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Customer-driven design of the recharge infrastructure and Vehicle-to-Grid in urban areas: A large-scale application for electric vehicles deployment

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ABSTRACT

The large scale deployment of electric vehicles in urban environment will play a key-role over the next decades to reduce air-pollutants in densely populated areas, but it will also require the development of an adequate recharge infrastructure. The purpose of this paper is to demonstrate how driving patterns databases and data mining can be used to appropriately design this infrastructure. This application focuses on the Italian province of Firenze, involving about 12,000 conventional fuel vehicles monitored over one month, estimating a fleet share shift from conventional fuel vehicles to battery electric vehicles ranging from 10% to 57%, and a mileage share shift from 1.6% to 36.5%. The increase of electric energy demand from electric vehicles ranges from 0.7% to 18% of the total demand in the province, with a number of charging spots three-to-six times higher than the number of circulating electric vehicles. Additionally the results show that a Vehicle-to-Grid interaction strategy can contribute to reduce from 5% to 50% the average daily electric energy demand in specific locations. This paper provides a description of the developed model and focuses on the valuable potential of the proposed methodology to support future policies for designing alternative fuel infrastructure in urban areas.

1. Introduction

The large scale deployment of EVs (Electric Vehicles) in cities will play a key-role in order to improve air quality in densely populated areas, limiting the negative effects of human exposure to air pollution from transport and reducing the GHGs (Greenhouse Gases) emissions.

The health risks related to air-pollutants are largely addressed in literature [1,2]. As far as pollutants from transport are concerned, the World Health Organisation highlights that drivers, pedestrians and people who live near roads characterised by heavy traffic flows are exposed to exhaust gaseous emissions and PM (Particulate Matter) levels three times higher than background levels, showing that tens of thousands of deaths per year can be attributed to transport-related air pollution, similar to the death toll from traffic accidents [3]. In addition, epidemiology and toxicology literature reviews derive that there is a causal relationship between human exposure to traffic-related primary and secondary gaseous emissions and exacerbation of respiratory and cardiovascular diseases for people living within 500 m from major roads [4]. These findings are confirmed by a large number of similar studies, from different regions of the world, such as [5–8], including the severe problems which are arising in Chinese megalopolis [9].

As far as the GHGs are concerned, it is estimated that road transport contributes to about one-fifth of the total carbon dioxide (CO_2) emissions in Europe, growing by nearly 23% between 1990 and 2010 [10]. In the European area, transport is the only major sector where CO_2 emissions are still increasing [10], and the EU (European Union) is committed reducing them by 20% below 1990 levels by 2020, and by 80–95% by 2050, in order to make a contribution to keep the global temperature increase below 2 °C, under the Kyoto protocol [11,12]. This will imply a whole revision of the mobility plans in Europe, following the guidelines outlined by EC White Paper 2011 [13]. In particular the White Paper identifies ten goals to achieve a 60% reduction target of GHGs emissions from transport below 1990 levels by 2050, including, among the others,

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Nomenclature

Acronyms

AC	Alternating Current
BEV	Battery Electric Vehicle
DC	Direct Current
EPA	Environmental Protection Agency
EU	European Union
EV	Electric Vehicle
GIS	Geographic Information Systems
GHG	Greenhouse Gas
GPS	Global Positioning System
G2V	Grid-to-Vehicle
HEV	Hybrid EV
ICE	Internal Combustion Engine
KPI	Key Performance Indicator
IEC	International Electrotechnical Commission
PHEV	Plug-in Hybrid Electric Vehicles
PM	Particulate Matter
POI	Point of Interest
SOC	State of Charge
SUV	Sport Utility Vehicle
V2G	Vehicle-to-Grid

halving the conventional fuel vehicles in urban areas by 2030, and phasing them out in the cities by 2050.

Such reduction of conventional fuel vehicles in cities will imply, on one hand, a shift of people's transportation choices to other solutions (i.e. modal-shift to the public transportation), whereas, on the other, the adoption of low-carbon vehicle technologies, such as Hybrid and Battery EVs (HEVs and BEVs) [14]. According to previous studies, the rate of adoption of these new technologies will depend on several factors, such as socio-economic boundary conditions [15], public incentives [16,17], and vehicles' usability [18–20]. However, although financial aids might play a key-role for the early-adoption of EVs (which are still an expensive technology compared to conventional fuel vehicles), these studies also underline the importance of the availability of a suitable infrastructure capable to support the shift of the energy demand from the oil-sector to the electric energy utilities. The design of this infrastructure is an open topic, and it is fundamental to identify the appropriate approaches in order to optimise public and private investments in this field.

The recent European Commission communication on clean power for transport [21] identifies the development of an alternative fuel infrastructure as a priority, including the electric energy distribution grid as an option for short-range road passengers' and freight transport. Additionally the Proposal for Directive on the deployment of alternative fuels infrastructure [22], highlights the main issues to address in order to facilitate low-carbon vehicles widespread, providing the initial legal framework to promote the deployment of the recharge network for EVs on a European basis.

The development of this infrastructure can be determined by coupling the electric energy demand from electrified vehicles with the electric energy offer. Several studies in literature address the electric energy demand from EVs. For example Kim and Rahimi suggest to model electricity loads from the large scale deployment of PHEVs (Plug-in Hybrid Electric Vehicles) [23], Dhong and Zhenhong, and Smith et al. propose to monitor electrified vehicles using GPS (Global Positioning System) [24,25], whereas Mu et al. propose using Monte Carlo simulation to predict the energy load from EVs over time [26].

As far as network studies are concerned, Xu et al. analyse the statistical trend of network development in cities by deriving an exponential dependence on the activity [27] and Ortega et al. propose to monitor the network development by means of GIS (Geographic Information Systems) technologies [28]. Additionally survey data might be also used to support infrastructural studies [29], exploring intelligent grid management solutions [30], to address the impact on power system operation, market and security policies for BEVs (Battery Electric Vehicle) [31–34] as well as their integration within renewable energy systems [35,36] and their use as flexible loads [37], contributing to the development of methods to enhance the stability of the electricity grid together with intelligent V2G (Vehicle-to-Grid) and G2V (Grid-to-Vehicle) energy management systems, (§ 13 of the EC Proposal for Directive [22]).

Although these studies provide useful insights into the topic of the electricity network design and integration with electric mobility, they all provide general results, without going into a detailed analysis of the energy demand-offer events, which is the basis to design an intelligent, customer-driven recharge infrastructure network for EVs.

Based on this consideration, the purpose of this paper is to provide the scientific community with the results of a model capable to design and size the recharge infrastructure for EVs in high detail, based on a large database of real-world driving patterns. The novelty of this approach consists in using, for the first time, real-world driving and parking events coupled with data mining to identify suitable locations for charging spots based on existing POIs (Points of Interest) databases and a minimum-distance criterion. The developed approach identifies a KPI (Key Performance Indicator) and a repetitiveness index per each considered location, and derives the number of charging spots and the electric power to be installed to meet the potential customers' demand.

The work relies on previous studies from the authors [38–40], and is carried out for the Italian province of Firenze, over an area of approximately 9600 km^2, currently served by the most developed recharge infrastructure in Italy [40]. The analyses involve approximately 15 million kilometres from about 12,000 conventional fuel vehicles, monitored for a period of one month by means of on-board GPS devices. The results present the layout of the derived recharge infrastructure network, by considering three different types of EVs, four different recharging strategies and different fleet scenarios. Additionally a V2G interaction strategy has been implemented at the charging stations level, to explore the potential of sharing small amount of energy from the battery of the parked vehicles to shave localised peaks of electric energy demand. The results are compared with the indications from Refs. [21,22].

This paper provides a full description of the developed model, focussing on the valuable potential of such methodology to support an intelligent and customer-driven planning, design and size of the recharge infrastructure network for EVs, representing a new insight towards future alternative fuel infrastructures for low-carbon vehicles.

2. Background information and methodology

2.1. Driving patterns database and electric vehicles recharging behavioural models

This study relies on a large driving patterns database from the Italian province of Firenze, an area with nearly one million inhabitants and 684,000 registered vehicles [38]. The database contains mobility data of 40,459 conventional fuel vehicles, equal to

Table 1
Summary of the considered BEVs.

Vehicle type	Curb weight [kg]	Electric motor [kW]	Battery size [Wh]	Energy consumption from driving tests [Wh/km]
Small size vehicle	1080	47	16,000	185
Medium size vehicle	1520	80	24,000	210
Medium size vehicle (high performance)	1815	125	32,000	205

the 5.9% of the fleet registered in this province. These vehicles have been equipped with an acquisition device that recorded time, GPS coordinates, engine status, instantaneous speed and cumulative distance. This data enables to derive the duration, length and average speed of the sequence of trip and parking events of the vehicles over a period of one month (i.e. May 2011) with no interruptions. Approximately 91% of the analysed vehicles are owned by private persons, whereas the remaining vehicles are owned by companies active in different commercial sectors. The data acquisition campaign has been carried out by Octotelematics [41], and the sample of vehicles has been chosen to represent the typical age distribution in this specific geographical area.

The GPS-logged data has been preliminary processed by filtering out the vehicles which made more than 50% of the trips out of the province boundaries, reducing the databases to approximately one-third of their original size. This was made to focus only on those vehicles which predominantly show urban driving behaviour, being the short-to-midterm deployment of EVs most likely going to happen in urban areas. The data was then submitted to a cleansing procedure, in order to remove possible errors from the records, due, for example, to the poor quality of the GPS signal. The final database reduces to 12,422 vehicles (i.e. 1.8% of the registered fleet in the province), equivalent to 32 million GPS records, 15.0 million kilometres and 1.87 million trips. All the analyses presented in this article refer to this sample.

These data has been processed with a customised data mining model developed in MATLAB® [42] and used for a number of different analyses, involving driving patterns characterisation [38], EVs' potential to replace conventional fuel vehicles [39], and emissions simulation [43]. The results presented in this paper are based on the electric vehicles and behavioural models developed and presented in Ref. [39], and here briefly summarised.

