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Estimating charging demand by modelling EV drivers' parking patterns and habits

Piero Macaluso[1], Angela Carboni[2*], Cristiana Botta[1], Paolo Lazzeroni[3], Francesco Deflorio[2], Maurizio Arnone[1]

[1]LINKS Foundation, Via Pier Carlo Boggio, 61, 10138, Turin, ITALY
[2]POLITECNICO DI TORINO, Engineering, Dept DIATI – Transport systems, Corso Duca degli Abruzzi 24, 10129, Turin, ITALY
[3]POLITECNICO DI TORINO, Engineering, Dept DENERG, Corso Duca degli Abruzzi 24, 10129, Turin, ITALY

Abstract

The diffusion of battery electric vehicles (BEVs) requires a proper charging infrastructure to supply users the chance to charge their vehicles according to energy, time, and space needs. Thus, city planners and stakeholders need decision support tools to estimate the impacts of potential charging activities and compare alternative scenarios. The paper proposes a modelling approach to represent parking activities in urban areas and obtain key indicators of the electric energy required. The agent-based model reproduces the dynamics of user parking and assesses the impacts on the electricity grid during the day. Since the focus is on parking activities, no detailed data on vehicle trips are required to apply the standard demand modelling approach, which would require Origin-Destination matrices to simulate traffic flows on the road network.

Preliminary results concerning the city of Turin are presented for simulated scenarios to identify zones where charging demand can be critical and peak events in electric power over the day. The model is designed to be scalable for all European cities because, as the case study shows, it uses available data. The results obtained can be used for the design of charging infrastructure (power and type) by zones.

Keywords: Electric vehicles; Charging demand; Parking-based model; Charging infrastructure; Decision support tools.

1. Introduction

The European Union, with the Green Deal (COM (2019) 640 final), aims to reduce greenhouse gas emissions from transport by 90% by 2050 compared to 1990. The decarbonization of the private transport sector can contribute to reach this goal by paving the way for the diffusion of electric vehicles (EV) and charging infrastructure. In 2020, there were approximately 285800 public charging stations for electric cars in Europe compared to just over 67000 in 2015 (Statista Research Department). Currently, Europe

* Corresponding author: Angela Carboni (angela.carboni@polito.it)

has 374000 public chargers, but two-thirds are concentrated in just five countries: the Netherlands, France, Italy, Germany, and the United Kingdom (Carey, 2022). Numbers are expected to increase in correlation with the forecasted increase in sales of electric vehicles; a Eurelectric-EY study predicts 130 million electric cars in the EU by 2035 from 3.3 million today (Colle *et al.*, 2022). Thus, city planners and stakeholders require decision support tools to estimate the impacts of these changes and needs in the urban context.

Classically, EV charging demand can be evaluated through driving patterns or traffic flows analysis (Feng *et al.*, 2020). These approaches include the use of the Origin-Destination (OD) matrix to study how EV flows and the driving paths are distributed around a city (ElBanhawy *et al.*, 2014), considering the charging behaviour of the users (Fu et al., 2020; Chen et al., 2020) and different range anxiety (Lazzeroni *et al.*, 2021). The latter use Floating Car Data to identify mobility habits, particularly parking patterns, to estimate energy demand for EVs. The parking-based approach is in common with this paper, which aims to use more quickly and commonly available mobility data. Another analytic framework considers charging demand determined by travel behavior (Yang *et al.*, 2020). In this last case, the daily charging demand of EVs is based on the analysis of the daily travel frequencies and the charging rule on each EV activity chain. Detailed trip chains can study the demand distribution for electric recharging and its dynamism with an agent-based trip chain model (Lin et al., 2019;Lin et al., 2018). The latter ones do not include GIS information on the land-use type, used instead in our model, which can help in planning recharging infrastructures. However, in general, data for identifying OD matrices are costly and typically with limited availability, so replicability is possible but only in limited contexts.

