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Review Article

Estimation of charging demand for electric vehicles by discrete choice models and numerical simulations: Application to a case study in Turin

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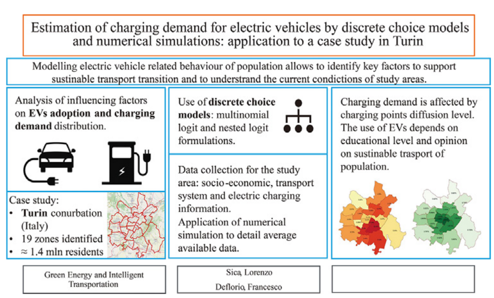
HIGHLIGHTS

- Charging demand for electric vehicles is estimated using discrete choice models.
- Modelling is based on socio-economic, transport system and electric charging data.
- The view on sustainability is a key factor to estimate the use of electric vehicles.
- The models are applied to a real case study collecting available data for the city.
- Demand concentrations are mitigated with diffused electric charging infrastructures.

GRAPHICAL ABSTRACT



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ABSTRACT

The electrification of vehicles is considered one of the most important strategies for addressing the issues related to energy dependence and climate change. To meet user needs, electric vehicle (EV) management for charging operations is essential. This study uses modelling and simulation of EV user behaviour to forecast possible scenarios for electric charging in cities and to identify potential management problems and opportunities for improvement of EVs and EV charging infrastructures. The conurbation of Turin was selected as a case study to reproduce realistic scenarios by applying discrete choice modelling based on socio-economic and transport system data. One of objectives of the study was to describe user charging behaviour from a geographic perspective to model where users prefer to charge in the area studied according to the variables that may affect decisions. Another objective was to estimate the number of electric vehicles in Turin and the characteristics of their users, both of which are helpful in understanding electric mobility within a city. Analysing these behavioural issues in a modelling framework can provide a set of tools to compare and evaluate a variety of possible modifications, indicating an adequate network of charging infrastructure to facilitate the diffusion of electric vehicles.

1. Introduction

1.1. Study context

The problem of pollution and its consequences have serious impact in our society. The transport sector has an important influence on pollutant emissions, and therefore, it has been necessary to develop new mobility solutions, including encouraging hybrid or fully electric vehicle (EV) diffusion in the car market. In studies related to mobility and transport, mathematical models are fundamental for forecasting demand and user behaviour. Models can be used to guarantee an adequate network of charging points or to generate future scenarios. The electrification of transport can be managed using predictive models, which allow forecasting the evolution of the electric mobility market and predicting user

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charging choices in several contexts. The development of EVs and their constant diffusion increase the importance of charging demand evolution in large municipalities to provide adequate public infrastructure and allow people to use their electric cars, avoiding charging problems and inefficient services. One of the main purposes for which the demand estimate is fundamental is related to the location of new charging points, depending on the spatial distribution of the demand. This study aims to analyse models generated to predict user behaviour and test their application in a specific study context: the city of Turin and its conurbation. As detailed in the next section, it is not easy to find studies on methodologies to estimate where charging demand is expected in a city. Therefore, the importance of this study is in the experiment performed to test the transferability of a method in a different context, including adaptation operations and assumptions needed for the application in a real case study, considering practical and inevitable limits, as not available but required data.

1.2. Literature overview

In recent years, the importance of mobility electrification has increased. Using various approaches, researchers have investigated electric vehicles' urban diffusion, particularly charging choice behaviour, to provide an adequate charging infrastructure network and understand the key factors that influence electric vehicle diffusion. To perform the study, several related studies conducted were referred to compare methodologies and approaches to address the proposed issue. One of the aspects widely included in the studies is the detectiion of factors influencing electric vehicle adoption. Several studies have used comprehensive models to estimate the areal diffusion of EVs considering the sociodemographic characteristics of the population, personal opinions, and travel-related information [1,2]. In Ref. [3] an agent-based model was used to simultaneously simulate how EVs and Vehicle to Grid (V2G) technology might diffuse spatially and over time, whereas the V2G-related charging strategies were explored in Ref. [4]. It was observed that several factors have crucial influence on electric vehicle penetration and diffusion in society. An important element is represented by policies adopted by governments to support EV diffusion in different countries [5]. Policies include rules, information, financial incentives, and non-financial incentives [6–8]. Other factors often considered in studies are social norms and individual opinions which can influence users' mobility choices [9,10]. Researchers have also analysed the influence of attributes as vehicle-related factors [11,12] or person-related information on EV adoption [13]. The investigation of electric vehicle users charging choices represents an important research topic. Several studies have been conducted to understand spatial and temporal charging decisions. Discrete choice models are often considered to predict user behaviour. A model based on cross-nested and mixed logit formulations was proposed to estimate the spatial charging demand distribution in urban areas [14]. Other studies aim, considering logistic formulations, predicted the charging behaviour of users based on different attributes as characteristics of potential charging opportunities [15], revealed preferences of interviewed users [16], vehicle state of charge, and user's habits [17]. In charging demand estimation, alternative formulations are also considered as deterministic approaches [18] or other specific approaches, such as decoupled demand forecasting based on the autoregressive integrated moving average (ARIMA) method [19]. Additional analyses, aiming to manage the demand and flow of electric vehicles, are based on stochastic simulation methodology to generate a schedule of daily travel and charging [20] and an intelligent charging scheduling system for the management of electric vehicles and charging operations [21,22]. A notable aspect of demand forecasting is the mid and long term charging load estimation, which includes predicting future EV ownership [23,24]. Several studies have focused on charging infrastructure; for which, different typologies are available, and comparing their characteristics [25] allows us to define optimal urban planning. Moreover, researchers have observed that investing in charging infrastructure is more efficient than investing in larger batteries to promote electric vehicle diffusion because of the importance of a widespread charging network [26,27]. An interesting field of study related to the electrification of urban mobility is charging infrastructure placement planning and existing optimisation techniques [28,29]. In the literature, different frameworks are proposed based on several factors, such as grid voltage stability [30] and sensitivity indices [31] and an alternative optimisation approach mixed-integer non-linear formulation for optimal placement and sizing of charging stations [32]. Several methodologies for charging infrastructure placement in urban environments use a node-based approach [33–36], whereas for highways or extra-urban contexts, trip-based approaches are more commonly used [37,38]. An alternative approach [39], based on the genetic algorithm-particle swarm optimization (GA-PSO) algorithm, is improved to obtain an optimal allocation of charging stations in smart grids estimating the charging demand as coupled with the users' daily activities and scheduling and modelled as a log-normal distribution. The impact of electric charging demand on the distribution network was investigated in Ref. [40] by modelling the demand and considering deterministic electricity load profiles to evaluate the effect on the charging infrastructure network.

2. Methodology

2.1. Selected modelling approach

Two models were selected and adapted to be applied to the Turin case study by analysing the existing literature on models that aim to predict user choices related to electric vehicles and charging operations. The first model [14] aims to estimate the spatial distribution of electric charging demand in a metropolitan area, assuming socioeconomic characteristics and infrastructure-related information as attributes, and considering nested logit and cross-nested logit formulations. The second model [2] aims to estimate the EV penetration rate at the zonal level considering an individual dataset containing households and personal attributes.