The model is based on the assumption that the urban driving patterns would not change with the transition from conventional fuel vehicles to BEVs. Six different BEVs models have been considered: a light quadri-cycle, a small size vehicle (typical city-car, four passengers), two medium size vehicles (a typical family car and a high-performance family car, five passengers) and two large size vehicles (a Sport Utility Vehicle, SUV, and a sport sedan), all equipped with Lithium-ion batteries. Each BEV model is applied to each trip and parking sequence contained in the database, replicating the driving behaviour of the conventional fuel cars over the analysed period. The vehicles start with a fully charged battery at the beginning of the month and each trip is associated to an energy consumption, whereas each parking to a recharge opportunity, which takes place if the recharging constraints are met. The applied energy consumption rate is assumed to be constant and is derived from real drive tests performed by the US EPA (Environmental Protection Agency) [44] (including the average consumption of auxiliaries [45]), whereas the recharging constraints vary according to fifteen different strategies [39]. These are designed in order to represent different charging behaviours (i.e. opportunistic/non-opportunistic), grid loads (i.e. on-peak/off-peak recharge) and infrastructure scenarios (i.e. Alternating Current, AC, single/tri-phase recharge and Direct Current, DC, recharge).

This paper presents the results of only three among the six BEVs models, and four among the fifteen recharging strategies. The chosen vehicles are the most representative BEVs technology currently available on the market, whereas the chosen strategies are considered representative of the behaviours of the early adopters of BEVs, and hence more relevant to address the infrastructure design at an early stage. The analysed vehicles are a small size vehicle and two medium size vehicles (Table 1), whereas the recharging strategies are labelled as Long-Stop Random AC, Short-Stop Random DC, Smart-AC and Mixed-Time AC/DC, (Table 2).

These strategies apply different constraints to the recharge, based on parking duration (i.e. long/short stops), beginning time of the parking event, recharge infrastructure (i.e. AC/DC) and stochastic variables. In detail:

- **Strategy 1** (Long-Stop Random AC) represents a scenario that requires a long stop of the vehicle (i.e. longer than 120 min) to enable the recharge of the battery. This is applied with a conventional Italian recharge infrastructure (i.e. AC, single-phase at 3.3 kW, IEC 62196 Mode 1/2 [46]), and it is representative of a recharge that can take place at home or wherever the vehicle is parked for long time (e.g. offices, shopping malls, airports, parking lots, etc.). The recharging power is scaled down to a constant value of 2 kW to account for the recharging profile (i.e. power modulation applied from the vehicle [39]), and the recharge is subject to a random-generated threshold parameter. Each time a vehicle meets the recharge time-constraint a random number generator algorithm produces a value between 0 and 1. Each value in this interval can be generated with the same probability and only if this number is higher than 0.6 (i.e. 40% of the probabilities) the recharge occurs. This random threshold represents two possible situations: the recharge station is not available at the parking lot or the driver forgets/does not want to recharge.
- **Strategy 2** (Short-Stop Random DC) is very similar to strategy 1, but the time threshold is set to 20 min (i.e. short-stop) and the recharge is applied in DC (55 kW, IEC 62196 Mode 4 [46]). The random threshold is the same as above. It is representative of the recharge which could take place in parking lots equipped with fast-charging devices. In this case the recharge power is scaled down to a constant value of 40 kW, to account for the recharging profile.

Table 2
Summary of the recharging strategies.

Strategy ID – name	Recharge constraints	Power [kW]	Recharge model inputs
1 – Long-Stop Random AC	Parking $\geq$ 120 min and random parameter $\geq$ 0.6	2	Parking duration and random parameter
2 – Short-Stop Random DC	Parking $\geq$ 20 min and random parameter $\geq$ 0.6	40	Parking duration and random parameter
3 – Smart AC	Off-peak AND 4 h ($\pm$2 h) time window around the minimum	2	Parking duration and smart recharge window
4 – Mixed Time AC/DC	Stop $\geq$ 120 min &	–	Parking duration and starting time of the parking
	If 10 p.m. < parking time $\leq$ 7 a.m.: AC	2	
	If 7 a.m. < parking time $\leq$ 10 p.m.: DC	40	

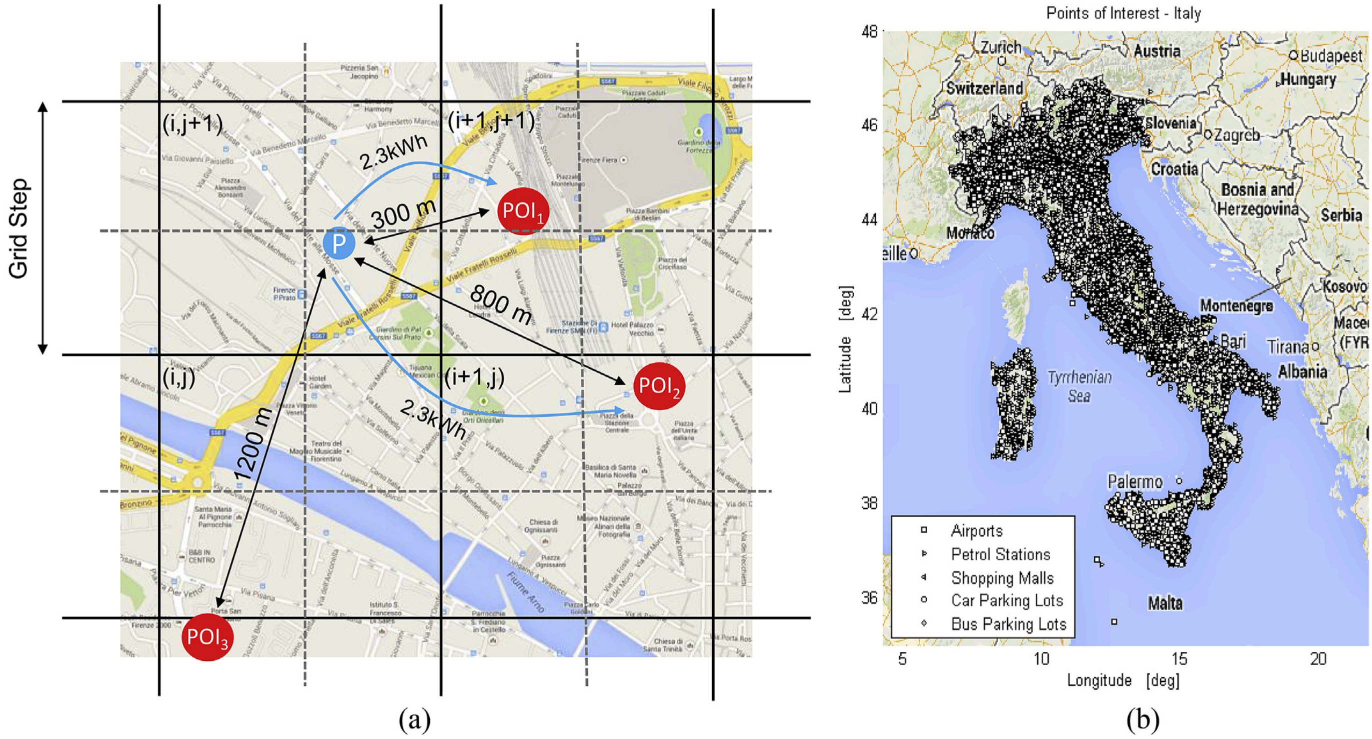


Fig. 1. (a) – Example of how a parking event associated to a recharge (i.e. blue *P*) is linked to three possible POIs. Black lines represent the main geo-grid, whereas dashed grey lines represent the staggered geo-grid. (b) – Italian map of POIs adopted, as retrieved from the web [49]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

- **Strategy 3** (Smart AC) applies a recharge only if the vehicle is parked in a specific time window of 4 h (±2 h) around the minimum of the electric energy grid load recorded in Italy in May 2011. This minimum occurs approximately at 04.00 in the morning from Monday to Saturday and at 07.00 in the morning on Sunday [47], meaning that the vehicles are allowed to recharge from 02.00 to 06.00 and from 05.00 to 09.00 respectively. The recharge is applied in AC single-phase (3.3 kW, IEC 62196 Mode 1/2 [46]) and the power scaled down to a constant value of 2 kW as in strategy 1. This strategy is representative of a scenario where the recharge takes place only overnight, filling the electric energy demand valley, as per § 13 of the EC Proposal for Directive [22], and associated to a discounted electricity fee.
- **Strategy 4** (Mixed Time AC/DC) applies a differentiation of the recharging infrastructure between AC and DC depending on the parking time. The vehicle is recharged in DC (55 kW, IEC 62196 Mode 4 [46]) during the day (i.e. between 7 a.m. and 10 p.m.) and in AC (3.3 kW, IEC 62196 Mode 1/2 [46]) during the night (i.e. between 10 p.m. and 7 a.m.). In both cases the recharge takes place only if the parking duration is longer than 120 min, the DC power is scaled down to 40 kW and the AC power is scaled down to 2 kW, as per the strategies above. This strategy considers, in a simple way, the availability of different charging stations around the city and at home, observing that EV users will unlikely use DC stations for overnight recharge.

The charging efficiency is always assumed constant and equal to 95% (i.e. typical recharge efficiency, as shown in Ref. [45]), and the allowed SOC (State of Charge) is limited between 20% and 95% of the nominal energy capacity of the battery (reported in Table 1) to preserve the integrity of the cells.

2.2. Geo-mapping of the energy demand, layout of the recharge infrastructure and implementation of V2G interaction strategy

The model described in Section 2.1 provides as output the sequence of trip and parking events, with the SOC time history over the analysed period for each vehicle. From this result is possible to determine which vehicles would not be capable of covering all their trips if they were replaced by a BEV (i.e. the SOC level goes below the 20% threshold). These vehicles are then filtered out, in order to focus the analysis only on the remaining vehicles that could be replaced by an electric car being the sequence of their driving patterns not interrupted (i.e. early BEVs adopters). The energy and power demands from these vehicles, during the parking events associated to a recharge, have been calculated to derive the impact on the electric energy distribution grid for the different deployment scenarios of BEVs, with the vehicles reported in Table 1. Additionally, being the GPS coordinates of the parking events known, the energy demand has been geo-referenced and dynamically linked to digital maps retrieved from the web [40,48]. This allows mapping the electric energy demand over the province area and deriving a customer-driven layout of the recharge infrastructure.

The spatial analysis is carried out over a geo-grid based on a rectangular window which embeds the province area. This window covers the area from 43.40 to 44.30 deg of latitude north, and from 10.60 to 11.80 of longitude east, accounting for 9631 km^2 divided in squared terrain tiles of 0.25 km^2 (500 m per edge, resulting in approximately 38,500 tiles for the province of Firenze). This geo-grid (black lines in Fig. 1) is used to associate each recharge into a specific tile (identified by indexes i-th and j-th), whereas a second geo-grid (i.e. staggered grid, dashed grey lines in Fig. 1-(a)), whose nodes are located in correspondence of the centroids of the main grid's tiles, is used to store the results per tile.