Hence, other different approaches have been exploited to overcome these limitations. For instance, the energy demand estimation due to EV charging is extrapolated by a statistical analysis of an available charging sessions dataset in van den Berg et al. (2021). Similarly, Xia et al. (2019) avoid the requirement of real-world traffic data, such as road topology and route length, with a statistics-based model. Machine learning and artificial neural network techniques trained using the available dataset of charging demand are adopted by Kim and Kim (2021). In their approach, data privacy issue needs to be carefully handled and the replicability is limited to data availability. Moreover, drivers' behaviour is not modelled. mobility data are instead considered in a spatial model, using the Markov chain, proposed and tested with data from electric charging stations by Shepero and Munkhammer (2017). Their results show that their model can better reproduce the behaviour of the most frequently used charging stations. Yi et al. (2021) present a time series prediction of the monthly charging demand of commercial electric vehicles using a deep learning-Sequence to Sequence approach, chosen for its better performance than other models, including long short-term memory. Within the framework of forecasting models, real-world traffic distribution data and weather conditions are used by Arias and Bae (2016) to predict the electric vehicle charging demand. Alternatively, an estimation of the number of cars owned by households is used by Thingvad et al. (2021) to define EV charging demand, assuming an average distance travelled by vehicles and an average parking time of EVs.

This paper aims to propose a method for estimating the expected energy demand in the city based on variables linked to the mobility behaviour of electric vehicle users. With the final purpose of producing a Decision Support System (DSS) for city planners and stakeholders, the proposed methodology uses widely and commonly available input data

for cities. From a survey of implemented cases of electric charging infrastructures in cities (Campisi *et al.*, 2021), it has been observed that planning urban charging opportunities for users could also be an integrated process taking into account the needs of other electric mobility services (e.g. sharing and public transport), since positive synergies can be activated.

The current work is developed within the European project INCIT-EV, in which a model capable of formalizing the city system and its characterization functions has been implemented to foster the development of electric mobility across Europe.

2. Methodology

The Decision Support System (DSS) developed within the INCIT-EV project is a tool that aims to support municipalities, authorities, agencies, and other stakeholders in planning the optimal charging stations framework in the city and estimating the impact of already planned scenarios. INCIT-EV DSS and, more generally, the whole INCIT-EV project focus on following a user-centric approach to make electric vehicles a universal technology. The tool has been developed mainly to facilitate the harmonious growth of electric mobility throughout Europe, especially in supporting cities without powerful tools, data, or competencies. For this reason, just open and Europe-wide datasets have been considered for the module implementations. These principal design objectives and strategies have been considered to build the model:

- Applicability in all EU cities (even if no specific mobility data are available): based mainly on official and publicly available data;
- Support the strategical Charging Points (CPs) location at the zone level: the output of the DSS should be based on user-defined zones to support operative decisions without the purpose of giving precise information (e.g., new CP geographical coordinates) on phenomena that may require access to detailed local data and interactions with local stakeholders/users;
- Robustness and reliability: simple, easy to calibrate and validate, without needing complex and data-demanding approaches that require lots of inputs from users;
- User-friendly and customizable by the users: the users can upload their data (e.g., city shapefile) and modify the configuration of the analyses;
- Fast computing: it should provide the results in a reasonable and possibly short amount of time.

The DSS comprises four modules: *User Behavior, Mobility, Charging Infrastructure, and Power*. The last two modules deal with aspects related to the supply of charging and the impacts on the energy system. Instead, User Behavior & Mobility Module (UB&M), covered in this paper, aim to outline and describe users' mobility habits and behavior given the input data provided by DSS users and/or coming from specific surveys in cities. Besides, these modules can support the decision-making of DSS users by offering insights related to the impact of user behavior in terms of mobility and charging habits.

The main components of UB&M modules are shown in Figure 1. Starting from the right side, there are the user input variables (car trips, zoning and city data) and the external datasets used as input to get the distribution of both the EVs number, and the User Behaviour and Mobility thanks to the Car Parked Estimation (section 2.2) and Charging Behaviour models (section 2.1). Their outputs converge in the Electric Mobility Simulation model (section 2.3), which returns the outcomes useful for power analysis.