2.1.1. Charging demand model review

2.1.1.1. Modelling framework and formulation. A model calibrated on the Amsterdam municipality (Netherlands) was proposed in [14] to predict the charging demand. The base frame of the model uses data on the usage of charging stations and the characteristics of different city zones to forecast the demand for electric charging in these zones. The authors applied various kinds of logit structures, in particular, nested logit (NL) and cross-nested logit (CNL). The idea was to start with a base logit structure and introduce expanded versions to outperform easier versions; the logit model is a restricted version of the cross-nested logit model, and both of them are outperformed by the mixed cross-nested logit model.

As aforementioned, a trial is proposed to transfer these three models to the area of Turin under study. Logit models were used for this application. These models are based on the principle of utility maximisation, in which users choose the alternative with the highest utility value. If the model is used to estimate the charging demand, the alternatives are the various zones of the city. The utility of choosing a zone (alternative) describes the value users assign to each option when they are compared during the selection process.

The utility is composed of a systematic component and an error component and can be evaluated as follows:

$$U_i = V_i + \epsilon_i = \boldsymbol{\beta} \cdot \boldsymbol{x}_i + \epsilon_i \tag{1}$$

where U_i is the utility of alternative i, V_i is the systematic part of utility, ϵ_i is the error term, $\boldsymbol{\beta}$ is the vector of model parameters, and $\boldsymbol{x}_i$ is the vector of attributes of alternative i.

Utility is a non-dimensional quantity and is computed as the sum of product of attributes and associated β parameters. To regard the non-dimensionality of utility, the $\boldsymbol{\beta}$ parameters assume the inverse of the unit associated with the corresponding attribute. In this study, the base model is built on a multinomial logit model (MNL), in which the error terms of all alternatives are independent and identically distributed (IID) following a Gumbel distribution. The formulation of the multinomial logit model application provides an estimation of the probability of selecting each alternative from the defined set of choices as

$$p(i) = \frac{\exp(V_i)}{\sum_j \exp(V_j)} \tag{2}$$

Another proposed formulation is the nested logit model (NL), which differs from the multinomial logit model (MNL) because, in nested logit, more levels of choice are considered by introducing a nested structure. In the nested logit model (NL), alternatives are divided into nests (Nm), and their error terms are independent if they are in different nests. In the case of the original model [14], the nests are represented by districts of Amsterdam, while the second level is composed of neighbourhoods belonging to a certain district.

In the nested logit model, the probability of selecting an alternative i is expressed as the product of the probability of selecting the related nest k and the conditional probability of selecting the alternative $\underline{i}$ in the nest.

$$p(i) = p(k)^* p(i|k) \tag{3}$$

$$p(i) = \frac{\exp(\mu_k \cdot Y_k)}{\sum_h \exp(\mu_h \cdot Y_h)} \cdot \frac{\exp(V_i)}{\sum_{i \in k} \exp(V_i)} \tag{4}$$

where $p(i)$ is the probability to select alternative i;

V_i is the systematic utility of alternative i;

μ_k is the nest coefficient related to coefficient k;

$$Y_k = ln \sum_{i \in k} \exp(V_j)$$

The nested logit enhances the multinomial logit because it introduces a correlation between alternatives included in the same nest. However, an estimate of nest coefficients is needed to apply the nested logit model. Because the version reported in the original model [14] referred to Amsterdam zones, to explore this solution in the new area under study, it is necessary to define a value for nest coefficients by assumption, as values estimated for Amsterdam districts containing neighbourhoods are not directly applicable in this case. The adaptation to the Turin case study is performed based on the magnitude of the districts to estimate values for our study context. In particular, three macro zones are considered.

1. City central zone (nest coefficient = 1);
2. City suburban zone (nest coefficient = 2);
3. First belt towns zone (nest coefficient = 4).

Another solution explored by the authors in Ref. [14], but excluded from this application, is to use the cross-nested logit model (CNL), in which alternatives can lie in more than one nest simultaneously. In this demand model, by using CNL, it is possible to allow a neighbourhood to lie in two different districts, preventing errors in neighbourhoods located on districts' borders.

2.1.1.2. Dataset description and model calibration. An important step in model building was the collection of a consistent dataset, which needed to be structured and populated. The one used in the original model version [14] was based on different kinds of variables that can be grouped into two main categories: socioeconomic characteristics of considered neighbourhoods of Amsterdam municipality and charging data of the same zones. Socioeconomic characteristics include number of inhabitants, gender distribution, age group distribution, average income, mean family size, number of cars (electric or otherwise) per inhabitant, number of homes per inhabitant, percentage of homes built after 2000, and percentage of homes owned or rented. The data related to charging operations include the number of infrastructures per zone and zonal charging history (number of charging sessions recorded monthly). For the analysis, users are split into three groups: regular users, participants in an electric carshare scheme, and taxis. Regular users are again divided into three sub-groups according to the time when their charging session mostly happens during the day and the subgroups are: residents (predominantly charge during the night), commuters (predominantly charge during work hours), and visitors (people who sporadically charge in the city). Different models are calibrated for the above-mentioned groups using nested logit (NL) and cross-nested logit (CNL) for the three separate user groups (regular users, electric carshare, taxi). Referring to the regular users' class-estimated parameters, a high influence on the charging demand of several attributes is observed. In Table 1, several estimated parameters for different user classes are listed.

Table 1
Extract of estimated parameters for different user classes in [14].

Attribute	Unit	Regular users (β)	Electric carshare (β)	Taxi (β)
Total number of inhabitants	#	−1.98	5.91	9.2
Average income	$/household	0.665	0.091,5	−0.839
Total number of cars	#	0.957	0.104	−0.077,6
Total number of homes	#	2.16	2.09	1.1
Charging history	#/month	2.49	N/A	2.06
Number of charging stations	#	N/A	0.449	N/A

2.1.2. Penetration rate model review

2.1.2.1. Modelling framework and formulation. The original study [2] was conducted to analyse the factors that might trigger the wide usage of EVs. Several characteristics of individuals were considered to generate a model which is able to define the probability of a person to be an EV user. Several methods were employed to build the prediction model, and model performance analyses were executed to determine which models were more reliable than the others. In the original version [2], several trials using different modelling techniques were performed and compared. Nevertheless, for this application, the logistic regression (LR) model was adopted, considering the good results reported in this paper and the simple implementation required. The regression model allows solving the classification problem between the two classes considered in this study: EV or CV (conventional vehicles) alternatives. The problem is formulated as follows:

$$Z_{mi} = \beta_m + \sum_{j=1}^{n} \beta_{mj}{}^* X_{mj} \tag{5}$$

$$p(Y_i = m|X) = \frac{Z_{mi}}{1 + \sum_h^M Z_{hi}} \tag{6}$$

where X_m is the independent variables vector associated to alternative m; β_m represents the $\boldsymbol{\beta}$-parameters vector estimated by original study; Y represents the independent variable (alternative).