Having defined the geo-grid, this has been interfaced with a POIs (Points of Interest) database. The POIs are sets of enriched GPS coordinates which contain coordinates and description of locations of interest (i.e. restaurants, hotels, train stations, etc.). These databases are normally used in a number of commercial GPS devices, and they can be retrieved from websites to update the navigation software for mobile applications. In this study five databases has been retrieved from Ref. [49]: airports, petrol stations, shopping malls, car parking and bus parking lots. They refer to Italy, as shown in Fig. 1-(b), accounting for 35,590 POIs, among which 632 located in the province of Firenze, as per Table 3. These databases are not considered exhaustive; however they are a dense geo-referenced network of locations which might be selected to host public recharge facilities for EVs.

On the basis of the GPS coordinates of the parking locations, the electricity demand from BEVs' recharging events is correlated to the POIs, with a distance-based criterion. The distance between the recharging event and the neighbour POIs is calculated, approximating the Earth geoid to a smooth sphere with a radius of 6371 km. If this distance is below 100 m, i.e. the parking location is very close to a specific POI, it is likely to assume that this POI might be chosen for parking and charging the vehicle, therefore a Geographic Key Performance Indicator (i.e. Geo_{KPI}) equal to 1 is associated to the POI. On the contrary if this distance is more than 1 km, it is likely to assume that this specific POI is not a candidate for the recharge (too far away from the original parking location), and the Geo_{KPI} is set to 0. If the distance is between 100 m and 1 km the Geo_{KPI} associated to the specific POI is linearly scaled from 1 to 0. Any time the Geo_{KPI} is more than 0 (i.e. distance below 1 km) the energy request from the vehicle is also associated to that specific POI location.

An example of how this algorithm works is provided in Fig. 1-(a). The parking event from the database, i.e. the blue spot in the terrain tile (i-th, j + 1-th), is associated to an energy request of 2.3 kWh and, in this example, it has three neighbour POIs. POI_1 is located at 300 m, therefore it could be considered as a good candidate to host the recharge with a Geo_{KPI} of 0.78. POI_2, located at 800 m, is also a candidate, but with a lower Geo_{KPI} (i.e. equal to 0.11), whereas POI_3, located at 1.2 km, is not a candidate and it has a Geo_{KPI} equal to 0. The energy demand of 2.3 kWh associated to this specific recharge event is transferred to both POI_1 and POI_2, which are market competitors to deliver the recharge, whereas POI_3 is excluded. This algorithm is applied to all parking events associated to a recharge, according to the results of the model described in Section 2.1.

This methodology enables to derive in each POI location, a sequence of charging events, each of them associated to a Geo_{KPI} and to a certain amount of energy requested in a specific time window. Therefore each POI location is characterised by:

- An average Geo_{KPI}, calculated as algebraic average of the Geo_{KPIs} of all charging events. This Geo_{KPI} can be considered as the averaged indicator of the ability of the POI to meet urban vehicles' charging request, in term of convenience of geographic location.
- A repetitiveness index (i.e. R), representative of the ability of the POI to meet the needs of a small or large share of customers. This is defined according to (1), where $N_{vehicles}$ is the number of different vehicles recharging in that specific POI, and $N_{recharges}$ is the total number of charging events. Therefore if $N_{vehicles} \sim N_{recharges}$, R will be close to 0 (i.e. low repetitiveness, each vehicle charges at that specific POI nearly once), whereas if $N_{vehicles} << N_{recharges}$, R will be close to 1 (i.e. high repetitiveness, each vehicle charges at that specific POI several times).

$$R = 1 - \frac{N_{vehicles}}{N_{recharges}} \tag{1}$$

- A plug-demand curve (i.e. number of vehicles plugged-in at the same time and at the same POI) and a power demand curve over the analysed month, providing the number of plugs and the electric energy demanded to the POI over time.

Table 3
Summary of the POIs adopted for the current analysis.

	No. of POIs (Italy)	No. of POIs (province of Firenze)	Legend
Airports	551	4	□
Petrol stations	28,144	404	▷
Shopping malls	1507	49	◁
Car parking lots	4688	153	○
Bus parking lots	700	22	◇
Total	35,590	632	–

The latter result is used to dimension the recharge infrastructure network in a specific POI and to develop the V2G interaction strategy. The infrastructure can be designed on the basis of the daily number of plugs required, whereas the power line can be designed on the basis of the daily energy request. According to these results, the design can be carried out according to two criteria:

- the maximum number of plugs/energy load registered in the average day, in order to be able to cope with the expected peak demand;
- the average number of plugs/energy load registered in the average day, in order to serve the average demand and design a smaller and cheaper infrastructure.

The second criterion is adopted in this work.

On the top of this, a V2G interaction strategy has been implemented. It considers each parking which is not associated to a recharge (according to the constraints set by the recharge strategies in Table 2), as a potential event during which the parked vehicle can release a small amount of the energy stored in its battery back to the grid to serve the neighbour vehicles which are charging. This application has been developed per POI, meaning that the average daily electric power offer from the parked vehicles is calculated in each POI location and compared to the average daily electric power demand in the same POI, to estimate the potential of the V2G in shaving localised peaks of electric energy demand. The energy that can be shared by each parked vehicle is set to 2% of the nominal battery capacity (according to the values given in Table 1), with a discharge power of 2 kW (AC single-phase, as per the recharge strategies set above) and a discharge efficiency of 95%.

3. Results and discussion

3.1. Mobility and energy demand results

The mobility results obtained by applying the method described in Section 2.1 have been exhaustively presented in previous works from the authors, see Refs. [38–40,43], and only the key aspects needed to apply the developed infrastructural model and interpret the results presented in Sections 3.2 and 3.3 are provided here.

Table 4
Fleet, trips and mileage shares for BEVs and HEVs (province of Firenze).

EV type		Strategy			
		Trips and mileage shares			
		Str. 1 Long-Stop R-AC	Str. 2 Short-Stop R-DC	Str. 3 Smart AC	Str. 4 Mixed Time AC/DC
Small size vehicle	BEV fleet	10.00%	16.78%	16.90%	30.05%
	HEV fleet	90.00%	83.22%	83.10%	69.95%
	BEV trips	0.77%	2.78%	2.04%	8.66%
	HEV trips (electric)	75.15%	81.55%	77.47%	73.22%
	HEV trips (ICE)	24.08%	15.67%	20.49%	18.13%
	BEV mileage	1.55%	4.43%	4.29%	12.94%
	HEV mileage (electric)	49.09%	60.79%	51.42%	58.94%
	HEV mileage (ICE)	49.36%	34.78%	44.28%	28.12%
Medium size vehicle	BEV fleet	14.90%	25.57%	22.76%	41.79%
	HEV fleet	85.10%	74.43%	77.24%	58.21%
	BEV trips	1.39%	4.97%	2.92%	12.97%
	HEV trips (electric)	75.47%	76.06%	72.81%	62.82%
	HEV trips (ICE)	23.14%	18.97%	24.27%	24.21%
	BEV mileage	3.35%	9.43%	6.89%	22.36%
	HEV mileage (electric)	53.90%	63.37%	50.29%	55.82%
	HEV mileage (ICE)	42.75%	27.20%	42.83%	21.81%
Medium size vehicle (high performance)	BEV fleet	23.22%	39.47%	31.24%	56.94%
	HEV fleet	76.78%	60.53%	68.76%	43.06%
	BEV trips	2.52%	8.47%	4.28%	18.58%
	HEV trips (electric)	73.09%	64.59%	67.11%	48.29%
	HEV trips (ICE)	24.39%	26.95%	28.61%	33.13%
	BEV mileage	7.30%	19.30%	11.46%	36.53%
	HEV mileage (electric)	58.05%	61.56%	50.41%	48.57%
	HEV mileage (ICE)	34.65%	19.14%	38.13%	14.90%

As described in Section 2.1, the developed model reproduces the sequence of the trip/parking events per each vehicle in the database, associating each trip to an energy consumption event and each parking to a recharge event, if the constraints given by the recharging strategy are met. One of the outcomes of this model is the fleet, trips and mileage shares which can be covered by a BEV, given a vehicle type and a recharge strategy. These values are derived considering the vehicles that can cover all the trips in the databases without any trip failure, i.e. the trip cannot be done because not enough energy is available in the battery.

The results of this analysis are reported in Table 4, which shows that a fleet share ranging from 10% to 57% can be converted to BEVs (i.e. BEV fleet), depending on the vehicle type and the recharge strategy. The remaining part can be switched to HEVs (i.e. HEV fleet), being their driving patterns only partially compatible with the characteristics of the electric vehicles. The BEV fleet shares corresponds approximately to a range from 0.8% to 19% of the trips shares (i.e. BEV trips), and from 1.6% to 36.5% of the mileage shares (i.e. BEV mileage). From this we can estimate that, approximately one-third of the current urban fleet can be converted to BEVs, representative of approximately one-fifth of the total fleet mileage.

The trips and mileage shares are also reported in Table 4 for the HEV fleet, where the additional split in trips and mileage done in electric mode and done with the ICE (Internal Combustion Engine) is reported.

Table 5 provides the monthly electric energy demand derived by considering the fleet share capable of driving only electric, given the vehicle type and the recharge strategy. The results are scaled-up to the fleet size of the province, and referred to the total and domestic electric energy demand of the province. The domestic electric energy demand is the share of the demand from private households only, whereas the total energy demand also includes industries and tertiary sector. The results show that the impact in terms of electric energy demand from BEVs ranges from approximately 0.7%–18.0% of the total electric energy demand in the province (i.e. from 3.6% to 96.4% of the domestic demand), as per [50].

3.2. Recharge infrastructure layout results

This section presents the results of the recharge infrastructure layout algorithm, described in Section 2.2. The results only refer to the fleet share that could be converted to BEVs, according to the data reported in Table 4. Given the sequence of recharges of these

Table 5
Electric energy demand per month [GWh] derived by considering the fleet share capable of driving only electric (BEV fleet share in Table 4, province of Firenze). The results are scaled-up to the fleet size of the province. The values in parenthesis represent the percentage of the energy demand with respect to the total energy demand of the province as per [50].

