number of objects/vehicles mobilized to cover all the demand points. This model assumes the availability of an unlimited number of resources, which is rarely the case in real world situations. To overcome this limitation Churche and Revelle [17] have proposed an extension of this problem by developing the "Maximal Covering Location Problem".

In [23] and [24], Hakimi introduced the "P-center" problem. The objective is to determine the allocation of p-centers in a network in order to minimize the maximum distance between all the users and the closest center (server) [25]. This model helps to determine the location of public facilities, such as schools and emergency services. The objective is to design a system that minimizes the distance traveled by the users, where each site could be reached within a reasonable time.

The "Median" models aim at minimizing the weighted distance between a requesting node and nearest facility. Many applications of this problem exist especially in the areas of computer networks (location and file servers) and communication (implementation of antennas), activities, service and military applications (strategic centers). Within this class, the most well-known approach is the P-median [23] [24].

In dispersion models, the main objective is to determine an assignment (location) server in order to maximize the dispersion of the latter. An application of this approach can be found in antenna's allocation where the objective is to maximize the dispersion in order to optimize the area covered. This point is critical to avoid interference and minimize wave frequencies transmitted by each antenna.

One progress in the discrete models family deals with the discrete multiple covers problems. Among these works, one can highlight Schilling et al. [24] contributions with three models: The Facility-Location Equipment Emplacement Technique (FLEET), the Tandem Equipment Allocation Model (TEAM) and the multi-objective version of the TEAM model (MOTEAM).

The Team/Fleet Models extend the classic "MCLP" model to include the distribution of specialized facilities. This approach is relevant when the demand needs to be covered with multiple server types. They proved that this representation can easily be applied to the location/allocation of stations.

Discrete models have shown some limitations, since when a given server is assigned to a demand zone, other demand zones in the same coverage area may potentially be uncovered [27]. Actually, it is more relevant to assign multiple servers in order to assure that all the demand zones are covered even if one of the servers is busy. To overcome this constraint several attempts focused on the probabilistic assignment problem. One of the first probabilistic models is the "Maximum Expected Covering Location" which was introduced by Daskin [27]. It assigns to each server a probability q, where q is the probability that a server is busy. This probability is estimated by dividing the total length of the intervention by the number of the servers.

Several extensions of this model exist, including "TIM-EXCLP" where the authors [28] have introduced uncertainty in the travel time of ambulances/servers, while keeping the structure of the initial model. Revelle et al. [29] proposed the "Maximum Availability Location Problem". Interested readers can refer to [19], [25], [30] for more details about different problems and their respective solutions.

The set-covering problem has then been adapted to the placement of refueling stations and more recently to electric vehicles. The pioneered attempts of Wang [8]–[11] reformulate the covering problem as a mixed-integer program that will determine the optimal placement of refueling stations. Frade et al. [12] proposed a model maximizing the covering of demand clusters during morning and evening peak hours.

The following table lists the major contributions to the domain with the type of models and the constraints considered for the electric vehicles charging station topic.

III. Modeling Approach

To address the problem of Electric Vehicle (EVs) charging station allocation, an adaptation of the fixed charge location model with a p-dispersion constraint is proposed. Hence the travel cost used in the classical formulation is modified so as to handle the specificities of EVs. Many factors influence the EV's range and consumption, such as Battery type (lead Acid, LI-Ion), distance traveled, road topology (elevation) and driving behavior (desired speed, acceleration, prevailing traffic conditions, the battery temperature…).

Many studies focused on the desired trip range to estimate the consumption needed for the charging stations location models. However, other factors need to be considered. In our model, we defined a methodology to deal with these factors. First, we used an OD matrix to determine the mobility needs and derive the energy demand. This

OD matrix was derived from the largest household travel survey conducted in the metropolitan area of Lyon, France [31]. We constructed the demand zones (or clusters) based on the OD demand trips on the destinations. From each OD couple a trip was constructed according to routing API where the optimum travel time was selected as the traveler choice criteria. Next, we enriched these trips with elevation information provided by the IGN Alti-Maps Database. Finally, we applied a dynamic consumption model from the VEHLIB library to provide realistic consumption estimation. Figure 1 summarizes our methodology.