2.1.2.2. Dataset collection and model calibration. The dataset was extracted by the authors [2] from the National Household Travel Survey (NHTS) 2017, which is the authoritative source on the travel behaviour of the American public. The dependent variable extracted from the dataset corresponds to the alternative chosen by users in terms of vehicle type; only two alternatives were considered: electric vehicles (EVs) and conventional vehicles (CVs). This simplification was applied because the analysis focused only on the EV penetration rate and considering more alternatives was not useful. Several independent variables were included in the model. Some of these attributes were related to households: household income, home ownership (if the household lives in a home of its property), household size, young child (number of children under 4 years old), household vehicle count, urban-rural (if the household lives in an urban or rural environment), and population density (of the zone in which the household lives). Other variables belong to the person-related dataset: price and place (opinion on cost and charging infrastructure location influence on EV adoption), age, gender, education, race, multi-job (if the interviewee have more than one job), occupation (job type), car sharing (if interviewee participate in car sharing programmes), time to reach workplace from home, miles travelled in a year by the interviewee. The aforementioned paper proposed a model calibration with estimated parameters to allow application in different case studies. It is observed that several attributes have a considerable influence on EV adoption such as educational level and home possession. In Table 2, several estimated parameters from the original study are shown.

Table 2
Extract of estimated parameters in [2].

Attribute	Unit	β-parameter	Std. Error	p-value
Household income	$/household	0.269	0.032	0
Home own	[1]Yes / [0]No	0.382	0.169	0.024
Urban-Rural	[1]U / [0]R	0.266	0.215	0.215
Education	Level [1 to 5]	0.524	0.061	1.689
Multi-job	[1]Yes / [0]No	0.38	0.186	1.463

2.1.3. Methodology framework

The objective of this study was to explore behavioural models and, in particular, to experience their application in a different case study to test their transferability. Two pre-existing models were applied in a case study of Turin conurbation to understand their validity in a different study context and obtain important parameters for the management of electric vehicle mobility in the city. In Fig. 1, the application procedure followed in the model application and integration is resumed. In particular, the work is divided into three main blocks: charging demand model application, penetration rate model application, and integration of models.

3. Application

3.1. Zoning

The first aspect to be considered in the model application was to identify meaningful zones in the Turin conurbation for which the aggregated data needed are available. The zoning operation was performed following administrative limits represented by the districts ("Circoscrizioni di Torino"), which divide the city into eight zones for the area internal to the city. For the municipalities located in the "first belt" around Turin, zones are generated considering municipalities' limits and merging neighbouring towns to have a considerable population. The software used to collect and manage georeferenced information was QGIS 3.4, and the zoning pro.cedure detected the 19 zones represented in Fig. 2.

The internal zones of the city (1–8), even though smaller in terms of areal extension, present a higher population density. Several zones, such as 1, 8, and 2, have important attraction poles (workplaces, monuments, and malls), which make more people reach these zones from other ones. The remaining Turin internal zones can be considered more residential. External zones present different features; fewer people live there, and the observed flow of people is generally lower. It is important to observe that some of these zones, such as those located in the north or south of Turin, differ from the others owing to the presence of important industrial and economic poles.

3.2. Charging demand model application

The previously analysed model was calibrated for Amsterdam to forecast the charging demand in different zones of the municipality. The aim of this attemt was to apply a simplified version of the model to the city of Turin to understand how the model can be transferred to a different city to estimate the charging demand distributed in the city. As reported before, different models were generated, and nested structures were considered, as Amsterdam was divided into statistical units

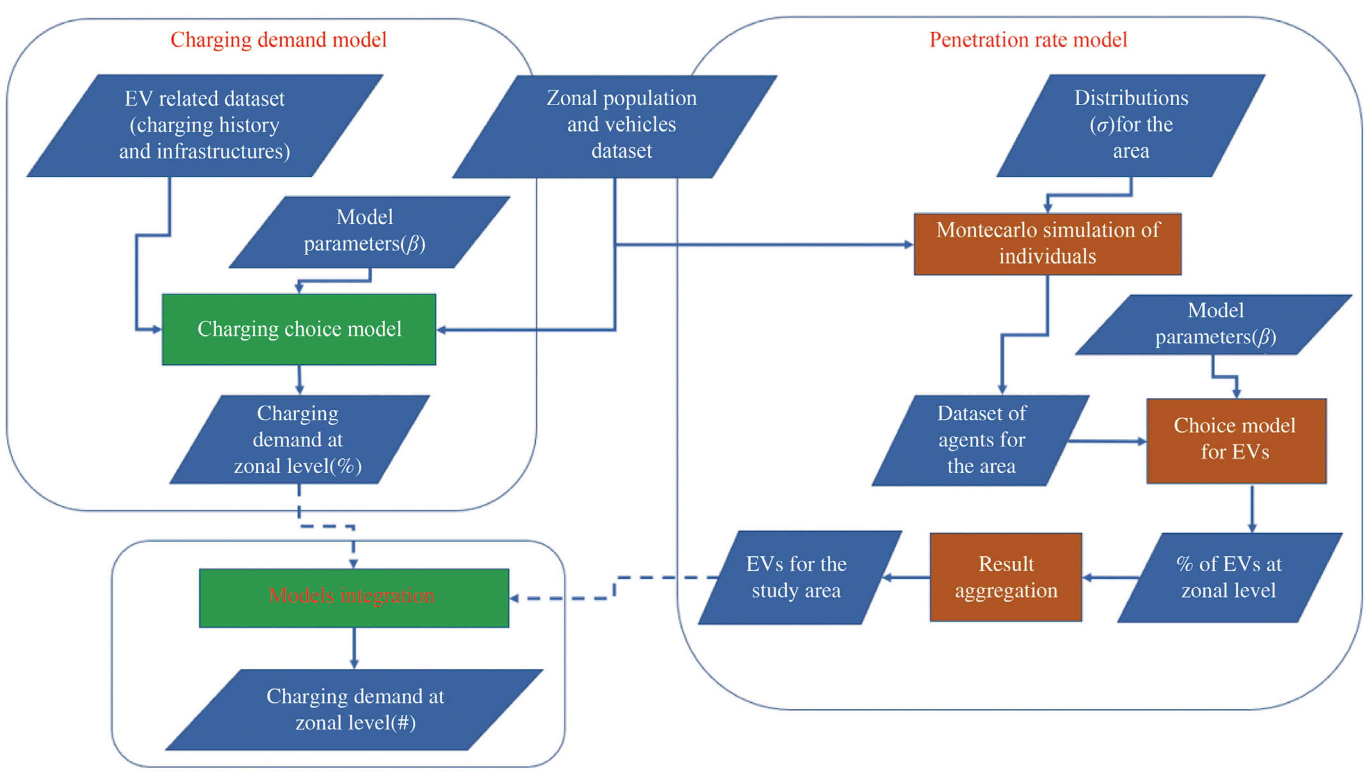

Fig. 1. Application framework of modelling and data.