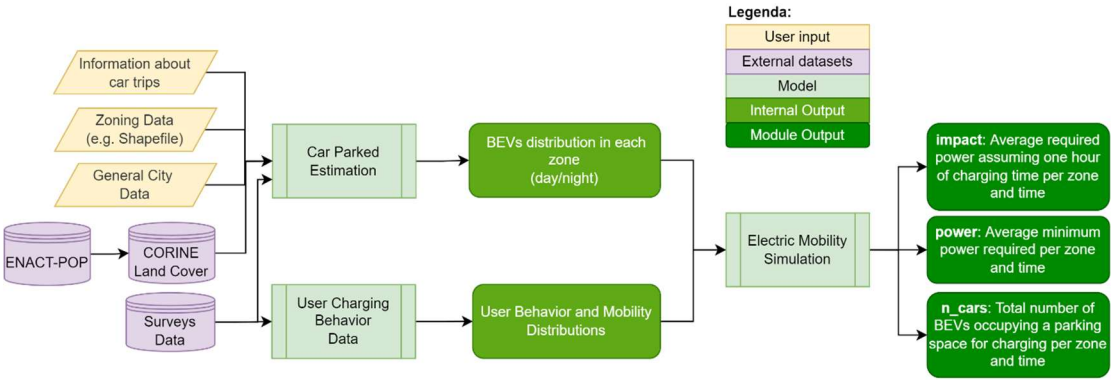


Figure 1: Schematic overview of the User Behaviour & Mobility Modules.

In the following, according to the selected approach, it is considered that the vehicle recharges when it is parked, excluding recharging along the trip. In addition, this first modeling considers only one type of battery electric vehicle (BEV) with the characteristics described below (Table 1), initially excluding other models and other types of vehicle electrification (e.g. plug-in).

2.1 User Charging Behaviour Data Model

This model provides charging preferences for electric vehicle users regarding charging location (private/public at home, private/public at work, in other places). The model also needs to formalize EV drivers' habits and actions by using typical statistical distributions such as:

- Daily km traveled distribution (urban, incoming/outgoing; weekday/Sat/Sun or total, from DSS user). Since the model performs an urban analysis, incoming trips are included only if their charging preference is at work or other, while outgoing trips if the charging preference is at home.
- Charging daily profile (per hour) (from specific city surveys or EU studies/statistics).
- Starting state of charge (SoC) distribution (from specific city surveys or EU studies/statistics).
- Final state of charge (SoC) distribution (from specific city surveys or EU studies/statistics).
- Parking time distribution at home, work, and other locations (from specific city surveys or EU studies/statistics).

The model comes from the calibration of a discrete choice experiment (DCM) designed ad hoc in other activities in the INCIT-EV project to evaluate where users usually recharge their electric vehicles (Gamba *et al.*, 2022). The model is based on a logit model in which the likelihood of charging at the generic location option is a linear combination of attributes related to the charging infrastructures (typology, availability, price, charging time, reservation, ancillary services, renewable energy, type of connection). If the DSS user does not have this information, default percentages can be used. On the other hand, if the user does have city-specific data, it is possible to use the available data directly.

2.2 Car Parked Estimation

In this parking-based approach, the population data (ENACT-POP) from a JRC study (Batista e Silva *et al.*, 2020; Schiavina *et al.*, 2020) and the land use data obtained by the Corine project (CORINE Land Cover) were taken as a reference to estimate the number of cars parked in the city zones during the day (work or other) and night (home) (Car Parked Module, Figure 1).

The ENACT-POP dataset is used to estimate the relative weights to re-proportion the stops of vehicles circulating in the city. It is a raster dataset that calculates the present people in daytime and night-time per month with a granularity of $1km^2$, considering the presence of residents, workers, students, and tourists. These grids were produced for all EU-28 countries by combining official statistical data at the regional level with geospatial data from conventional and non-conventional data sources for the reference year of 2011 (the most recent round of censuses). The CORINE Land Cover (CLC) data are used to adapt the estimated data on regular grids to the city zoning; the DSS user chooses that for the analysis. This project was set up at the European level to detect and monitor land cover and land use characteristics. It provides land cover/use for most areas of Europe, according to 44 different classes, with a raster granularity of $100m^2$.

These data, available for the major EU city, were used for calculating relative weights to assign the stops of the total daily vehicles traveling in the town and disaggregated as urban, incoming, and outgoing (data asked as input to DSS users). The estimation is done concerning the city's zoning. In this way, the number of vehicles parked per zones during the day and at night is obtained. To achieve the demand for charging, it is necessary to know how many of these parked vehicles are electric.