A. Optimization Model

Our optimization model selects a set of charging stations to place from the candidate location sites, with the objective of minimizing the charging station fixed cost and the EVs travel cost. Our model includes three sets of constraints. One is that each demand cluster is associated to one charging station. The second is the capacity restriction constraint, which requires that the total power provided to vehicles does not exceed the capacity of the selected charging station. The third is the non-proximity constraint, which forces the model to locate the charging stations with a minimum radius r. In what follows we introduce the models parameters with more details:

J: set of candidates charging stations sites.
I: set of demand clusters.
f_j: cost of locating a charging station in candidate site i.
D_i: energy demand at cluster i.
d_{ij}: energy needed for a vehicle to travel from demand cluster i to charging station j.
r: minimal distance between two charging stations.
dist_{ij}: distance between charging station i and charging station j.
C_j: capacity of charging station j.
α: kilowatt hour cost (can be multiplied by a pay-off period T).
$n_i^{(ev)}$: number of EVs traveling to zone/cluster i.
Decision variables:

$$x_j = \begin{cases} 1 & \text{if we locate a station } i \text{ in candidate site } j \\ 0 & \text{Otherwise} \end{cases}$$
$$y_j = \begin{cases} 1 & \text{if demand cluster } i \text{ is covered by the station } j \\ 0 & \text{Otherwise} \end{cases} \tag{1}$$

Model:

$$\mathrm{Min} \sum_{j \in J} f_j x_j + \alpha \sum_{i \in I} \sum_{j \in J} n_i^{(ev)} d_{ij} y_{ij} \tag{2}$$

$$\sum_{j \in J} y_{ij} = 1, \forall i \in I \tag{3}$$

$$y_{ij} - x_j \leq 0, \forall i \in I, \forall j \in J \tag{4}$$

$$\sum_{i \in I} n_i^{(ev)} (D_i + d_{ij}) y_{ij} \leq c_j x_j, \forall j \in J \tag{5}$$

$$r x_i x_j \leq \mathrm{dist}_{ij}, \forall i, j \in I \tag{6}$$

$$x_j \in \{0,1\}, j \in J, r \geq 0 \tag{7}$$

$$y_{ij} \in \{0,1\}, i \in I, j \in J. \tag{8}$$

The equation (2) represents the optimization function. The objective is to minimize the total cost and the total distance traveled by all vehicles to access the selected charging stations. Equation (3) and (4) assume that each demand cluster is covered by one charging station. The constraint (5) ensures that the demand assigned at location j is not beyond the capacity c_j of that charging station. Indeed, since demand D_i at a cluster i is the sum of all the downstream trips derived from the OD matrix, this implies that the total energy to be covered by a charging station j must include the travel energy cost from this cluster to the located charging station.

The last constraint is derived from the p-dispersion problem [5]. This non-linear constraint forces each server to be separated with a minimum radius r. It can be simplified to a linear constraint, see below:

$$r + (M - d_{ij}) x_i + (M - d_{ij}) x_j \leq 2M - d_{ij}. \tag{9}$$

Where M is a big number (fixed to max (dist_{ij})). Finally, constraints (7) and (8) define y_{ij} and x_j as 0 or 1 integrals and r > 0.

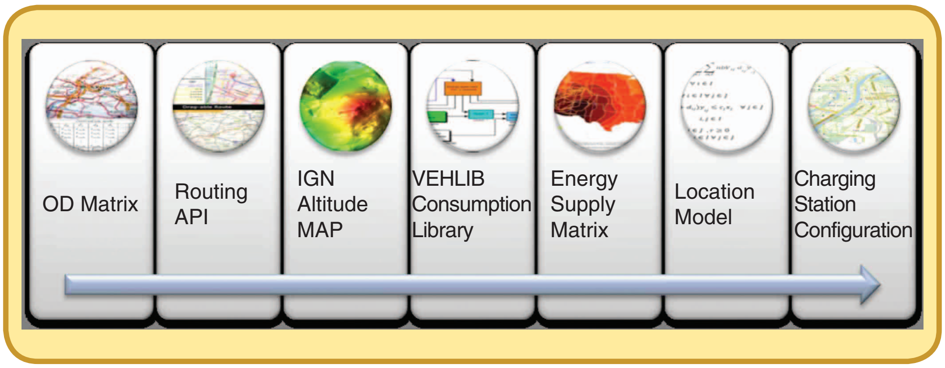

FIG 1 Charging station location methodology.

B. The Vehicle Consumption Model

In this paper, we use an accurate consumption model to derive the cost of the energy needed. For this purpose, we use a real time consumption model from the VEHLIB library [7].

VEHLIB is a modular library that combines different vehicle models. The approach used in the modeling is to consider the studied vehicle as an association of different sub-systems, each sub-system representing a component of the vehicle (figure 2). The parameters of the components may be either identified by experimentation or directly given by the manufacturer data.