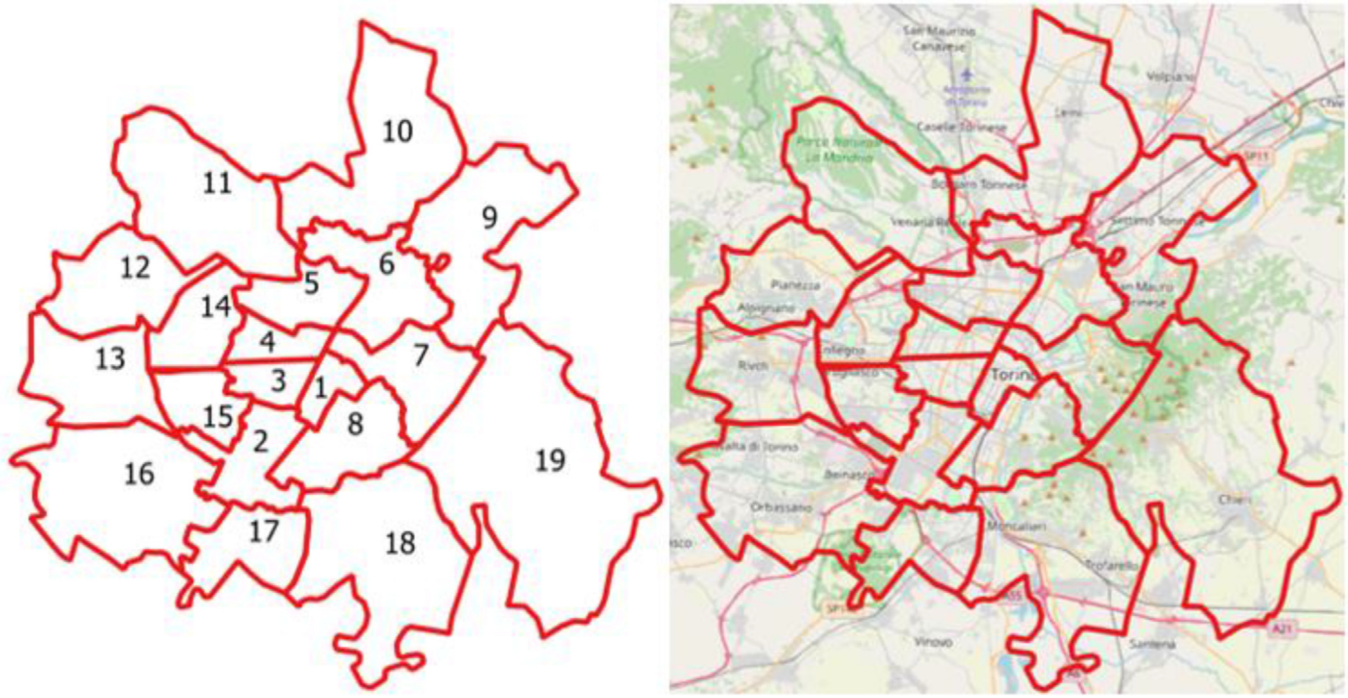

Fig. 2. Turin conurbation zoning.

(districts) and sub-units (neighbourhoods). In this experimental application, the original model was also simplified, assuming a negligible role of the nested structure, and working on a multinomial model, in which there is a unique choice level. This decision can be justified considering that only one level is designed in the adopted zoning, which also impacts the zone choice process. However, it should be noted that this simplification is possible because the systematic utilities of alternatives for the two models are the same as the nested structure only introduces the correlations between the utilities of alternatives, which can be assumed to be negligible.

3.2.1. Dataset collection

One of the main steps in model application is data collection, and a new dataset based on the study context properties is generated. The dataset considered in the original application must be adapted and replicated in the Turin metropolitan area. As previously mentioned, data were aggregated at the zonal level, and for each zone, the following set of data was needed.

- Population: zonal number of inhabitants;
- Gender distribution: zonal number of inhabitants divided by gender;
- Age range distribution: zonal number of inhabitants divided by age range;
- Household sizes: zonal average of number of household members;
- Income distribution: zonal average of individual annual income ($);
- Number of homes: total number of homes per zone;
- Types of home (own/rent): zonal number of owned and rented homes;
- Homes built after 2000 (%): percentage of homes built after 2000 per zone;
- Number of cars per individual;
- Number of charging infrastructures;
- Charging history: number of monthly charging events in the zone.

All sociodemographic data were available for the area considered for the study, from the ISTAT dataset [41] which is an open-source database containing a large amount of data at several levels of aggregation belonging to Italy. The zonal number of charging infrastructures for Turin zones was extracted by an open charge map which contains information about the charging point location. The charging history, being private data owned by supply companies, was not available, and it was estimated by following a method based on available data for the Turin case study. It was considered as uniform average of number of daily charging events per infrastructure and a zonal variation was generated by assuming a coefficient related to the zonal annual stop count extracted from a work applied to the same city [42].

$$Ch = CIz \cdot AACE \cdot Cs$$

where:

- Ch is the zonal charging history;
- CIz represents the number of charging infrastructures;
- $AACE$ is the average of annual number of charging events per charging point;
- Cs is the stop related coefficient per zone.

This approximation generates a charging history dependent on the stop distribution in the area and may represent a significant limitation in model transferability because charging history datasets are not available everywhere.

3.2.2. Application and results

Having the required dataset and knowing the parameters of the reference model, it was possible to apply the model to the chosen study context. As previously mentioned, the original study calibrated different types of models and considered different categories of users. In this application, several solutions were explored considering the set of parameters estimated for the regular user class using the original model. The model was applied considering two different formulations: the multinomial logit model (MNL) and nested logit model (NL). For application, a Python code was elaborated and used by the Python IDE

"Anaconda Jupyter Notebook", which allows the use of a wide range of libraries useful for managing datasets.

Results were computed for the MNL formulation (see Fig. 3).

(Moncalieri, Nichelino) present a relevant supply of charging points due to the importance of these cities with regard to their considerable population and their economic and industrial vocation.

N.Zone	V(utility)	P(charging demand)
1	22.025	39.81%
2	19.482	3.13%
3	15.704	0.07%
4	15.640	0.07%
5	19.028	1.99%
6	19.298	2.61%
7	15.229	0.04%
8	22.204	47.61%
9	18.015	0.72%
10	17.414	0.40%
11	−0.957	0.00%
12	16.255	0.12%
13	16.783	0.21%
14	17.823	0.60%
15	−0.954	0.00%
16	16.814	0.22%
17	18.393	1.05%
18	18.638	1.35%
19	14.002	0.01%