The percentage of electric vehicles by vehicle type can be estimated by applying a model based on the calibration of the discrete choice experiment to assess interest in electric cars. It requires, as input, the attributes related to the ownership of EVs (e.g., car price, autonomy with a full battery, operating cost, electric charge infrastructure diffusion, incentives). This section will be developed in future research activities, following the approach described in (Gamba *et al.*, 2022). In case of missing data, default percentages can be used based on current values of the market penetration rate.

2.3 Electric Mobility Simulation Model

The Electric Mobility Simulation Model represents the core part of the methodology implemented within the tool. It consists of an agent-based model capable of simulating the activities of each car in the city, considering both behavioral and population distributions resulting from the calculations made by the previous models. Implementing an agent-based model was driven by the necessity of flexibility in defining the characteristics of every single vehicle and the rules that make them interact with the surrounding environment. Therefore, it is an emergence, a process that aims to model higher-level system properties of complex phenomena from the interactions of lower-level subsystems where agents follow simple directives. In the case of this work, the outcomes coming from numerous iterations on different experiments on a pre-selected number of days lay the foundation for a Monte Carlo simulation to calculate energy, power, and parking pressure indicators in each zone of interest for each hour of a reference day.

The model takes as input a set of distributions resulting from the analysis carried out in the User Charging Behavior Model (2.1) and the Car Parked Estimation Model (2.2). Given this group of variables, the tool can generate the set of agents that will interact with the simulation.

Table 1: BEV Characteristics.

Property Name	*Description*
Battery Size [kWh]	Hardcoded to 52 kWh taking Renault Zoe as a template model
Average Consumption [kWh/km]	Hardcoded to 0.177 kWh/km, taking Renault Zoe as template model.
State of Charge (SoC) [%]	Current SoC to keep track of the BEV status. They are initialized randomly at the start of each epoch.
Starting SoC [%]	SoC threshold for starting recharging. Sampled from related distribution.
Final SoC [%]	The State of Charge until the car will charge. Sampled from related distribution.
Daily km traveled [km]	The number of km the car will travel each simulation day. Sampled from related distribution.
Parking Time [h]	The number of hours in which the car stays parked. Sampled from related distribution.
Day Zone ID	Identifier of the assigned daily zone. Sampled from related distribution.
Night Zone ID	Identifier of the assigned night zone. Sampled from related distribution.
Charging Place	Charging place preferred (home/work/other, public/semi-public/private). Sampled from related distribution.
Charging Period	Charging preference (day/night). Sampled from related distribution.

Each BEV is characterized by a collection of properties presented in Figure 1. Furthermore, each agent (i.e., BEV) possesses two functions to formalize the travel process and the charge one. The former considers the average consumption and the daily km traveled by the vehicle to calculate and update the SoC when the car will decide to park. At the same time, the latter compares the current SoC with the Starting SoC, considers the amount of km that the vehicle will cover in the coming day, and decides whether the agent will charge the vehicle. Then, it is calculated and returned for each car (i.e. each agent) and each day of the simulation.

In addition to the amount of energy demanded by the BEV to arrive at the final SoC, the algorithm gets information about the charging preference of the agent to attribute the charging process to the right zone and the number of hours the car is expected to stay parked. All information contributes to calculate the energy impact and the minimum charging power required to reach the final SoC within the provided amount of parking hours. The vehicle choices will contribute to populating one of the three matrixes used to disaggregate short (<3h), medium (3≤ and ≥8h), and long parking (>8h).

The estimation of these values for each vehicle and each simulation day generates a set of matrixes meant to be the result of a single epoch of the simulation. By iterating on numerous epochs, it is possible to proceed with calculating the running mean and the standard deviation of these variables. This allows estimating confidence intervals that can be used to determine the reliability of the measurement but also as a threshold to stop the simulation. The confidence level selected for the calculation was 95%.

3. Preliminary application and results

3.1 Case study description

The methodology proposed and described in the previous section was tested with a preliminary application on a case study in the city of Turin in northern Italy to verify the model.

Turin has a population of around 870,000 inhabitants on an area of 130.2 km². At the end of 2021, there were 196 public recharging points in the city, which rose to 387 if private points with public access were also included. The total number of registered electric vehicles in Italy in 2021 was 136754, with an increase of +128% compared to the year 2020. Thirty percent of these (both fully electric and plug-in hybrids) are concentrated in north-western Italy (Motus-E, 2021).