Two type of approaches can be used for simulation in VEHLIB: backward and forward. The backward approach enables a consumption estimation given a velocity profile whereas the forward approach, more suitable for the vehicle control studies, shows the speed behavior of the studied vehicle according to a required speed profile using a driver model.

Figure 2 shows a synoptic of the EV model developed under VEHLIB and used in this paper. One can identify two main parts: the mechanical and the electric drive train. For the mechanical part, the VEHLIB library is based on the reproduction of the forces acting on the vehicle according to the desired acceleration (a) and speed (v) to define the necessary drive train torque output T_{drive} from the Newton's second law:

$$T_{\text{drive}} = {J_{\text{veh}} \times a}/{R_{\text{tire}}} + F_{\text{res}}(v)\, R_{\text{tire}}, \tag{10}$$

where J_{veh} is the equivalent vehicle inertia, R_{tire} is the tire radius and the resistance forces F_{res} depend on the vehicle speed. It can be computed as a sum of rolling resistance, aerodynamic drag and road grade on the chassis (see figure 2).

$$F_{\text{roll}} = C_r\, M_{\text{veh}}\, g \cos(\alpha) \tag{11}$$

with C_r the coefficient of rolling resistance, which depends on the vehicle load and wheel radius, g is the gravitational constant and M_{veh} the vehicle's total mass (chassis, drive train, engine and passenger).

$$F_{\text{aero}} = \frac{1}{2}\, \rho_{\text{air}}\, S_f\, C_x(\alpha_r)\, V_r^2, \tag{12}$$

where ρ_{air} the volumic mass of the air, S_f is the front surface of the vehicle, C_x the shape coefficient, α_R is the relative angle of the wind and V_R is the relative vehicle velocity according to the wind velocity.

$$F_{\text{grade}} = M_{\text{veh}}\, \text{g} \sin(\alpha) \tag{13}$$

with g the gravity acceleration and α the inclination of the road segment.

For the electric drive train, the Electric Engine and its inverter (the power electronics) are modeled using an efficiency map identified on the entire use area of the motor. The most critical component of the EV, which is the battery, is modeled using electric equivalent circuits. The parameters of these circuits depend on the State of Charge (SoC) and the temperature of the battery. A simple thermal model of the battery is also available but difficult to calibrate because it depends on the battery blocs' arrangement and the cooling device used (air, water, flow). For all the simulations in this study, the battery temperature is supposed to be kept constant at 20 °C. The impact of this assumption on the energy consumption is minor if the ambient temperature lies in the following range: 10 °C to 30 °C. At very low temperature a part of the battery's energy is used to its self-heating. At very high temperature, the battery supplies energy to the coaling device which consumption could be low but not negligible. In order to assess the impact on the energy consumption, an accurate thermal and cooling model is needed and different scenarios of use should be studied. This is beyond the scope of this paper.

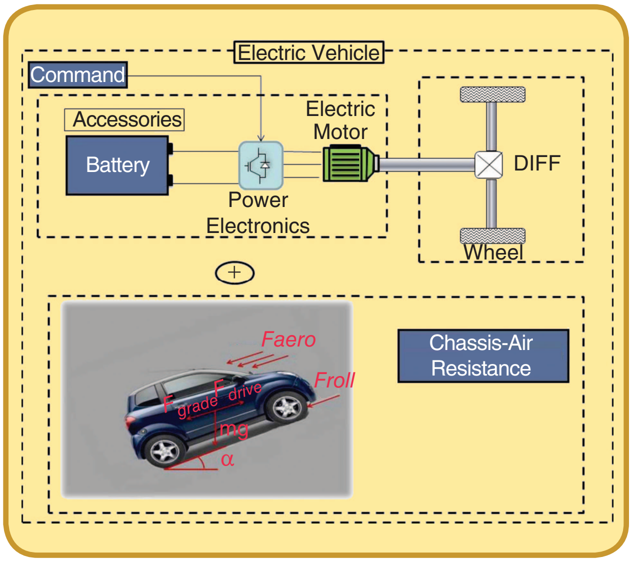

FIG 2 Synoptic of EV model within VEHLIB Library.