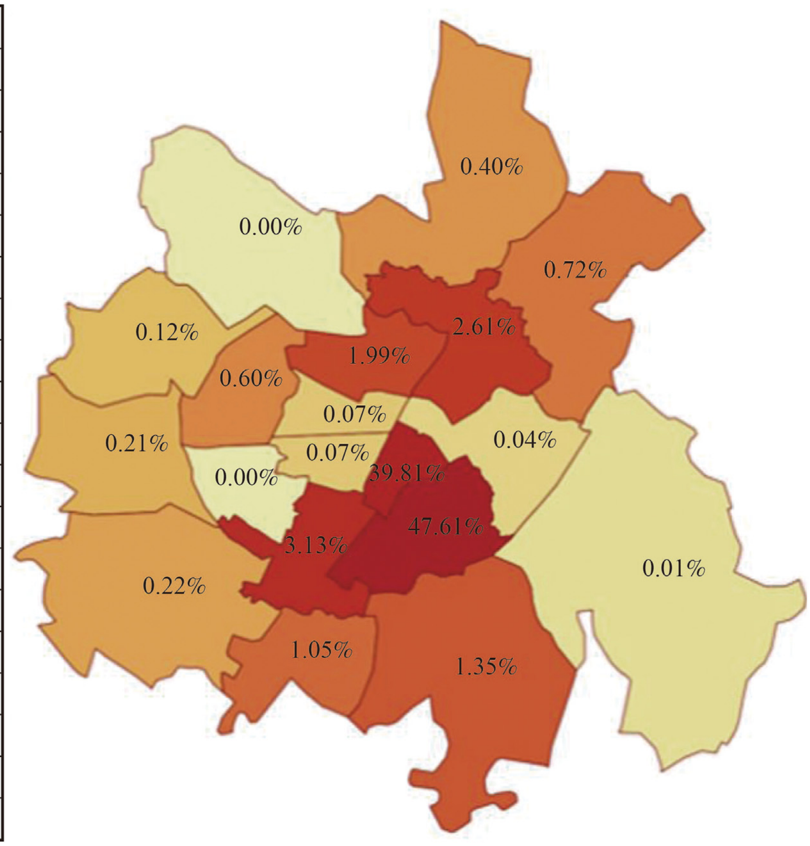

Fig. 3. Estimated charging demand (MNL formulation).

The results indicate that two zones (1 and 8) have the highest charging demand, and a significant number of zones present low values. This result is partially in line with expectations because zones 1 and 8 are central zones of Turin, in which there exists maximum attraction points, such as main stations, and a high flow of people and vehicles. At the same time, it seems unrealistic to have zones in which demand is too low, particularly in zones external to the city.

A new set of results was computed for nested logit formulation considering the nest coefficients previously set for macro zones.

1. City central zone: zones 1 and 8;
2. City suburban zone: zones from 2 to 7;
3. First belt towns zone: zones from 9 to 19.

Results for NL formulation are presented in Fig. 4.

As expected, the effect of the nested structure and assumed nest coefficients generated a less extreme distribution of charging demand. The results of central zones (1 and 8) decreased owing to the increase, caused by coefficients of other zones. Globally, the results seemed to be coherent with expectations; the most attractive zones being 1 and 8, but a meaningful demand level was also experienced in the northern and southern suburbs, which owe the demand to a large number of offices and industries (workplaces) present there. Residential Turin districts exhibited a low demand level, presumably caused by the preference of users to charge in public stations in attraction poles where a higher offer is available. Regarding Turin's first belt, only a part of the zones has a relevant demand level, particularly the cities located in the southern part of the area. The reason for this difference is that cities in those zones

3.2.3. *A new scenario to test the influence of infrastructure network on demand*

An interesting aspect of the considered model is the strong influence of the presence and use of charging infrastructure on the charging demand distribution. It is evident that the charging supply network observed for the Turin area in 2021 needs to be improved to satisfy considerable demand. For this reason, a new experiment was performed to understand how demand can be affected, assuming an enhanced supply[1] according to existing requirements from Italian regulation. The new question encountered in this study was to understand if and how the charging demand would vary if the requirement of a charging point for every 1,000 inhabitants was fulfilled. The previous dataset was considered to simulate this scenario, modifying only data related to charging infrastructure and considering the same sociodemographic characteristics of the original scenario. Changing the number of charging infrastructures in a zone makes it possible to obtain a long-term effect on population which can change its attributes however, in this study, we focused on actual population characteristics and on the effect of a new charging infrastructure network on the same population. In each zone, the number of charging infrastructure was computed by considering the mentioned legislative criteria based on the population of each zone.

[1] To realize the new scenario, we applied the article 57 of D.L. 16/07/2020 n.76, a law entered into force in Italy in July 2020 which requests municipalities to plan and realize an adequate public charging infrastructures network by the installation of at least one charging point for every 1,000 inhabitants.

N.Zone	Macrozone	$p(k)$	$p(j\|k)$	p(charging demand)
1	1	0.716,82	0.455,38	32.64%
2	2	0.129,70	0.396,03	5.14%
3	2	0.129,70	0.009,06	0.12%
4	2	0.129,70	0.008,49	0.11%
5	2	0.129,70	0.251,33	3.26%
6	2	0.129,70	0.329,46	4.27%
7	2	0.129,70	0.005,63	0.07%
8	1	0.716,82	0.544,62	39.04%
9	3	0.153,48	0.154,34	2.37%
10	2	0.153,48	0.084,57	1.30%
11	2	0.153,48	0.000,00	0.00%
12	2	0.153,48	0.026,54	0.41%
13	2	0.153,48	0.045,00	0.69%
14	2	0.153,48	0.127,39	1.96%
15	2	0.153,48	0.000,00	0.00%
16	2	0.153,48	0.046,44	0.71%
17	2	0.153,48	0.225,19	3.46%
18	2	0.153,48	0.287,73	4.42%
19	3	0.153,48	0.002,79	0.04%

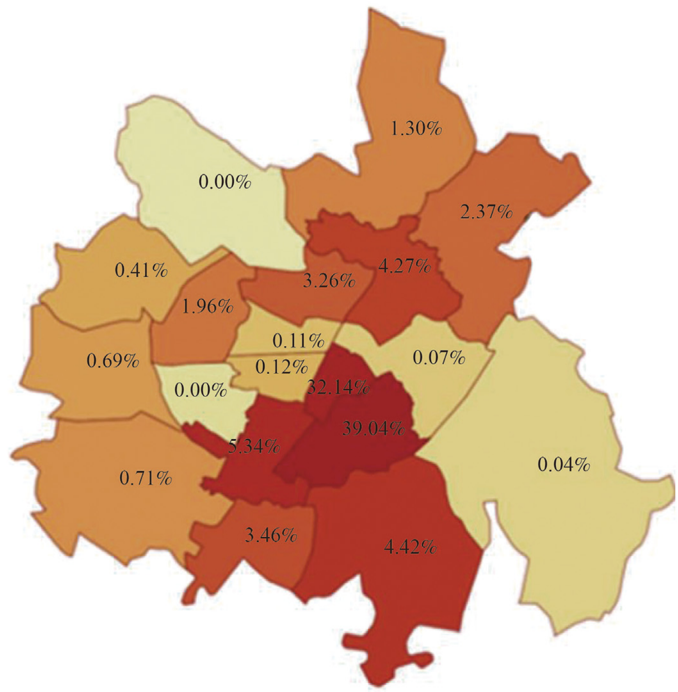

Fig. 4. Estimated charging demand (NL formulation).