The simulations presented in the following have been carried out on a PC with a CPU Intel(R) Core (TM) i7-8565U CPU @ 1.80GHz (8 cores) and 32GB RAM. The running time ranges from about 5 minutes for 1000 iterations to 30 minutes depending on the scenarios.

Following the procedure reported in Figure 1, the input values related to the proposed case study include: a city zoning composed of 183 zones; the ENACT-POP raster dataset, and the CORINE Land Cover raster dataset for the Turin city; the total cars estimated from daily trips available in (Agenzia della Mobilità Piemontese, 2016) (89243 urban, 50515 incoming and 28423 outgoing for weekdays) and the distribution of kilometres travelled (the most common trips are those between 10 and 50 km).

In Table 2, the distribution used for the parking time at home, work, and other locations in the case of the current situation in Turin as observed in (Brancaccio and Deflorio, 2021) are shown. In Table 3 there is a realistic distribution representing a current situation of parking duration according to the main types of activities, especially by differentiating work and other. Finally,

Table 4 reports the distributions used for the start time of the stop in the three types of activities identified (home, work, and other). It is assumed that 65% of users recharge at home, 30% at work, and the remaining 5% in other places (e.g. supermarkets, gyms). The charging infrastructure at home and work can be either public or private.

Table 2: Current parking time distribution at home, work, and other locations

Parking time [h]	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*12*	*14*	*16*	*18*	*20*	*22*	*24*
Home								2%		11%	19%	23%	17%	11%	9%	7%	1%
Work	43%	21%	13%	7%	6%	3%	3%	2%	1%								
Other	43%	21%	13%	7%	6%	3%	3%	2%	1%								

Table 3: Parking time distribution at home, work, and other locations.

Parking time [h]	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
Home									5%	10%	20%	30%	20%	10%	5%
Work				10%	5%	10%	5%	15%	40%	15%					
Other	40%	30%	20%	10%											

Table 4: Time to start charging at home, work, and other locations (extracted and revised from Corchero et al., 2015)

Start of parking [%]	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*
Home	3	2	4	0	0	0	1	2	4	4	4	4	4	4	5	4	6	7	10	10	9	6	5	4
Work	0	0	0	0	0	1	2	7	14	8	6	6	7	7	11	9	7	3	2	1	1	8	0	0
Other	1	1	0	0	0	1	2	5	9	8	7	6	6	8	7	7	6	5	5	5	5	3	2	2

3.2 Scenarios

To stress the model, different scenarios are built investigating some challenging situations. In the first results reported in this paper, the daily traveled km distribution was related to a typical weekday. Then, different market penetration rates were assumed to change the number of parked vehicles per zone (output of the car parked estimation module). With the highest percentage used for future scenarios, 8409 BEVs are simulated, while in the current scenarios they are 1682. Secondly, the SoC threshold for starting recharging was modified on two levels to simulate two different user behaviors, assuming that all arrive at full charge. Finally, two additional parking time distributions have been considered (section 3.1). Table 5 shows the combination of these input variables to compose the different scenarios investigated.

Table 5: Input values for the different scenarios investigated.

Scenarios		*Daily km traveled distributions*	*Market rate penetration*		*Initial SoC (Final SoC 100%)*		*Parking time distribution*	
		Weekday	1%	5%	40%	20%	Table 2	Table 3
S0	Current observed	x	x		x		x	
S1	Current	x	x		x			x
S2	Future	x		x		x		x
S3	Future + anxiety recharging	x		x	x			x

3.3 Results

According to section 2.3, one output of the model is the total number of BEVs occupying the parking space in each zone (*n_cars*), i.e. the occupation of the parking space during the day. Then the average required power assuming two different charging times are obtained. Firstly, one hour of charging time per zone (*impact*) is considered. Secondly, a less stressed condition (*power*) is depicted since the energy demand of the vehicle is spread over the entire duration of the parking period, in a "smart charging" perspective. Figure 2 shows the trend of this last variable during the day, aggregated for the city, in the different scenarios examined. The trend in the current scenario observed (S0) is interesting as there is a peak at 8 a.m. that is not found in the other scenarios. this is probably due to the fact that the distribution of dwell times is different (see Table 2 and Table 3): short stops begin at that time and therefore require energy distributed over a shorter time. On the other hand, it can be seen that in the late afternoon the trend is decreasing, almost constant, due to the start of night stops with very high durations, even over 20 hours.