In order to get realistic simulation results from VEHLIB, two validation phases are used: the first one studies the components independently and the second one is a complete validation of the entire system where all the sub-systems are connected. The resulting models are validated by measures on engine, electric motor and battery test benches as well as on chassis dynamometer for the entire vehicle. In the case of the studied EV, battery model parameters have been identified using a single bloc charge and discharge tests. The battery bloc is installed in a thermostatic container in order to control its temperature. Electrical supply and load allow steady state and transient battery current variation. The vehicle manufacturer has provided the electric motor and mechanical transmission data. The whole vehicle has been tested on the Laboratory chassis dynamometer by reproducing real-word recorded driving profiles. The simulation model presents an energy consumption error of about 5% compared to the chassis dynamometer tests.

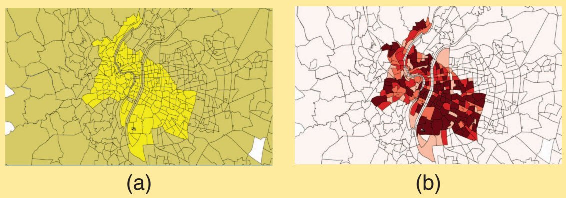

FIG 3 (a) Test site within the Lyon metropolitan area. (b) Energy demand map.

IV. Data and Result

A. Data Description

The resolution of the Fixed Charge Dispersion Location Model (FCDLM) is proposed for the Lyon Metropolitan Area. This city is composed of 9 districts with more than 500 000 inhabitants and a motorization rate of 0, 47 [32]. The OD matrix used for this section was derived from the household travel survey of the Rhone Region, France. Initially, this OD matrix was composed of 843×843 OD pairs, the dimension being reduced to 42×42 for the 9 districts of Lyon (cf. figure 3).

The EV mobility demand was modeled as energy clusters: these clusters were constructed from all the OD couples. Between an origin and a destination, shortest paths were computed using two routing tools:

1) OSRM: An open source API based on Open Street Map [33].
2) Bing Map: a web mapping service provided by Microsoft [34]. A free academic license was used.

These two routing APIs' yield shortest paths outputs as GPS traces (GPX and JSON format). Then, these files were adapted and transformed to speed profiles (speed time series) and completed by elevation profiles collected from the IGN (French Geographical Institute) Alti-Map database. The resulting speed/elevation profiles were computed on a backward version of the VEHLIB library to evaluate the energy consumption of each OD pair. The studied vehicle is an urban model characterized by a 20 KWh battery capacity. We chose this configuration to be close to the vehicles fleet currently available on the market. This enabled us to construct the demand matrix D_i (42×42) and supply cost matrix d_{ij} (42×72). The distance matrix dist_{ij} (72×72) can be computed using an Euclidean distance (or by shortest path distance) between all the potential sites.

For the first study, the potential charging sites were selected from the existing petrol stations and public parking facilities. We assume that the fuel station will be equipped with fast chargers (43 KW AC/50 KW DC) whereas the parking lots with semi-fast chargers (22 KW). We also define two proportion parameters, one for the number of slow chargers depending on the size of the parking (e.g. 2% of the total capacity) and the other for the EVs penetration rate. The minimal radius r was fixed to 1 km (i.e. 0.62 miles). The fixed cost of the servers is summarized in Table 1.

B. Results

The modeling approach was validated on a real case study. The resolution of the linear integer program was achieved by the Matlab® extension of ILOG CPLEX Solver. The studied model is composed of 1,869 constraints and 1,796 binary variables.

It should be noted that the classic Fixed Charge Location Model belongs to the NP-hard problem class [12] and that the resolution depends on the problem instances even

Table 2. Literature review about the electric vehicles charging station allocation problem.

Author	Objectives	Constraints	Type of Terminal
[9]	Minimization of the CS location cost for electric scooter	Demands to be satisfied	Type I or II
[8]	Minimization of CS location cost	Limit on the amount of charging vehicles Number of stations	Battery change
[10]	Minimization of the charging stations allocation cost	Limit on the amount of charging vehicles Number of stations	Type III or battery change
[11]	Minimization of maximal covering and minimum allocation cost	Constraint on the amount of charging vehicles Number of stations	Type III or battery change
[12]	Maximizing the covering of demand clusters during morning and evening peak hours	Constraints on the slot numbers in charging stations Limit on the number of charging stations	Type I
[14]	Maximization of the charged vehicles/the energy recharged	Constraints on the number of charging vehicles Capacity constraint	Type I
[16]	Minimization of trips to charging stations	Demand satisfaction Limit on the number of charging EVs	Type I
[15]	Minimization of vehicles trips to a set of CS	Demand satisfaction Limits on the number of CS	Type I, II or III

with powerful solvers. We studied instances where the time resolution is consistent (limited to up to 24 hours per instance). We simulated different configurations of charging station locations with different parameters. The first simulation consisted in varying the number of vehicles that require simultaneously to be recharged. We will name these vehicles "recharge-needed vehicles—RNV". The EVs penetration rate was fixed to 10%. This rate has been chosen based on one of the EVs European penetration rate schemes for 2020 (see [2] and [35]).