It can be noted from Fig. 5 that almost all zones present a quantity of charging points significantly far from the standard requirement. The previously estimated charging demand is influenced by this issue: zones with a quantity of charging points closer to the target, such as zones 1 and 8, receive a very high demand. The expectation for the new estimation was to observe more distributed demand, especially in zones where the original demand was not significant. The second attribute related to charging, the charging history (number of monthly charging events for the zone), was computed using the new number of charging points and the procedure described in Section 3.2.1. In Table 3, the new data is listed.

Using the same model applied to the new dataset related to this scenario, different estimations were obtained and are shown in Table 4. considering multinomial logit and the nested structure (see Fig. 6).

When the results obtained are compared with the previous results, it can be observed that considerable demand is obtained in every zone internal to Turin. The most charged area remains zone 8, which exhibits a percentage similar to that previously obtained. This is an expected result because this is the most extended and populated zone in the area under study. A considerable decrease is observed in zone 1; the high demand in the previous experiment was due to the actual high infrastructure concentration that makes this zone the closest to the law requirements. The

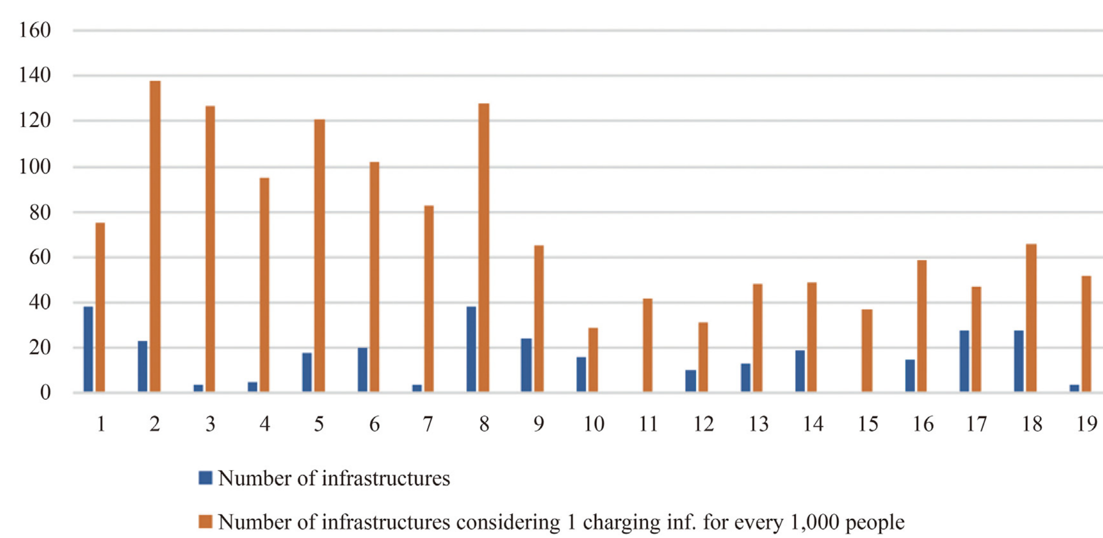

Fig. 5. Actual/potential number of charging infrastructures.

Table 3
Modified charging history for the new network.

N. Zone	Population	N. Inf.	Charging history	N. Zone	Population	N. Inf.	Charging history
1	75,966	75	13,500	11	42,177	42	3,780
2	138,595	138	23,532	12	31,062	31	2,790
3	127,187	127	24,063	13	48,632	48	4,320
4	95,238	95	13,500	14	49,083	49	4,410
5	121,608	121	22,926	15	37,194	37	3,330
6	102,188	102	18,360	16	59,886	59	5,310
7	83,381	83	11,794	17	47,851	47	4,230
8	128,204	128	31,528	18	66,786	66	5,940
9	65,396	65	5,850	19	52,103	52	4,880
10	29,143	29	2,610				

Table 4
Results of simulation for the new scenario.

N. Zone	MNL		NL		Population (%)
	P (actual) (%)	*P* (potential) (%)	*P* (actual) (%)	*P* (potential) (%)	
1	39.81	8.72	32.64	5.58	5.42
2	3.13	10.94	5.14	14.00	9.89
3	0.07	15.84	0.12	20.28	9.07
4	0.07	4.13	0.11	5.29	6.79
5	1.99	9.21	3.26	11.79	8.68
6	2.61	6.07	4.27	7.77	7.29
7	0.04	3.42	0.07	4.38	5.95
8	47.61	39.48	39.04	25.28	9.15
9	0.72	0.35	2.37	0.89	4.67
10	0.40	0.07	1.30	0.18	2.08
11	0.00	0.00	0.00	0.00	3.01
12	0.12	0.08	0.41	0.21	2.22
13	0.21	0.22	0.69	0.56	3.47
14	0.60	0.25	1.96	0.65	3.50
15	0.00	0.00	0.00	0.00	2.65
16	0.22	0.27	0.71	0.68	4.27
17	1.05	0.15	3.46	0.40	3.41
18	1.35	0.46	4.42	1.18	4.76
19	0.01	0.35	0.04	0.89	3.72

other internal zones of the city have increased demand, indicating that the actual network situation is inadequate and far from the target. Despite the increase in terms of charging infrastructure, several zones, such as zones 2 and 4, exhibit a low increase in terms of demand because these zones represent suburban areas of the city with several attributes (such as sociodemographic attributes of the population) which contribute to reducing the attractiveness of the zone. For zones external to the city, a demand redistribution is observed, although not with a considerable increase. For neighbouring towns, a lower demand is estimated as expexted, and the low variation obtained shows that the gap from the target is not that large. Considering the results of this experiment, it is evident that a more widespread and larger network of charging point allows a more distributed demand and a lower dependence on charging point location for users in charging choices. The simulation of this new scenario reveals the sensitivity of the charging demand model to this attribute, which is one of the key elements for planning. The demand distribution changes, especially among zones in the area, as variables are modified, particularlyif a new infrastructure distribution is simulated. These kinds of experiments can help municipalities during the planning phase and supply companies to understand the effects of new charging-point configurations. Several factors must be considered as problems caused by the non-homogeneous distribution of charging demand that are observed in the original scenario, in which two zones (1 and 8) have