EV type	Strategy			
	Vehicles monthly energy demand in the province [GWh] (percentage of the: monthly total energy demand [%] – monthly domestic energy demand [%])			
	Str. 1 Long-Stop R-AC	Str. 2 Short-Stop R-DC	Str. 3 Smart AC	Str. 4 Mixed Time AC/DC
Small size vehicle	2.45 (0.67%–3.60%)	7.07 (1.94%–10.38%)	6.88 (1.88%–10.11%)	21.12 (5.78%–31.01%)
Medium size vehicle	5.96 (1.63%–8.76%)	16.99 (4.65%–24.95%)	12.40 (3.40%–18.20%)	41.19 (11.28%–60.48%)
Medium size vehicle (high performance)	12.78 (3.50%–18.76%)	34.65 (9.49%–50.88%)	20.04 (5.49%–29.43%)	65.67 (17.99%–96.43%)

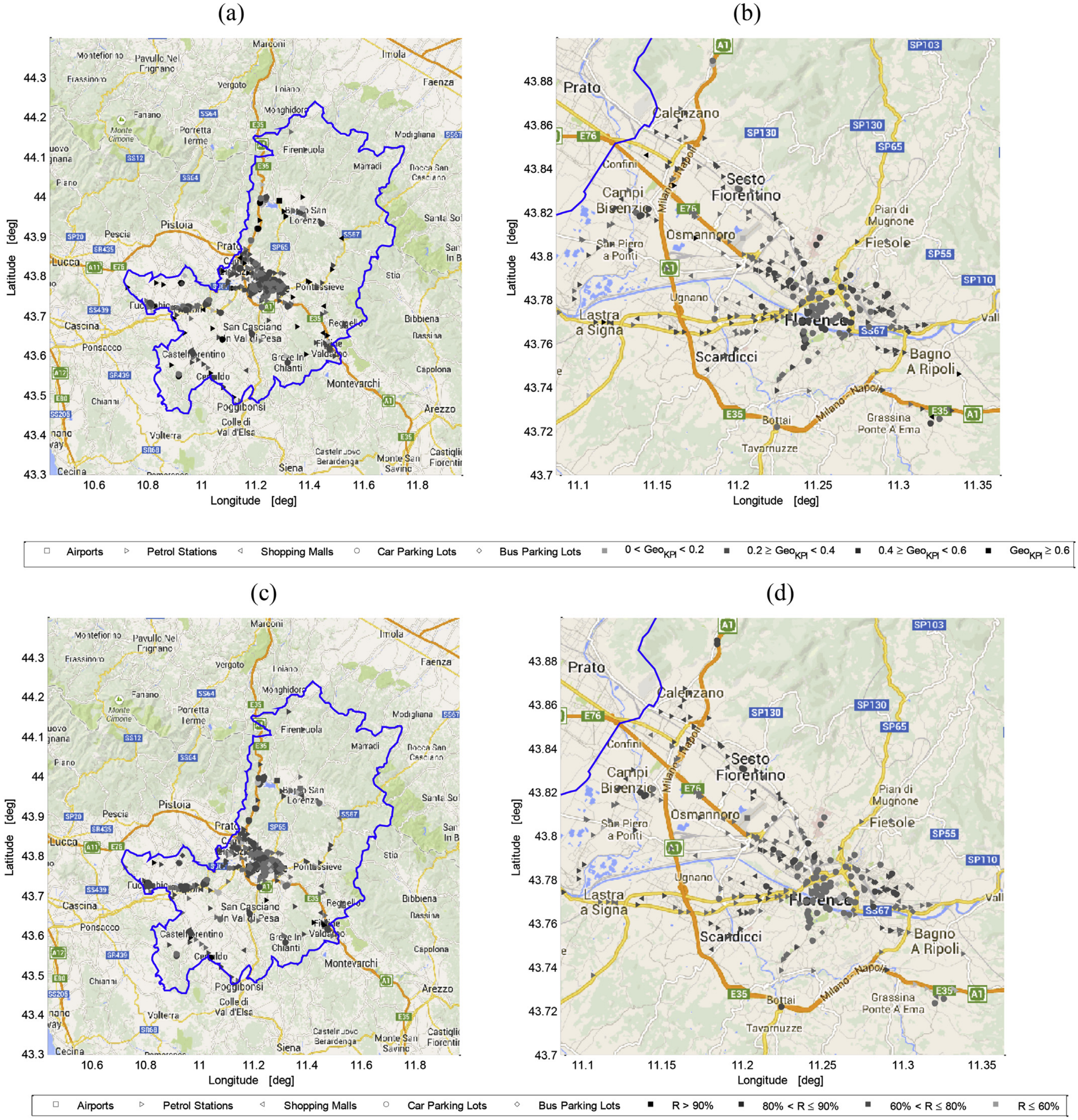


Fig. 2. Geo$_{KPI}$ per POI, over the province area ((a), the blue line indicates the province border), and zoom on the city of Firenze (b). Repetitiveness index *R* per POI, over the province area (c), and zoom on the city of Firenze (d). Medium size vehicle, recharge strategy 1 (i.e. Long-Stop Random AC). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

vehicles and their locations versus the POIs network, it is possible to associate each recharge event to one or more POIs. This allows to derive the compatibility of the different POIs to the demanded recharges (i.e. averaged Geo$_{KPI}$), the recurrence of the load/usage patterns (i.e. repetitiveness index *R*), and the average daily electric energy demand profile.

Fig. 2 reports an example of the derived Geo$_{KPI}$ and *R* maps for the medium size vehicle and the recharge strategy 1. Left pictures (i.e. (a) and (c)) depict an overview of the results over the entire province area (identified with the blue line), whereas right pictures (i.e. (b) and (d)) the zoom on the city of Firenze. The shape of the markers indicates the type of POI (according to the classification reported in Table 3), whereas the grey scale gives the magnitude of the reported quantity. As we can see from the picture the Geo$_{KPI}$ assumes average values (i.e. between 0.2 and 0.4 and between 0.4 and 0.6) in the city area Firenze (the most densely populated area in

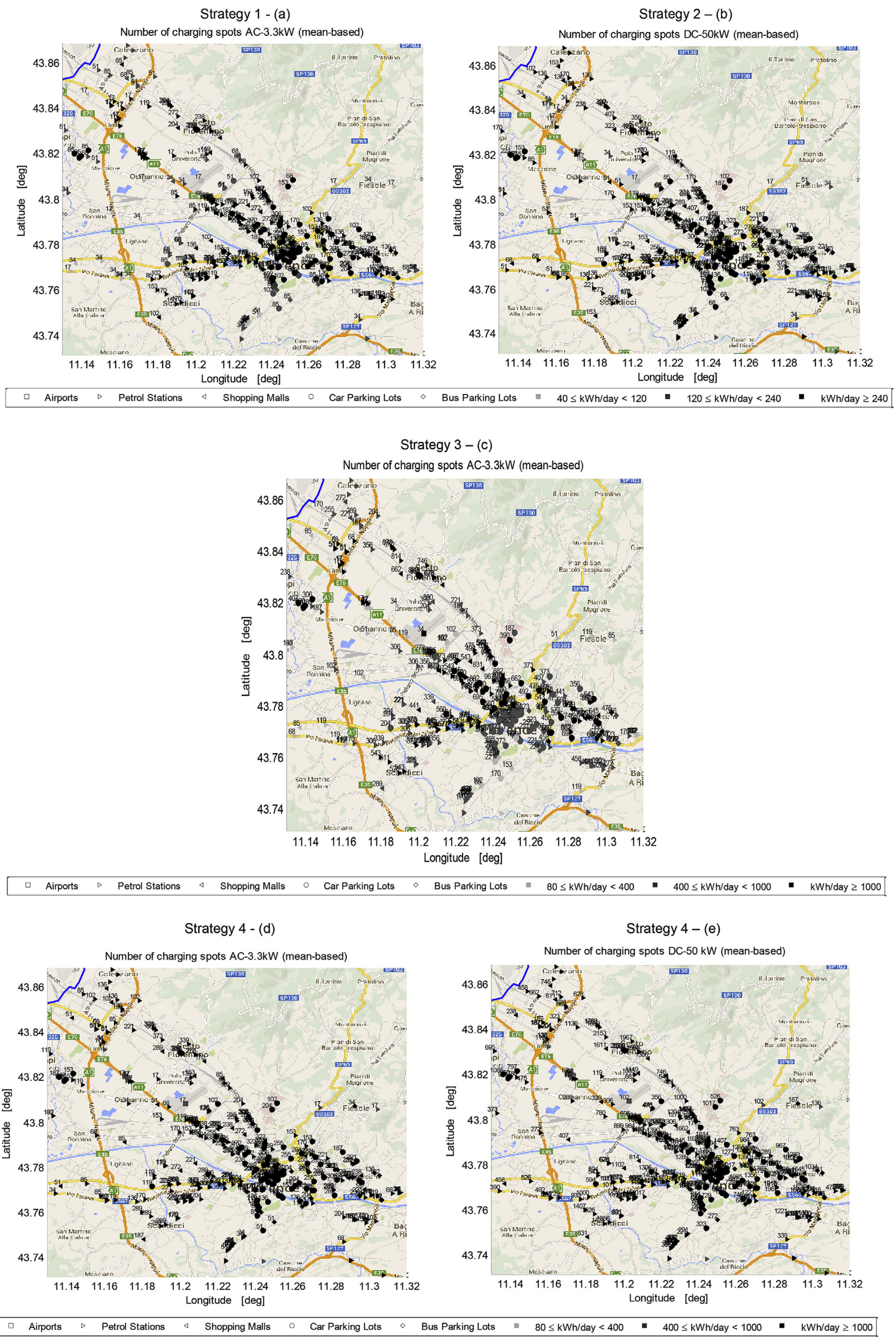


Fig. 3. Number of charging spots per POI based on the average electric energy demand (the results are scaled-up to the province fleet size). The type of charging spot (i.e. AC/DC) is given by the recharge strategy, according to Section 2.1. The results refer to the small size vehicle, province of Firenze.