Charging stations are located at attractor areas such as shopping centers or Center Business District. The model is robust and shows a relevant evolution according to the evolution of simultaneous recharge-needed vehicles.

The second simulation optimizes the location configuration by varying the penetration rate and total satisfaction of all this demand simultaneously (see Figure 4 for the model output).

Table 3 shows the results of the first simulation, for all these instances no fast charging station was selected. This is due to the high cost of such device (55 k €) and the limited number of chargers (6 chargers max by fast CS) compared to the semi-fast charger (5.2 k€ – 7 k€). Moreover the number of chargers depends on the size of the park site. The total location cost and the amount of energy supplied are also provided.

This preliminary analysis highlights consistent results. Charging stations are located at attractor areas such as shopping centers or Center Business District. The model is robust and shows a relevant evolution according to the evolution of simultaneous recharge-needed vehicles.

The second part of the simulation (Table 4) provides the deployment of the CS according to a given demand (note that the goal here is to satisfy all the 50% of the EV) with a variable penetration rate.

The results show the located charging stations and the chargers needed to satisfy 100% of the demand for 1% to 20% of vehicle integration based on the real travel demand in the LMA during afternoon peak hour (17:00).

In contrast with the first simulation that was prospective in terms of penetration rate (10% as predicted for the 2020 horizon), the second simulation is very close to current penetration rates figures in Lyon. For both simulations, we can see that charging stations are well separated thanks to the dispersion constraints.

As a first conclusion, the proposed model is robust and able to adapt to the demand changes. The model outputs can be seen on figure 4. In addition to these preliminary conclusions based on realistic parameters values, sensitivity analyses are carried out in order to have a closer look at the model's behavior.

Note that the α parameter defined on section III.C can be weighted (using a multiplication) by the pay-off period T to achieve a long-term optimization scheme. For our study

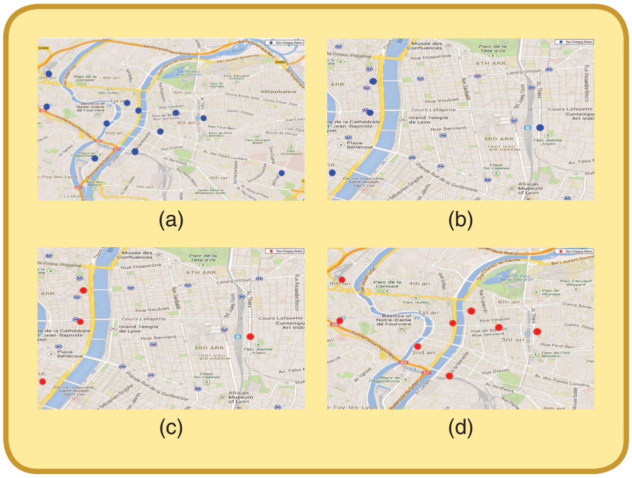

FIG 4 Simulation results. Lyon (France) Using Google Maps. (a) In blue: 20% EVs rate and 50% Simultaneous RNV. (b) In blue: 2% EVs rate and 50% Simultaneous RNV. (c) In red: 10% EVs rate and 10% Simultaneous RNV. (d) In red: 10% EVs rate and 70% Simultaneous RNV.

Table 3. Demand satisfaction for 10 % electric vehicle penetration rate.

RNV	10%	20%	30%	40%	50%	60%	70%	80%
EV integration rate	10%	10%	10%	10%	10%	10%	10%	10%
Radius (meters)	1000	1000	1000	1000	1000	1000	1000	1000
Semi-fast CS	4	2	7	7	8	8	8	11
Fast CS	0	0	0	0	0	0	0	0
Number of chargers	117	231	352	469	581	682	810	934
Kwh charged	754	1557	499	613	650	582	524	722
Location cost (k–€)	819	1617	2464	3283	4067	4788	5670	6538

Table 4. Variation in the electric vehicle integration rate.

RNV	50%	50%	50%	50%	50%	50%	50%
EV integration rate	1%	5%	8%	12%	15%	18%	20%
Radius (meters)	1000	1000	1000	1000	1000	1000	1000
Semi-fast CS	3	7	8	9	10	9	11
Fast CS	0	0	0	0	0	0	0
Number of chargers	56	293	468	721	878	1044	1135
Kwh charged	987	675	629	522	506	455	912
Location cost (k–€)	392	2051	3276	5047	6146	7308	7945

Table 5. Nominal parameters values.