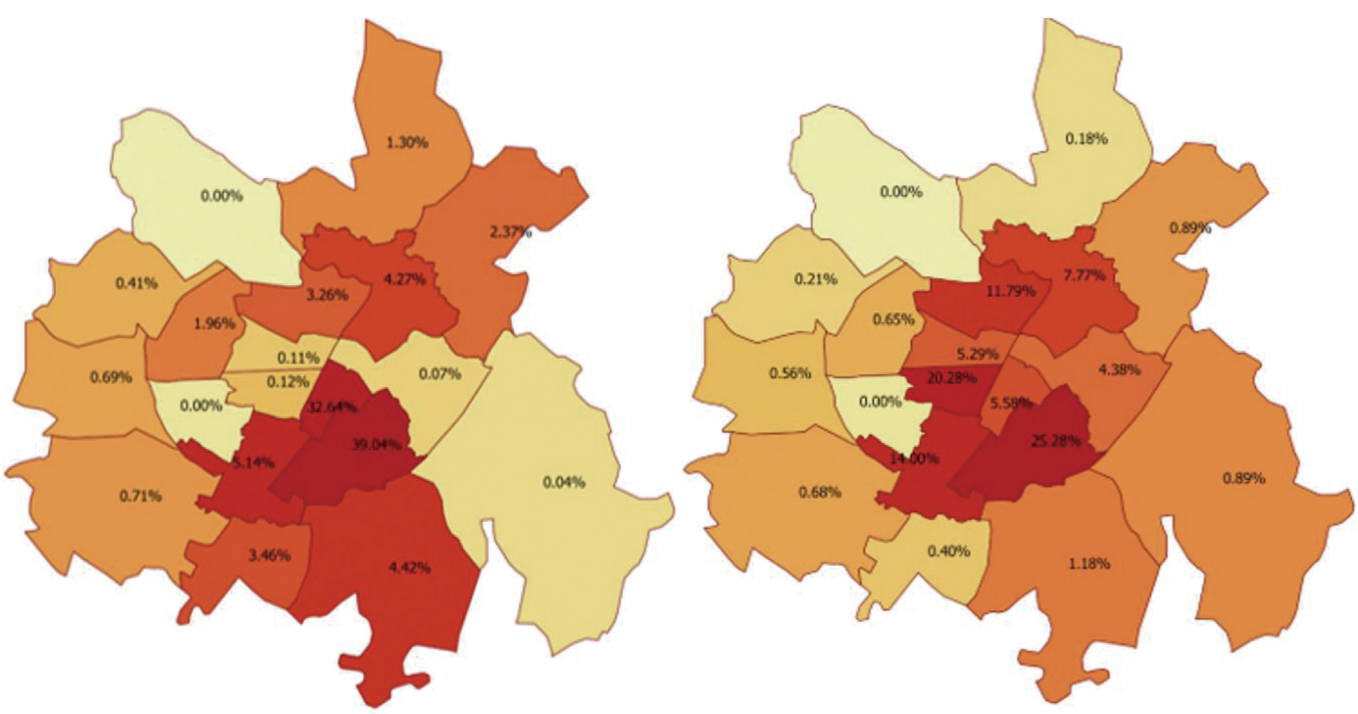

Fig. 6. Comparison between original and new scenarios.

high demand. Some can be related to congestion in the road network of these zones to access charging points. In the newly explored scenario, though this inhomogeneity problem was reduced, it was still present in the area. Therefore, an appropriate policy can be planned by integrating the new charging infrastructure configuration with a pricing system according to zones to shift part of the demand in less charged zones.

3.3. EVs penetration rate model application

To estimate the percentage of electric vehicles in the area under study and in the defined zones, the previously described EV penetration rate model was applied. This analysis can be useful for understanding which zones of the area under study have a population that is more suitable for the adoption of electric vehicles. The model was applied following the logistic regression formulation and performing a Monte Carlo simulation to have a dataset of individuals needed as input by the original model.

3.3.1. Dataset collection

In this case, the zoning generated was the same as that considered for the previous model application, which includes 19 zones belonging to Turin and its metropolitan area. For the application of this model, attributes belonging to two main categories were needed.

- Household-related variables: household income, home ownership (if the household lives in a home of its property), household size, young child (number of children under 4 years old), household vehicle count, urban-rural (if the household lives in an urban or rural environment), and population density (of the zone in which household lives);
- Person-related variables: price and place (opinion on cost and charging infrastructure location influence on EV adoption), age, gender, education, race, multi-job (if the interviewee have more than one job), occupation (job type), car sharing (if interviewee participate in car sharing programmes), time to reach workplace from home, miles travelled in a year by the interviewee.

Most of the information needed was contained in the ISTAT dataset [41] or in local mobility surveys. As previously mentioned, an issue in dataset collection was related to the statistical unit considered by the model: data required as input for the model were aggregated at the individual level, whereas data available for the Turin area considered for the study, were aggregated at the zonal level. This problem was solved by generating a simulated dataset in which the variables describing our problem were associated with sampled individuals. This technique, based on a Monte Carlo simulation, allows obtaining a synthetic dataset based on the distribution of a zonal variable. For several variables, it was decided to assume a uniform value, while for the majority, a normal distribution was generated. For the second case, Python libraries were used to generate a random number from normally distributed values, knowing the mean and standard deviation of the variable. In particular, the mean was available from the previous dataset or other sources for most of the variables, whereas the standard deviation was assumed to be equal to the values found by the authors [2] for their data. Other variables, such as educational level, were simulated by generating random values reproducing the observed frequency distribution for each class of the attribute.

3.3.2. Results

The model's target was the penetration rate of EVs aggregated at the zonal level. For each sampled individual, the model output is the probability of EV adoption. The probabilities of individuals belonging to the same zone were aggregated to obtain a zonal value of the penetration rate of electric vehicles (Fig. 7). The overall electric vehicle penetration rate

N.Zone	Penetration rate(%)
1	2.879
2	1.429
3	1.998
4	1.957
5	1.226
6	1.194
7	1.533
8	1.871
9	0.776
10	0.669
11	0.629
12	0.825
13	0.843
14	0.946
15	1.035
16	0.794
17	0.920
18	0.842
19	0.735
Tot area	1.377

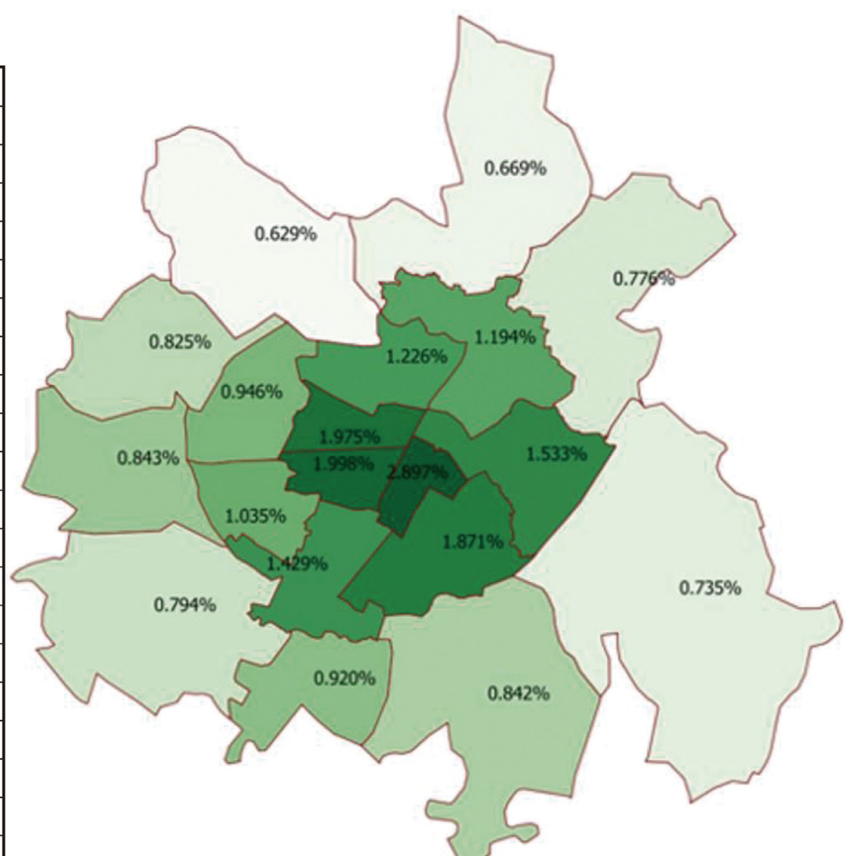

Fig. 7. Estimated EV penetration rates.

of the area under study was approximately 1.4%. It is interesting to observe how the rate varies between different zones and how several parameters play a significant role.