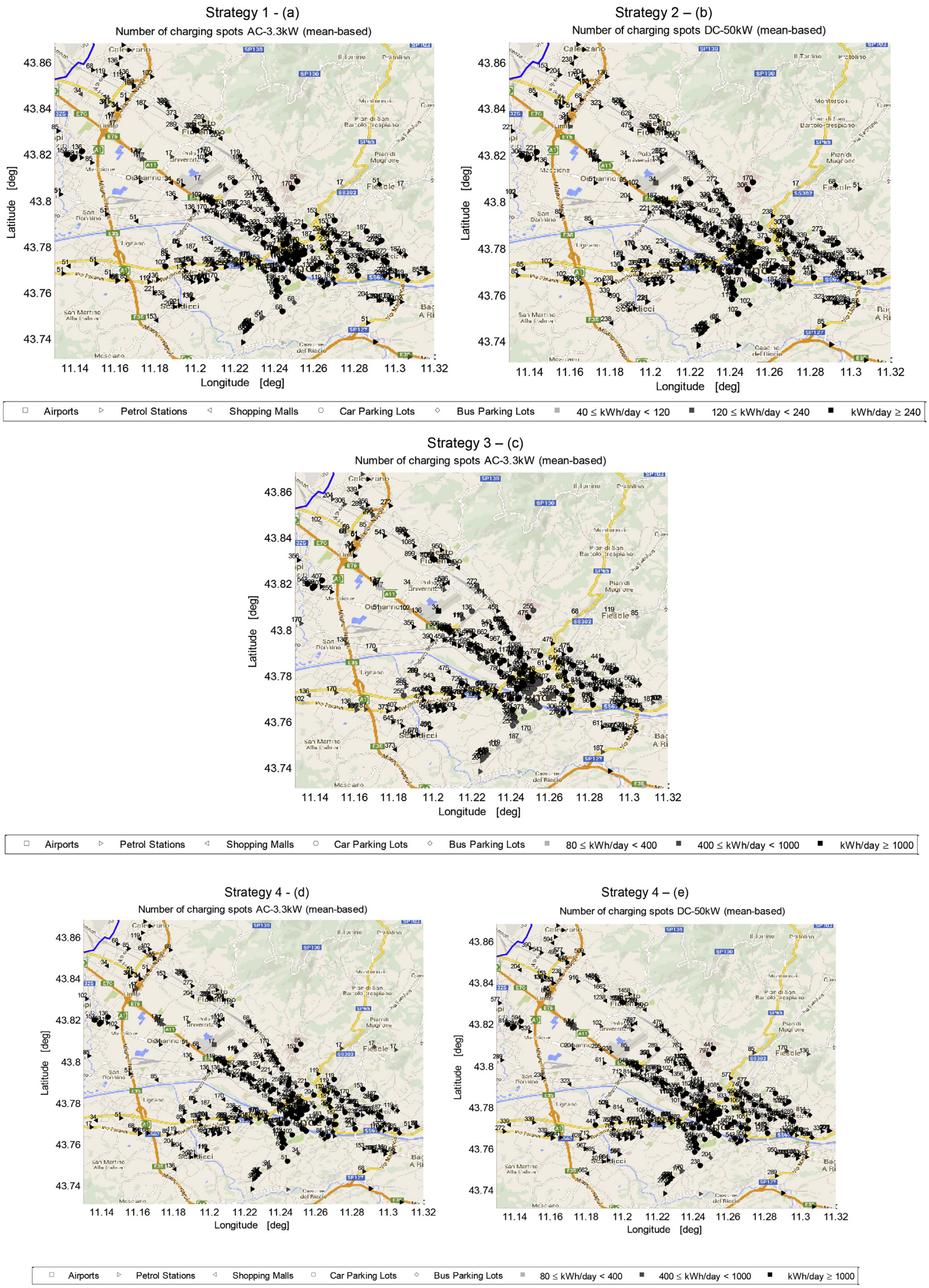


Fig. 4. Number of charging spots per POI based on the average electric energy demand (the results are scaled-up to the province fleet size). The type of charging spot (i.e. AC/DC) is given by the recharge strategy, according to Section 2.1. The results refer to the medium size vehicle, province of Firenze.

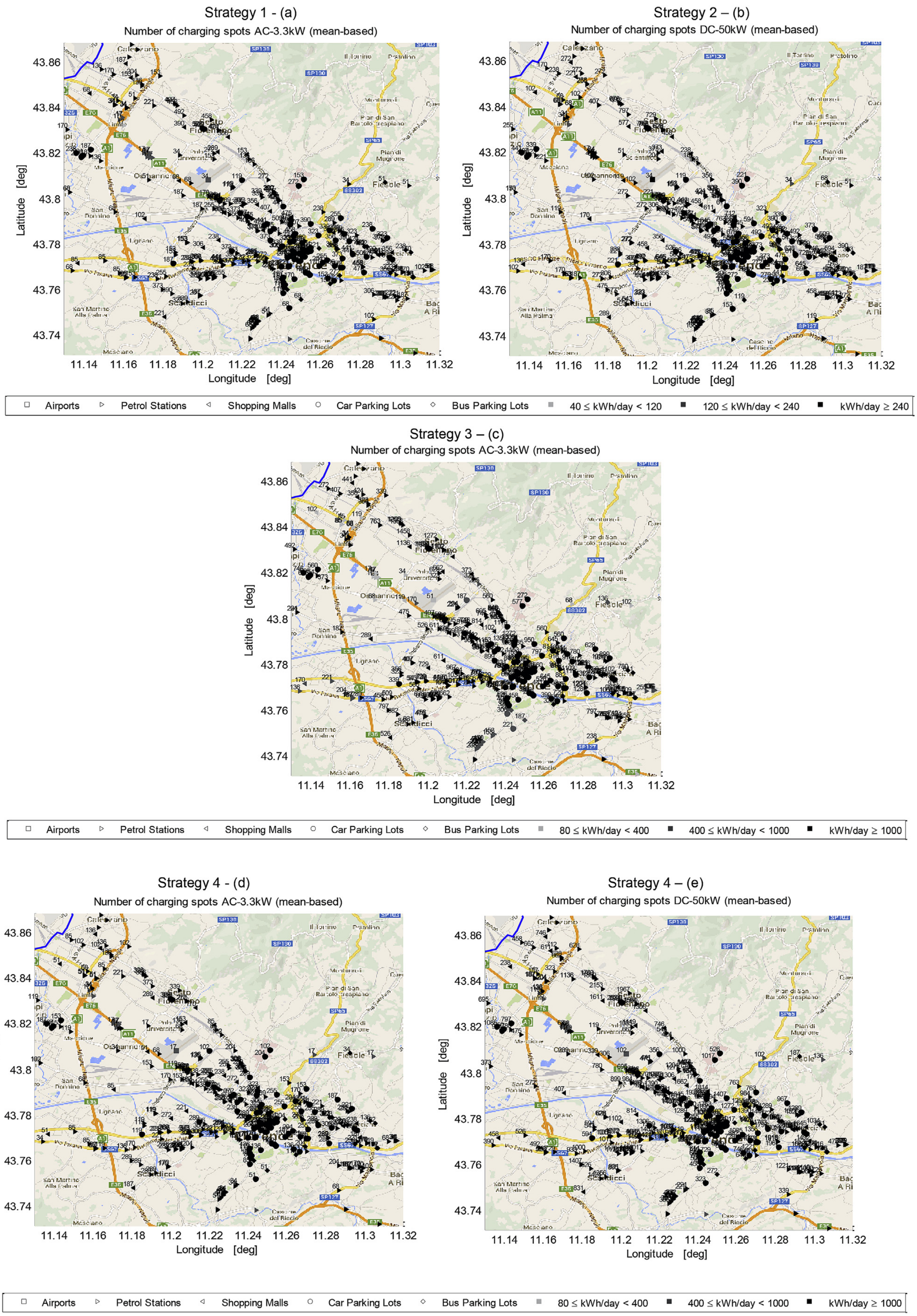


Fig. 5. Number of charging spots per POI based on the average electric energy demand (the results are scaled-up to the province fleet size). The type of charging spot (i.e. AC/DC) is given by the recharge strategy, according to Section 2.1. The results refer to the medium size (high performance) vehicle, province of Firenze.

the province, see Fig. 2-(b)), whereas assumes very high values in some isolated spots in rural areas outside the main districts (see black spots in Fig. 2-(a)). This means that each vehicle has several possibilities to recharges (i.e. several neighbour POIs) in the densely populated areas, whereas these possibilities are significantly lower in rural areas.

Similarly the repetitiveness assumes a value between 60% and 80% for most of the POIs located in the inner city area of Firenze, whereas it tends to assume higher values (i.e. between 80% and 90%) in residential areas as Sesto Fiorentino or Scandicci (see Fig. 2-(d)). Also in this case some black spots (repetitiveness above 90%) are visible in rural areas in the province (see Fig. 2-(c)), confirming that isolated spots with high Geo_{KPI} are characterised by high repetitiveness too, and therefore by a small number of potential customers.

However, although the Geo_{KPI} and R together provide a key-information to characterise the POIs in terms of potential energy market and customers' pool, the real demand is determined by the forecast of the electric power load at the POI and by the total amount of charging spots needed to deliver the requested energy. Hence the full set of data (i.e. Geo_{KPI}, R, time-dependent power load and total amount of energy requested) is needed to completely characterise the POI, suggesting if and to which extent it could be considered a candidate to install charging stations, how many spots are needed and how much profitable the investment can be.

Figs. 3–5 depict the derived recharge infrastructure layout, for the small, medium and medium high performance size vehicle. The shape of the marker indicates the type of POI, the colour of the marker indicates the required electric energy per day (according to the legend), and the numbers reported at the top-left corner of the markers indicate the number of charging spots to be installed according to the average daily plug-demand at the POI.

Table 6 summarises these results for the analysed province area, per vehicle type and per recharge strategy. The first column indicates the number of vehicles that can be converted to BEVs (as described in Section 3.1), scaled-up to the fleet size of the province, whereas the second column indicates the average number of recharges per day that can be associated to these vehicles, given the recharging constraints set by the different strategies.

The labels “demand” and “offer” respectively refer to the number of recharges demanded by the electric vehicles and to the potential number of the recharges offered by the POIs (i.e. events compatible with the POIs layout, as per constraints defined in Section 2.2). The number of offered recharges is higher than the number of demanded recharges because a single charging event might be typically compatible with several POIs, based on the choice criteria described in Section 2.2.

The third and the fourth columns give respectively the absolute and the percentage number of POIs involved in the recharges and the average daily demanded and offered electric energy (cumulative value over the entire POIs database). The last two columns indicate the offer/demand ratio (i.e. ratio between the offered and demanded average daily electric energy at the POI) and the cumulative number of charging spot demand in the province, given a vehicle type and the recharge strategy (AC, DC or both, according to the case).

This table provides the reader with an overview of the recharge infrastructure, giving quantitative key information of the electric energy demand and offer, the competitiveness framework (i.e. each vehicle can chose a number of different POIs to recharge) and the number of charging spots that might be needed for each scenario considered.