Parameter	Nominal Value
Recharge-needed vehicles	50%
EV rate	10%
Minimum radius (m)	1000

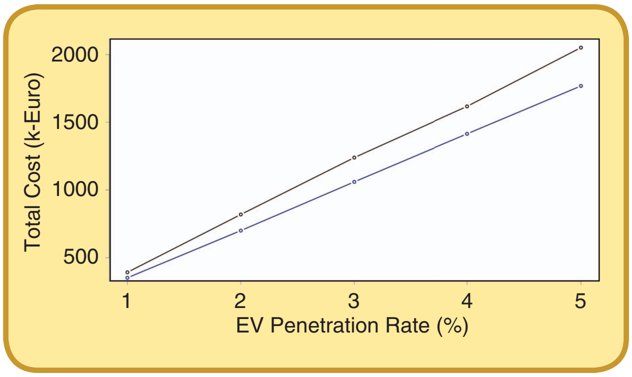

FIG 5 Simulation results. Evolution of the total cost (k€) compared to the EV penetration rate. Configuration 2 (black) and configuration 1 (blue).

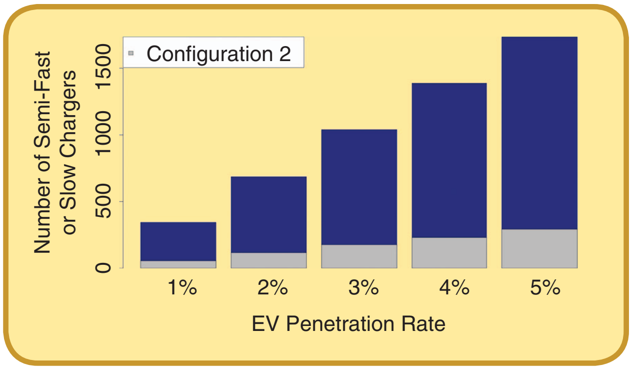

FIG 6 Number of semi-fast (configuration 2 in grey) and slow (configuration 1 in blue) chargers proposed by the model to satisfy the demand.

we used several combinations (from 1 day to 2 years) and all the solutions converged to almost the same CS assignment when keeping fixed all the other parameters. Since it had no major influence on the computed solutions we have used a fixed value for T for the whole simulation process.

C. Sensitivity Analyses

In order to assess the robustness of the model's outputs to parameters' uncertainties, a set of sensitivity analyses is conducted [36]. The penetration rate scheme was derived from [37], in which 15 European studies analyzing the 2020 forecasts were reviewed. It shows that the expected part of EVs ranges from 5% to 20%.

Three types of chargers are available: (i) Level 1—slow chargers (3.6 kW), (ii) Level 2—semi-fast chargers (22 kW) and (iii) Level 3—fast chargers (50 kV~43 KW). We set up two types of configurations:

- Configuration 1: Level 1 and Level 3 chargers (terminals),
- Configuration 2: Level 2 and Level 3 fast.

It is worth noticing that for configuration 1, identical results are obtained by replacing fast chargers by semi-fast chargers. Therefore, the experimentations will consist in comparing a "power configuration" (configuration 2) to a "number configuration" (configuration 1). The first step is to observe the evolution of the total cost compared to the penetration rate of EVs. The method is the basic "One Factor At a Time" (OFAT) method that consists in making one parameter vary on time while keeping the others to their nominal values. Nominal values are presented in Table 5.

To be close to current EV vehicles penetration rate the model was firstly run with an increasing penetration rate from 1% to 5%. Figure 5 shows the evolution of the total cost for the different configurations. It is clear that the increase of the EV penetration rate, and thus the demand, goes together with a cost increase. Although both models satisfy the demand, it can be noticed that as expected configuration 2 lead to a higher cost than configuration 1, but 5% integration rate is the limit of the configuration 1 for the actual data collected for LMA (no feasible solution found by the solver).

In a context of low penetration rate, one can see a balance between power (configuration 2) and cost (configuration 1). However, while the number of fast chargers is null for both configurations, one advantage of the power solution is the limited number of semi-fast chargers needed compared with the amount of slow chargers used in configuration 1. This contrast is exhibited in the figure 6.