The daily energy required for all city changes in the different scenarios is almost similar in the two current scenarios (S0 and S1) but increases by 360% in the future scenario (S2) and by 400% in the one that considers a user charging already with SoC at 40%.

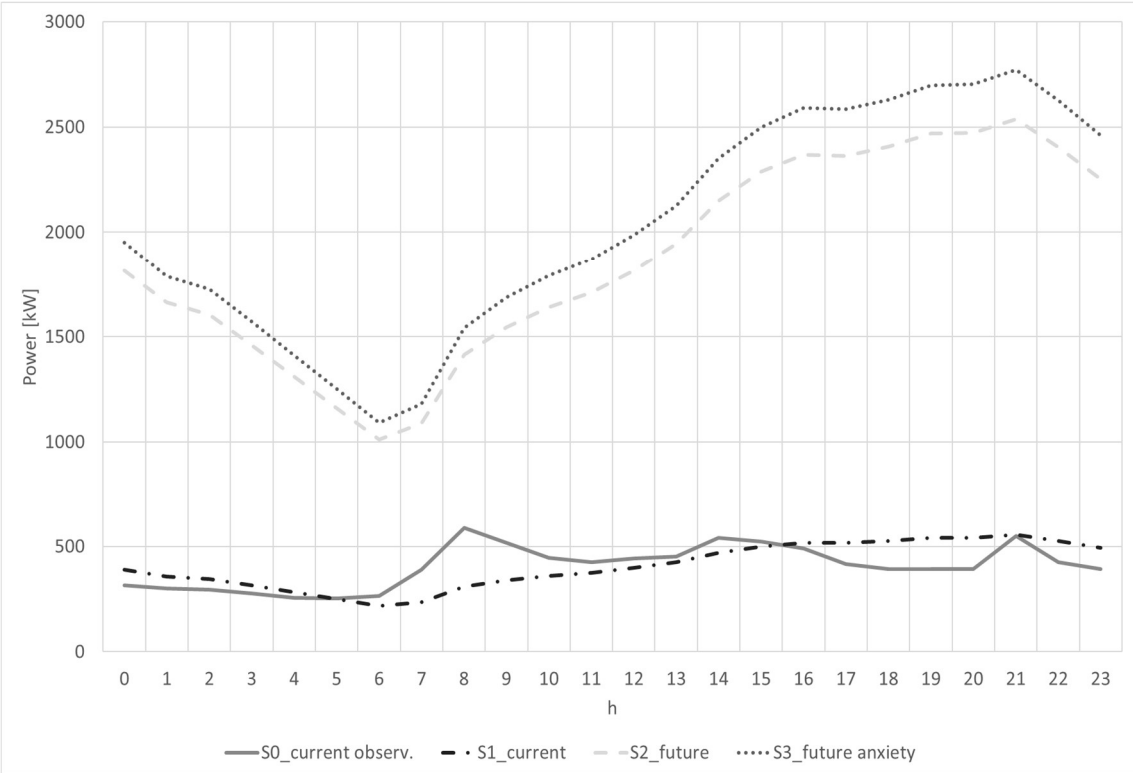


Figure 2: Average minimum required power to satisfy the agent's needs for Turin city in different scenarios.

Considering the peak at 8 am, the disaggregated value of BEVs occupying the parking space in each city zone is shown in Figure 3 for the two extreme scenarios (S0 and S3). As expected, the number of vehicles increases in the future scenario due to the rise of the market penetration rate, and the most heavily loaded zone remains the "*Environment Park.*" This densely populated district of the city is also enriched by the presence of offices and shopping areas, making 8 a.m. a peak hour. In the current scenario, the difference between the zones is less pronounced, while in the S3, the variability is more significant.

The graph in Figure 4, reported for the future scenario, shows the two opposed charging conditions: the green line (*power*) could represent a charging that uses the whole vehicle parking time, while the orange line (*impact*) could be the case where the charge is completed in the first hour of parking. This could be helpful information for the energy supplier and the stakeholders involved to know their range of action (grey bars) which can vary throughout the day. The night and day trends are reversed since fewer users start charging at night than during the day. The model is able to provide this information also disaggregated by zones of the city.