It is interesting to highlight that the energy offer/demand ratio ranges between five and eight, and that the derived number of charging spots is approximately three times higher than the number of vehicles for the recharge strategies 1 and 2, whereas it increase to five-to-six times higher than the number of vehicles for the recharge strategies 3 and 4. This difference can be ascribed to the time and stochastic filters applied for the recharge strategies 1 and 2, which limit the number of events compatible with the recharge.

These results can be compared with the guidelines for the deployment of alternative fuels infrastructures, under the Europe 2020 strategy [22]. This proposal recommends that recharging points must be built with sufficient coverage, at least twice the number of the circulating EVs, and located in accessible points, such as parking lots, residential areas or business blocks, with a share of at least 10% located in publicly accessible areas. The proposal gives also some indicative numbers per EU member state, with 1.2 million charging spots for Italy per approximately 600,000 circulating EVs by 2020.

By scaling these numbers down to the size of the province of Firenze, we can consider that the 684,000 vehicles registered in this province accounts for approximately 1.8% of the Italian fleet [38], and hence approximately 11,000 of the 600,000 EVs envisaged in Italy will be registered in this province, with nearly 22,000 charging spots. Although these numbers suggest a still limited EVs deployment compared to the scenarios presented in this work, we can notice how the proportion resembles, to a certain extent, the results presented in Table 6. In particular, it is interesting to notice how the model prediction of having a ratio of charging spots and BEVs approximately equal to three for the recharge strategies 1 and 2 is very close to the Proposal for Directive's indication of having the charging spots twice the number of the circulating EVs, and how this finding comes from different background data. In fact, the Proposal for Directive is likely based on European averaged urbanistic data, whereas the model is based on matching real-world conventional fuel vehicles driving patterns and POIs locations. Therefore, the benefit of the model, in view of the future implementation of the directive, is that it provides a detailed layout of the infrastructure that can be used for steering future public and private investments in this sector.

On the other hand, the recharging strategies 3 and 4 foresee a significantly higher charging spots-to-BEVs ratio, representing different scenarios with respect to that of the Proposal for Directive. Additionally we may also notice that the higher proportions found can also be partially ascribed to the POIs datasets adopted (Table 3). In fact the analyses presented include petrol stations (i.e. two-thirds of the POIs considered), implicitly assuming a partial reconversion of this infrastructure to e-mobility, whereas the Proposal for Directive does not refer to petrol stations as locations for installing charging spots. The scenarios presented in this work can represent the mid-to-long term perspective for BEVs' deployment in cities, and can support the short-term scenario (i.e. 2020) from the Proposal for Directive.

3.3. V2G results

This section presents the results of the V2G interaction strategy, described in Section 2.2. It is important to notice that it is designed to work with on-peak recharge strategies, meaning that its application makes sense in a scenario characterised by many vehicles that are parked at the same time, where some of them recharge whereas some others don't (e.g. they do not meet recharge requirements, i.e. minimum parking duration, random threshold etc.). For this reason, the current section presents only the results of the recharge strategies 1, 2 and 4 (see Section 2.1), being the recharge strategy 3 (i.e. off-peak Smart AC) not relevant for this application. The vehicles that are parked and do not recharge represent the electric energy offer, whereas those that are parked

Table 6
Summary of the results about the recharge infrastructure network layout (province of Firenze).

			No. of vehicles	Average no. of recharges/day	No. of working POIs (% tot. POIs)	Electric energy/day [MWh]	Energy offer/demand ratio	No. of charging spots (AC/DC)
Small size vehicle	Str. 1	Demand	17,712	7630	598 (94.6%)	22	7.9	54,100
		Offer		59,680		174		(AC)
	Str. 2	Demand	32,644	28,115	611 (96.7%)	68	6.7	87,017
		Offer		194,150		458		(DC)
	Str. 3	Demand	30,525	19,039	613 (98.6%)	58	7.3	169,480
		Offer		146,010		425		(AC)
	Str. 4	Demand	60,119	87,170	624 (98.7%)	199	5.8	50,848–282,970
		Offer		549,800		1156		(AC) (DC)
Medium size vehicle	Str. 1	Demand	27,119	13,740	611 (96.7%)	55	7.1	74,306
		Offer		98,283		388		(AC)
	Str. 2	Demand	50,932	50,449	619 (97.9%)	166	6.3	124,880
		Offer		325,710		1040		(DC)
	Str. 3	Demand	41,492	27,367	617 (97.6%)	106	6.8	219,680
		Offer		199,080		723		(AC)
	Str. 4	Demand	84,203	130,550	625 (98.9%)	388	5.4	67,458–367,460
		Offer		771,950		2097		(AC) (DC)
Medium size Vehicle (high-perf.)	Str. 1	Demand	43,915	24,837	617 (97.6%)	118	6.5	114,340
		Offer		168,170		768		(AC)
	Str. 2	Demand	79,831	86,072	624 (98.7%)	333	5.6	177,800
		Offer		511,890		1869		(DC)
	Str. 3	Demand	57,169	39,840	617 (97.6%)	170	6.6	289,240
		Offer		279,940		1116		(AC)
	Str. 4	Demand	115,290	186,920	627 (99.2%)	620	5.1	89,543–483,980
		Offer		1,065,500		3174		(AC) (DC)

and recharge represent the electric energy demand. Synchronising the offer and the demand is the key to implement the V2G interaction that is capable of shaving the peak of the electric energy load in a specific location.

Fig. 6 depicts the time-dependant demand and offer average daily electric power curve for the three most loaded POIs (i.e. the POIs that, according to the results from each recharge strategy, exhibit the higher daily cumulative energy demand). The black curves indicate the electric power demand from parked and recharging BEVs, the grey curves indicates the electric power offer from parked and not recharging BEVs, whereas the dashed curves indicate their difference. The results are scaled-up to the province fleet size and refer to the medium size vehicle and recharge strategies 1, 2 and 4 ((a), (b) and (c) respectively). The results show how the electric power can be substantially decreased by the V2G electric power offer, and that, in some cases the offer can also be larger than the demand, resulting in the release of electricity back to the grid (see Fig. 6-(a)).

Additionally it can be highlighted that, regardless the different recharge strategies depicted in Fig. 6-(a), (b) and (c), there is a recurrence in the identification of the most loaded POIs. For instance, POI ID-31372 (i.e. a shopping mall) appears to be the most loaded POI for strategy 1 (i.e. Fig. 6-(a)), the third most loaded POI for strategy 2 (i.e. Fig. 6-(b)) and the second most loaded POI for strategy 4 (i.e. Fig. 6-(c)). Similarly, the POI ID-29010 (i.e. a car parking lot) appears in all the strategies, among the three most loaded POIs. This suggests that, regardless the recharge behaviours and infrastructure, some POIs behave as hubs, playing the role of pivotal nodes for the electric energy offer/demand matching.

Fig. 7 depicts the average daily electric energy offer versus demand (i.e. integral of the power curves from Fig. 6); the left pictures depict the absolute value whereas the right pictures depict the relative percentage value (i.e. electric energy offer/demand ratio). Each black dot represents a POI and the results are scaled-up to the province fleet size and refer to the medium size vehicle and recharge strategies 1, 2 and 4 ((a), (b) and (c) respectively).

This figure provides an overall overview of the V2G potential impact, showing how the electric energy load decrease from V2G varies according to the different recharge strategies. In particular the recharge strategy 1 shows to have the higher potential for the V2G, being most of the POIs' average daily electric energy offer between 30% and 50% of the respective demand, whereas strategy 2 and strategy 4 reduce this contribution to a range from 20% to 30% and from 5% to 10% respectively. Although the recharge strategy 1 presents the higher potential for V2G, it must be noticed that it is also the recharge strategy that exhibits the lowest number of vehicle that can be converted to BEVs (i.e. approximately 27,000 vehicles compared to the 41,000 and 84,000 of the strategies 2 and 4, referring to the medium size vehicle in Table 6). This results in a lower electric energy demand on the POIs (i.e. up to approximately 2 MWh/day compared to the peak values of 6 MWh/day and 40 MWh/day predicted for recharge strategies 2 and 4, as shown in Fig. 7) and consequently in a higher relative impact of the V2G electric energy offer. Additionally it must be noticed that, being the V2G energy offer always operated at a nominal discharge power of 2 kW (see the V2G model assumptions in Section 2.2), its relative weight decreases when compared with recharge strategies based on DC recharges operating at 40 kW (i.e. strategies 2 and 4).

The substantial reduction offered by the V2G application in term of local energy demand per POI, together with the ability to some POIs to play a hubs for the recharges suggests the valuable potential of such designed application.

3.4. Extension of the results to other geographical areas

The results presented in this paper refer to the province of Firenze, and are based on the GPS driving patterns of conventional fuel vehicles collected in May 2011. The same data is available for the Italian province of Modena for the same period, and the presented model has been applied to this data, in order to benchmark the results of the two provinces.