As the EV penetration rate is expected to increase in the coming years, it is relevant to achieve a prospective experimentation with higher penetration rates. In realistic

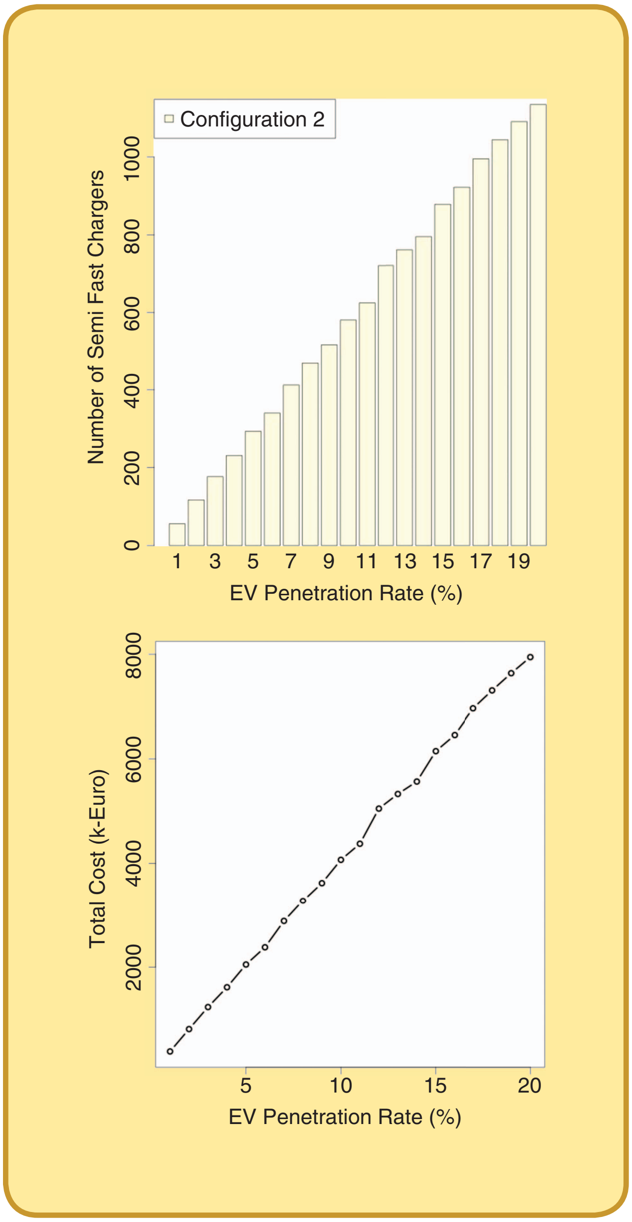

FIG 7 Simulation of an increasing penetration rate. Only configuration 2 is able to satisfy the demand with an increasing cost and number of semi-fast chargers.

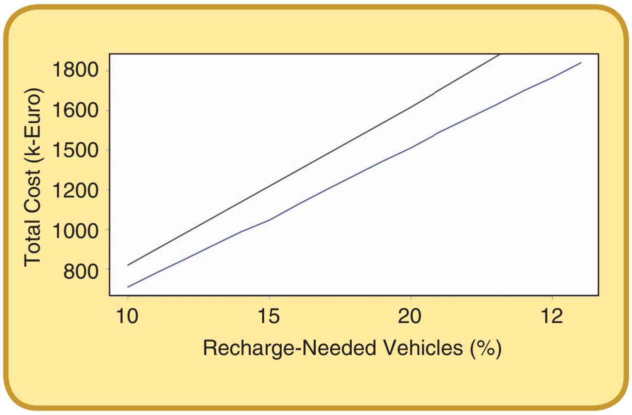

FIG 8 Increasing number of recharge-needed vehicles.

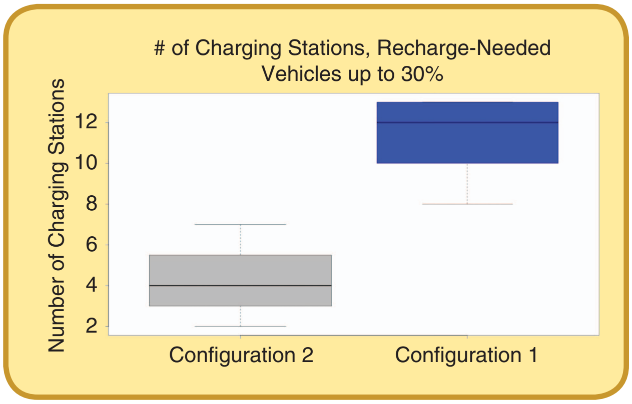

FIG 9 Boxplots of the number of charging stations selected by the model in case of a proportion of recharge-needed vehicles ranging from 0 to 30%.