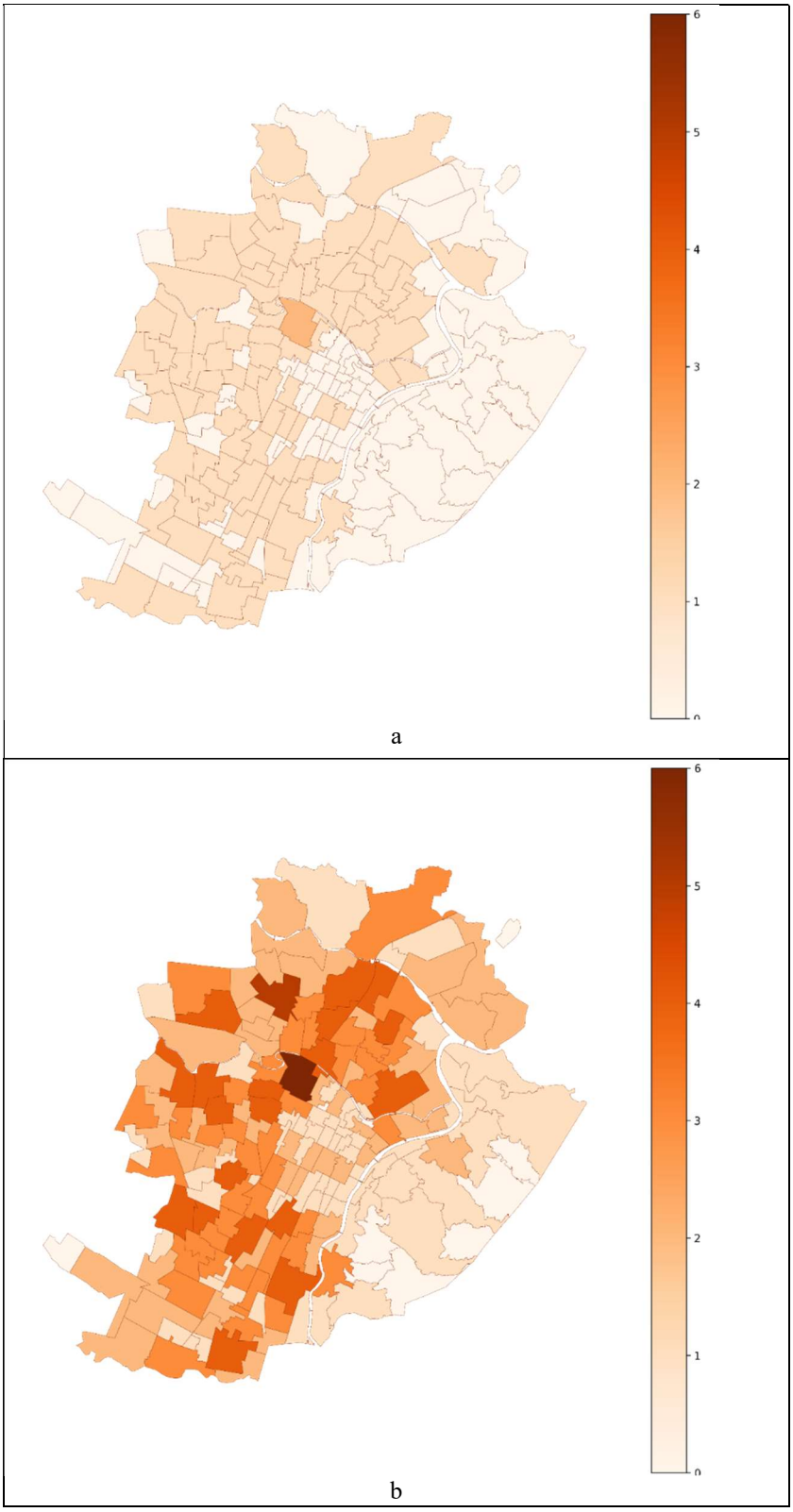
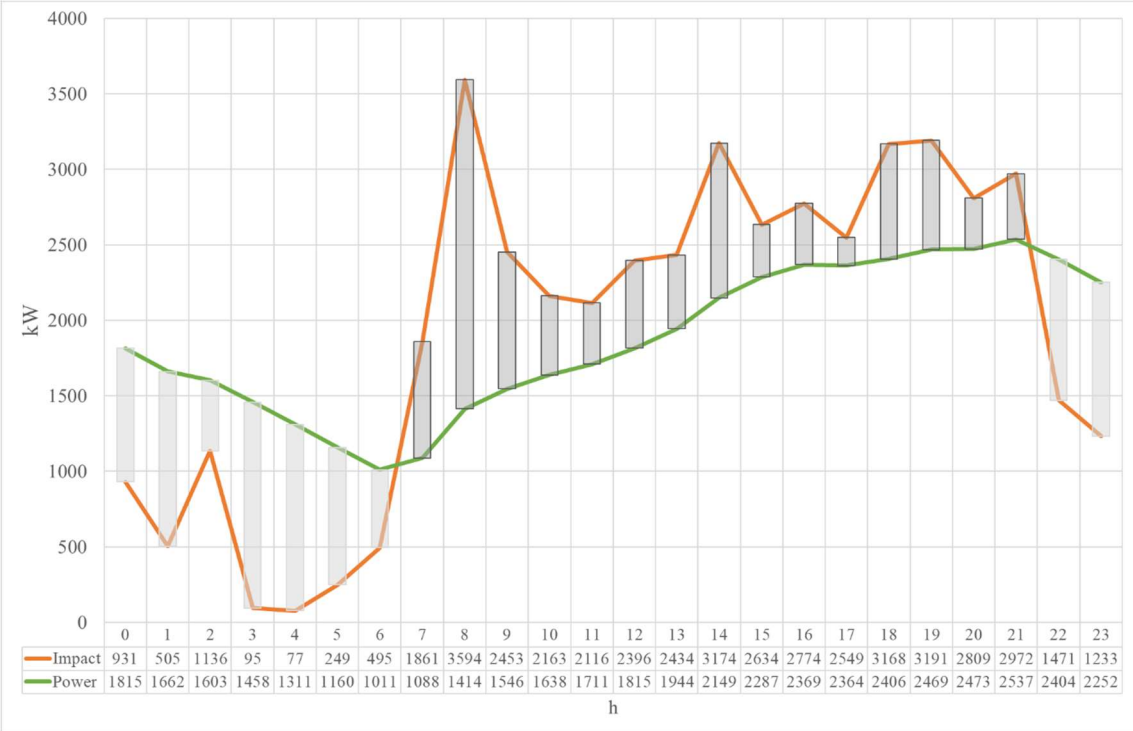