The penetration rate estimation of EV is expected to be higher because several important attributes present remarkable differences. Indeed, the average income is higher in the city area than in the first belt area, and the same difference is observed in the population density. Another important influencing variable, which presents a large gap between the city, where there is a high average level, and the first belt, is the education level, which has a high-magnitude β-parameter. It isnotable how this attribute seems to be considerably important in EVs adoption. It is possible to assume that more cultured people tend to appreciate the advantages and importance of transportation electrification. Observing the rates associated with the Turin zones, zone 1 presents the highest value in the area under study. Indeed, the inhabitants of this zone have attributes which, according to the model, make them more suitable for EV purchase, in particular high income, population density, and average education level. Comparing the results with the zonal dataset, it can be noted that the three zones with higher population density correspond to the zones exhibiting a higher penetration rate (zones 1, 3, 4). The zones with similar characteristics exhibit similar results: zones 3 and 4 (both residential areas), and 5 and 6 (both suburban areas). For zones belonging to the first belt, the computed rates were lower than the overall rate. This result was anticipated owing to the important differences between city and town inhabitants. Certain external zones exhibit a higher rate of respect to the others (zones 14, 15, and 17), and these zones correspond to towns (Nichelino, Grugliasco, and Collegno) which are more linked to Turin.

3.4. Integration of models

Once the considered models were applied and the results in terms of charging demand distribution and EV zonal penetration rate were obtained, a further step was possible by performing a trial of integration of the two models. The results were combined to estimate the number of vehicles charging in each zone. The idea was to combine the charging demand distribution (%) obtained by the first applied model and the number of electric vehicles in the area estimated by the penetration rate of the second model. By combining the results, it was feasible to obtain a charging demand expressed in terms of the number of vehicles instead of percentages. Basically, by the penetration rate model, the areal EV penetration rate was obtained and, knowing the total number of vehicles in the area under study, the total number of electric vehicles was estimated. Successively, the distribution in percentages of charging demand in zones, obtained by the first model, was considered to split the vehicles into zones and obtain an average charging catchment area for each zone in terms of the number of users served. The charging activities, in terms of frequency, duration, and power required of these users, depend on several factors, such as travel patterns, energy consumed, and vehicle battery capacity, which were not considered in this model approach. Therefore, the demand level was expressed as the number of users interested in charging in a specified zone of the city, independently from the activity of other users. The total number of vehicles (independent of the type) in the area under study, which corresponds to 886500, was obtained from the original dataset. Considering the EV penetration rate for the area estimated in the previously performed application (equal to 1.377%), it was possible to estimate that there are approximately 12210 electric vehicles. The average number of vehicles in each zone was estimated using the computed charging demands for public infrastructure. For this operation, the total number of electric vehicles in the area under study was considered and distributed according to the estimated charging demand, assuming that users are free to choose where to charge independently from the zone in which they live (see Table 5).

Table 5
Estimated charging demand (in terms of number of vehicles).

N. Zone	N. Vehicles	Penetration rate (%)	N. EVs	Charging demand (%)	Charging demand
1	886,501	1.377	12,210	32.64	3,986
2				5.14	627
3				0.12	14
4				0.11	13
5				3.26	398
6				4.27	522
7				0.07	9
8				39.04	4,767
9				2.37	289
10				1.30	158
11				0.00	0
12				0.41	50
13				0.69	84
14				1.96	239
15				0.00	0
16				0.71	87
17				3.46	422
18				4.42	539
19				0.04	5

4. Conclusion

This paper presents a methodological approach to estimate charging demand for electric vehicles by adapting and applying two different models available in the literature in a conurbation, such as the Turin conurbation. The results include evaluations at zonal and areal levels of EV penetration rates. One of the main purposes of this work is to test the applicability of the demand models to a real case study, although the models were originally built for different areas, such as Amsterdam or the USA. The transferability to a different study context requires an adaptation process and consideration of the available data in a particular area. The application of the charging demand model provided remarkable results related to the case of Turin. Considering all the demand scenarios produced, it is evident that certain parts of the area under study present a higher attractiveness for users, in particular zones in which more attraction poles (workplaces, industries, and malls) are present. Moreover, the distribution of demand is strongly influenced by supply. This means that the charging supply network present in the area under study (in 2021) is not sufficiently homogeneously distributed, and the presence of charging infrastructure is still too limited to allow users a freer choice of where to charge. The comparison between the scenarios produced considering real zonal attributes and the hypothetical situation with homogeneous and increased supply demonstrates this issue. Regarding the applicability and transferability of the model, it is important to consider that several approximations in the methodology and dataset collection were introduced. Apart from this issue, the global scenario given by the model application seems to be coherent with the real Turin scenario; the zones in which the estimated value of charging demand is higher were the ones in which more charging operations were expected, according to the author's knowledge. However, a limitation of this application is found in the magnitude of the results in relation to the description of the real scenario. Most charged zones have reached more than half of the global demand in some trials. In contrast, other zones had no significant demand, even if a considerable number of charging operations were expected. This eventuality is not completely realistic and requires further research. It is possible to conclude that the considered modelling framework worked properly in the tested study context, considering the datasets required and the applicability of the mathematical formulation and numerical simulation. The model applied for EV penetration rate estimation predicts the zones whose population presents characteristics which identify possible EV users. A key point of the study is the Monte Carlo simulation used to consistently replicate observations at the individual level, starting from data with a zonal level of detail. From the results of explorative scenarios, the importance of attributes related to education and opinion is highlighted as a significant effect of it on EV penetration is observed. The internal zones of the city present higher values. This can be explained by considering attributes such as income and average educational level, which are higher than those of external zones. Further research can be performed to verify whether, in future scenarios, the distributions of EVs among zones of the city are confirmed by real data regarding EV purchases. The methodology and results could support the management of EVs in cities considering charging infrastructure placement and the diffusion of electric mobility.

Data availability

The data and materials used to support the findings of this study are available from the corresponding author upon request.

Declaration of competing interest

The authors declare the following: All authors have participated in (a) conception and design, or analysis and interpretation of the data, (b) drafting the article or revising it critically for important intellectual content, and (c) approval of the final version.

This manuscript has not been submitted to, nor is it under review at, another journal or other publishing venue.

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