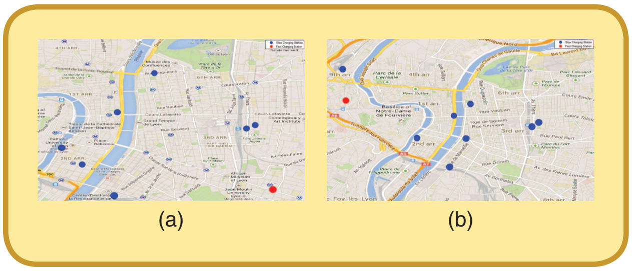

FIG 10 Assignment scheme with Fast CS (reduced cost to 10 k*) in Red and semi fast CS (Blue). Lyon (France) using Google Maps. (a) EV rate 7%, RNV 50%. (b) EV rate 12%, RNV 50%.

conditions, there is no more solution in configuration 1, the power configuration being the only one to satisfy the demand, as showed on figure 7.

The solution cost depends also on the number of recharge-needed vehicles. With the advances in charging technology, the time needed to charge partially of totally the battery will dramatically decrease in coming years. Hence, the rate of vehicles that will need to recharge before completing their trip will increase. Figure 8 illustrates the cost impact of such an increase.

Regarding the solutions the model selects details, once again, no fast charging stations and there is only a competition between a significant amount of slow charging stations (and thus, chargers) and a reasonable amount of semi-fast stations.

Figure 9 shows this contrast by observing the distribution of the number of charging stations for both configurations for a proportion of recharge-needed vehicles ranging from 0 to 30%. The non-selection of fast charging stations in the proposed solutions underlines that the single cost is too high to enable the choice of these technologies, given the current context.

However, a numerical investigation offers insights on the requirements and a mix of CS for a future implementation.

FIG 11 Geographical allocation of charging stations according to minimum radius variations. Lyon (France) using Google Maps. (a) Minimal distance: 1000 m. (b) Minimal distance: 2000 m. (c) Minimal distance: 3000 m. (d) Minimal distance: 4500 m.

Indeed, by dividing the individual cost by 5, i.e. shifting from 55 k€ to 11 k€, first, fast charging stations are selected (see Figure 10).

Another parameter of interest is the minimum distance between the stations, i.e. the radius r. Figure 11 shows the sensitivity of the model to this critical parameter. It clearly indicates that a small radius r results in a high concentration of stations in the city center (center of the map). Increasing this value leads to a dispersion of charging stations towards the suburbs. As a matter of fact, the minimum distance is a key parameter to be tuned by the electro-mobility operator. A higher distance between the stations will reflect on the cost but provides an efficient geographical coverage while a small distance could be effective in dense and smaller networks such as large French cities.

V. Conclusion

We have presented a study on the location of EV charging stations for the city of Lyon. Results show that the EVs will mainly have to be refueled at public-parking with semi-fast type chargers (22 KW) and in private petrol station-like for the fast charging (50 KV~43 KW). The methodology proposed in this study brings many innovative contributions as it relies on accurate estimates of both travel demand based on a comprehensive OD Matrix and the energy demand is computed by a dynamic consumption model from the VEHLIB library. This model is applied to real trips constructed with routing tools enhanced with an elevation profile to reflect the real vehicle consumption. This refined approach allows to obtain relevant energy-demand profiles. Next, the locations of charging stations are modeled by a modified Fixed Charge Location Model mixed with a p-dispersion constraint. This model minimizes the trip energy and total location cost and satisfies all the mobility energy demand. A sensitivity analysis has been carried out in order to validate our model according to the electric vehicle penetration rate and the total simultaneously refueled vehicles.

Based on these findings, some conclusions can be stressed. First, a dynamic consumption model derived from the VEHLIB library provides a high accurate energy consumption. This model takes into account all the parameters that influence the vehicle consumption estimation (speed, acceleration and road profile). It also shows that this model can easily be adapted to the electric charging station location problem as long as OD matrix data and OD trip are available. Simulations have shown that increasing the number of semi-fast chargers enables a demand satisfaction and a cost-effective investment in rapid charging station.

As a future extension of this work, the studied case will be enlarged to the city of Lyon and its suburbs. Additional cars models will also be used as inputs of the consumption model. With respect to the optimization model, the performances have to be compared with other variants or constraint configurations. A more complete sensitivity analysis will be performed including a stochastic extension in terms of vehicles arrival at a charging station.

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