Figure 3: (a) Number of cars parked in scenario S0 and (b) in scenario S3 for each zone at 8.00 a.m.



	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Impact	931	505	1136	95	77	249	495	1861	3594	2453	2163	2116	2396	2434	3174	2634	2774	2549	3168	3191	2809	2972	1471	1233
Power	1815	1662	1603	1458	1311	1160	1011	1088	1414	1546	1638	1711	1815	1944	2149	2287	2369	2364	2406	2469	2473	2537	2404	2252

Figure 4: Trend of impact and power variables in the future scenario (S2) to simulate two charging strategies.

4. Conclusions

The presented modelling approach estimates the electric energy required for charging operations in urban areas simulating parking activities of battery electric vehicles (BEVs) and their energy needs. An agent-based model is used to simulate the dynamics of parking and assesses the electricity demand during the day. The model is designed to be scalable for all European cities, therefore using readily available data or open datasets, moving away from the classical mobility data to follow a parking-based approach. Indeed, the population data (ENACT-POP) and the land use data obtained by the Corine project, available for the major EU city, were taken as a reference to estimate the number of cars parked in the city zones during the day (work or other) and night (home).

Other pieces of information, such as the daily km traveled, the percentage of EVs or the charging daily profile can be obtained from specific city surveys or EU studies and statistics. The amount of energy demanded by the BEVs is affected by the charging preference of the agents selected for the various zone and their parking time duration.

The outputs of the model, applied in different scenarios of the case study, could provide an estimation of the energy demands of electric vehicles during the day in different city zones as well as the range of applicability of different charging strategies. The type of recharging offered and the recharging infrastructure supply resulting from energy demand, although developed in the INCIT-EV project, are not in the scope of the paper. As a possible future development, Electric Road Systems (ERS) concepts and related methodologies will be considered and formalized within the model to improve the estimation of the charging demand for future scenarios.

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