The province of Modena consists of an area with approximately 700,000 inhabitants and 442,000 registered vehicles [38]. The driving pattern database includes mobility data of 52,834 conventional fuel vehicles (i.e. 12.0% of the fleet registered in the province), and the analysis is carried out on 16,263 vehicles (according to the filtering

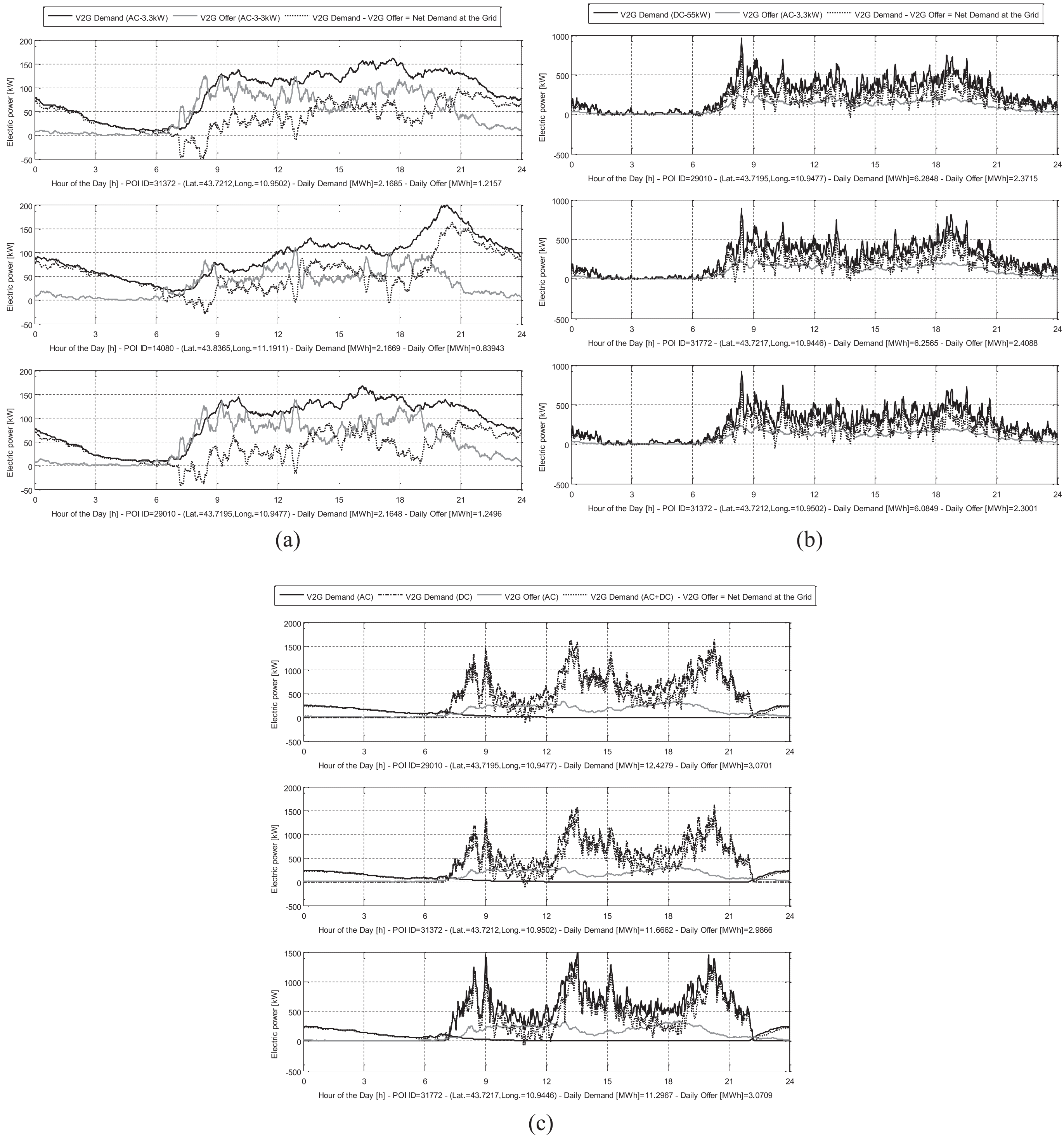
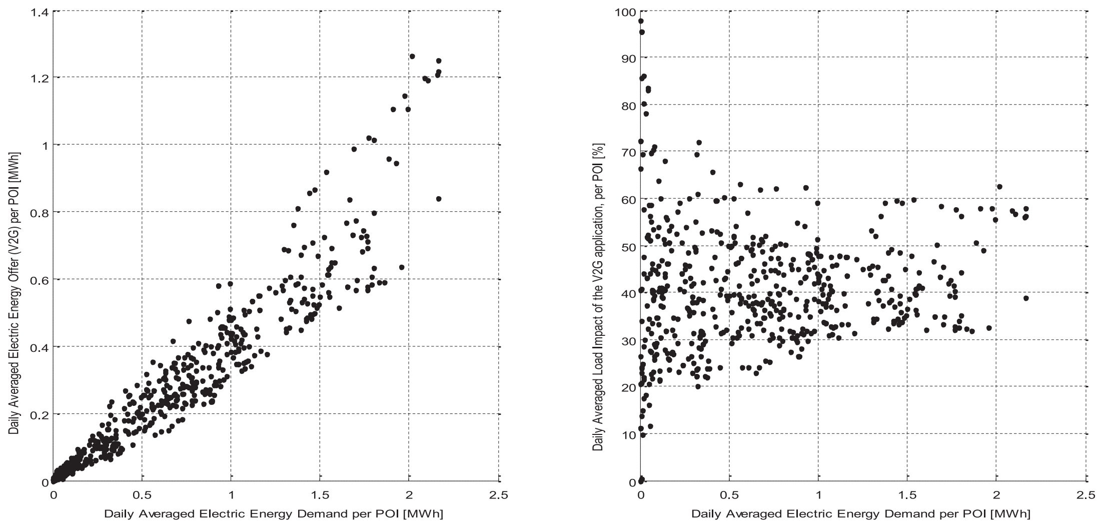


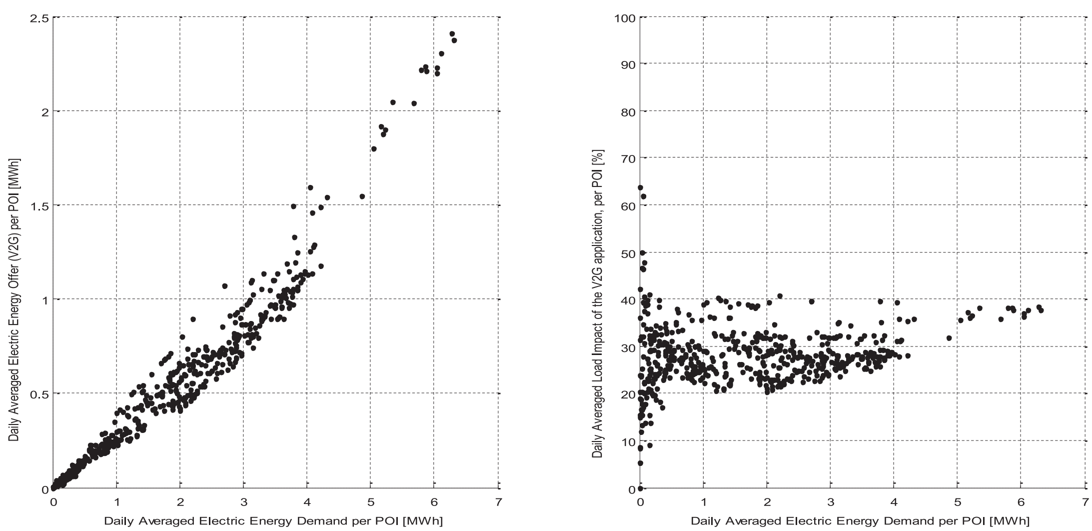
Fig. 6. Results of the V2G application on the three most loaded POIs according to the analyses performed. Black curves indicate the averaged electric power demand from parked and recharging BEVs (AC/DC, according to the specific recharge strategy); grey curves indicate the averaged electric power offer parked and not recharging BEVs; dashed curves give their difference at a specific POI location. The results are scaled-up to the province fleet size (province of Firenze), and refer to the medium size vehicle and recharge strategies 1, 2 and 4 ((a), (b) and (c) respectively).

criterion discussed in Section 2.1). The spatial analysis is carried over an area from 44.10 to 45.00 deg of latitude north, and 10.40 to 11.40 of longitude east, equivalent to approximately 7390 km^2 [40]. The POIs databases adopted consists of 423 locations, as per Table A1. The model has been applied to this data with exactly the same assumptions and hypotheses described in Sections 2.1 and 2.2, (i.e. small, medium and medium high performance size vehicles and recharge strategies).

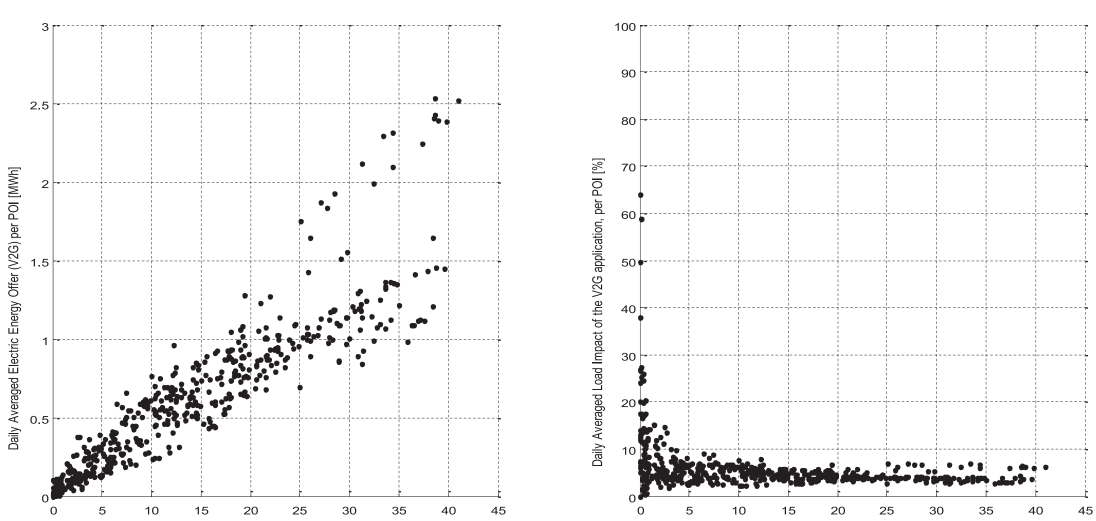
The mobility results presented in Table A2 show that a fleet share from 8% to 59% can be converted to BEVs (i.e. BEV fleet), representative of approximately a trips share from 0.7% to 20% and a mileage



(a)



(b)



(c)

Fig. 7. Summary of the results of the V2G application. The pictures on the left indicate the average daily electric energy offer from the V2G versus the average daily electric energy demand, whereas the pictures on the right indicate the percentage value of the offer with respect to the demand. Each black dot represents a POI, the results are scaled-up to the province fleet size (province of Firenze), and refer to the medium size vehicle and recharge strategies 1, 2 and 4 ((a), (b) and (c) respectively).

share from 1.3% to 39.7%. The results for HEVs are also reported for completeness. Table A3 reports the monthly electric energy demand from these vehicles, showing that they impact from approximately 0.4%–12.6% of the demand of the province (i.e. from 2.1% to 71.5% of the domestic demand). Fig. A1 depicts the recharge infrastructure layout, for the medium size vehicle (zoom on the city of Modena), and Table A4 reports the summary of the recharge infrastructure results per vehicle type and per recharge strategy.

The results presented for the province of Modena looks very similar to those of the province of Firenze, showing how the similar socio-economic conditions between different areas lead to similarities in the mobility patterns [38–40], and therefore to similar electric energy demand and recharge infrastructure layout. The only difference that can be noticed is the lower electric energy offer/demand ratio, which ranges from 3.3 to 4.5, and that can be ascribed to the lower number of POIs considered in this case (i.e. 423 for the province of Modena compared to the 632 of the province of Firenze).

However, in spite of the similarities between the results from Modena and Firenze, different infrastructure layouts are expected by applying the model in areas characterised by different socio-economic environment with respect to the two analysed provinces (e.g. US and Asian megalopolis). In particular, the effect of capillary public transportation systems, restricted traffic zones and multi-modal transportation choices can be reflected in substantially different results from those depicted in the present study.

In general, the model can be applied to every geographical area where driving patterns data and databases of POIs are available, and, at the moment, it does not account for local or regional regulations, congested areas subjected to particular traffic restrictions or specific urban policies. However, such features might be implemented by pre-filtering POIs databases (e.g. processing exclusively POIs where parking is allowed according to the local regulations) or by applying time and spatial filtering in the infrastructure layout processing. However, it is remarkable that the model is able to adapt itself to different boundary conditions, so it can be used as a valuable tool for urban transport policies in almost every geographical environment. As future development of the present study, the authors foresee the extension of the analyses to different EU countries, addressing the urban mobility and electrification of transport on a continental scale.

4. Conclusions

This paper provides the scientific community with the results of a model capable of designing the layout of the recharge infrastructure for electric vehicles based on driving patterns data from conventional fuel vehicles. The presented application focuses on the province of Firenze, considering mobility data from 12,478 vehicles in a period of one month, accounting for more than 20 million kilometres and 1.87 million trips. Based on this data, the model investigates the driving patterns of the vehicles in real-world conditions, deriving the fleet, trip and mileage shares which can be shifted to battery electric vehicles and the increase of electric energy demand, given the vehicles performance and recharge strategies constraints. The scenarios derived are used as input to design the recharge infrastructure, pivoted on databases of Points of Interest retrieved from the web. The model considers the POIs as possible locations for installing charging spots, estimating in each of them:

- A Geo_{KPI}, which quantifies the ability of the POI to meet urban vehicles' charging request, in term of convenience of its geographic location;
- A repetitiveness index, which quantifies the ability of the POI to meet the needs of a small/large pool of customers;
- Total amount of electric energy delivered per POI, which gives an indication of the market profitability of a specific location in terms of energy demand from EVs;
- Time dependent plug-in demand and power demand curve, which allows estimating the number of charging spots to be installed in a specific location.

The model also implements a Vehicle-to-Grid interaction strategy, which estimates in each POI the possible time dependent electric power offer curve from parked vehicles by sharing the 2% of the nominal energy capacity of their battery, to investigate the potential of such application for shaving localised peaks of electric energy load demand.

The results show a fleet share shift from conventional fuel vehicles to battery electric vehicles ranging from 10% to 57%, representative of a mileage share from 1.6% to 36.5%, depending on the scenario. This corresponds to an electric energy demand increase ranging from 0.7% to 18% of the total electric energy demand in the province, depending the vehicle type and on the recharge strategy, and it results in a fully developed infrastructure accounting for a number of charging spots three-to-six times higher than the number of circulating electric vehicles (i.e. fully developed recharge infrastructure). The results partially resemble the indications provided by the recent Proposal for Directive [22] for the deployment of alternative fuel infrastructures. The V2G application suggests a substantial reduction of the electric power peak load, and, consequently, a reduction from 5% to 50% of the average daily load, according to the considered scenarios.

The developed model shows the potential of using driving patterns databases and data mining to investigate several aspects of the deployment of battery electric vehicles and recharge infrastructures technologies, providing a valuable insight into practical and technological implications that this technology might have. Among them, quantifying the capability of BEVs to replace conventional fuel vehicles, the increase in the regional and national electric energy demand and the customer-driven planning, design and size of the recharge infrastructure network are key issues to formulate effective policy directions and incentives to enable the large-scale adoption of BEVs and the effective deployment of an alternative fuel infrastructure. Moreover the results could serve as basis to quantify the potential of reducing the gaseous pollutants and GHGs emissions from transport in densely populated areas, thus providing the background for regional and national policies for improving the quality of the air and mitigate the climate change.

The results can be extended to different geographical areas, as shown herewith for the province of Modena, and the model is capable of adapting itself to different boundary conditions, being in principle applicable to every urban environment as well as to different kinds of infrastructures (e.g. liquefied petroleum gas, compressed natural gas, biofuels and hydrogen distribution networks). The authors foresee the extension of the analyses to different EU countries, addressing the urban mobility and the electrification of transport on a continental scale, in view of supporting future policies for low-carbon vehicles deployment and alternative fuel infrastructures.

Appendix

Table A1
Summary of the POIs adopted for the current analysis (province of Modena).

	No. of POIs (province of Modena)
Airports	12
Petrol stations	328
Shopping malls	43
Car parking	35
Bus parking	5
TOTAL	423

Table A2
Fleet, trips and mileage shares for BEVs and HEVs (province of Modena).

EV type		Strategy			
		Trips and mileage shares			
		Str. 1 Long-Stop R-AC	Str. 2 Short-Stop R-DC	Str. 3 Smart AC	Str. 4 Mixed Time AC/DC
Small size vehicle	BEV fleet	7.99%	14.81%	14.65%	29.70%
	HEV fleet	92.01%	85.19%	85.35%	70.30%
	BEV trips	0.68%	2.62%	1.78%	8.87%
	HEV trips (electric)	75.74%	82.54%	77.91%	73.34%
	HEV trips (ICE)	23.58%	14.84%	20.31%	17.79%
	BEV mileage	1.35%	4.29%	3.91%	14.10%
	HEV mileage (electric)	51.79%	64.19%	53.80%	60.94%
	HEV mileage (ICE)	46.86%	31.51%	42.29%	24.96%
Medium size vehicle	BEV fleet	12.98%	25.84%	21.02%	43.71%
	HEV fleet	87.02%	74.16%	78.98%	56.29%
	BEV trips	1.29%	5.33%	2.70%	13.98%
	HEV trips (electric)	76.33%	75.03%	72.86%	61.18%
	HEV trips (ICE)	22.38%	19.64%	24.44%	24.84%
	BEV mileage	3.14%	10.63%	6.69%	25.15%
	HEV mileage (electric)	56.58%	65.17%	51.93%	55.45%
	HEV mileage (ICE)	40.29%	24.20%	41.38%	19.39%
Medium size vehicle (high performance)	BEV fleet	22.15%	41.42%	30.01%	58.67%
	HEV fleet	77.85%	58.58%	69.99%	41.33%
	BEV trips	2.57%	9.40%	4.10%	19.69%
	HEV trips (electric)	73.12%	61.67%	66.73%	46.01%
	HEV trips (ICE)	24.31%	28.93%	29.17%	34.30%
	BEV mileage	7.67%	22.32%	11.65%	39.68%
	HEV mileage (electric)	59.48%	59.86%	51.08%	45.69%
	HEV mileage (ICE)	32.85%	17.81%	37.27%	14.63%

Table A3
Electric energy demand per month [GWh] derived by considering the fleet share capable to drive only with the considered BEVs (BEV fleet share in Table 4, province of Modena). The results are scaled-up to the fleet size of the province. The values in parenthesis represent the percentage of the energy demand with respect to the total energy demand of the province as per [50].

EV type	Strategy			
	Vehicles monthly energy demand [GWh] (percentage of the: monthly total energy demand [%] – monthly domestic energy demand [%])			
	Str. 1 Long-Stop R-AC	Str. 2 Short-Stop R-DC	Str. 3 Smart AC	Str. 4 Mixed Time AC/DC
Small size vehicle	1.45 (0.37%–2.13%)	4.85 (1.25%–7.12%)	4.26 (1.10%–6.26%)	15.70 (4.05%–23.05%)
Medium size vehicle	3.93 (1.01%–5.77%)	13.36 (3.45%–19.62%)	8.22 (2.12%–12.07%)	31.60 (8.15%–46.40%)
Medium size vehicle (high performance)	9.11 (2.35%–13.38%)	26.53 (6.84%–38.96%)	13.91 (3.59%–20.43%)	48.70 (12.56%–71.52%)

Table A4
Summary of the results recharge infrastructure network layout (province of Modena).

			No. of vehicles	Average no. of recharges/day	No. of working POIs (% tot. POIs)	Electric energy/day [MWh]	Energy offer/demand ratio	No. of charging spots (AC/DC)
Small size vehicle	Str. 1	Demand	8767	4554	396 (93.6%)	13	4.5	15,334
		Offer		21,531		59		(AC)
	Str. 2	Demand	18,342	18,219	412 (97.4%)	45	4.1	27,750
		Offer		78,248		183		(DC)
	Str. 3	Demand	16,700	11,346	404 (95.5%)	35	4.5	52,442
		Offer		52,309		156		(AC)
	Str. 4	Demand	37,900	61,304	420 (99.3%)	146	3.6	17,992–103,480
		Offer		237,530		522		(AC) (DC)
Medium size vehicle	Str. 1	Demand	14,925	8610	405 (95.7%)	35	4.2	24,242
		Offer		38,170		148		(AC)
	Str. 2	Demand	32,792	37,328	418 (98.8%)	126	3.9	46,959
		Offer		153,030		490		(DC)
	Str. 3	Demand	24,067	17,162	411 (97.1%)	68	4.3	72,050
		Offer		76,072		289		(AC)
	Str. 4	Demand	56,133	96,675	420 (99.3%)	294	3.4	26,667–145,640
		Offer		360,740		1003		(AC) (DC)
Medium size vehicle (high-Perf.)	Str. 1	Demand	26,533	17,378	414 (97.9%)	84	3.9	40,284
		Offer		73,014		331		(AC)
	Str. 2	Demand	53,592	65,824	419 (99.1%)	260	3.7	72,509
		Offer		256,130		952		(DC)
	Str. 3	Demand	34,475	25,824	414 (97.9%)	115	4.1	99,900
		Offer		111,140		470		(AC)
	Str. 4	Demand	75,717	136,290	422 (99.8%)	453	3.3	36,242–187,710
		Offer		491,890		1483		(AC) (DC)

Fig. A1. Number of charging spots per POI based on the average electric energy demand (the results are scaled-up to the province fleet size). The type of charging spot (i.e. AC/DC) is given by the recharge strategy, according to Section 2.1. The results refer to the medium size vehicle, province of Modena.

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