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Integrating bottom-up GIS and machine learning models for spatial-temporal analysis of electric mobility impact on power system

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ABSTRACT

The ongoing electrification in the light-duty transportation sector represents a pivotal shift that deeply influences electricity distribution networks' operations, introducing a peculiar demand profile characterised by spatial and temporal variability. To address these challenges posed by the increasing adoption of Electric Vehicles (EVs), this work integrates a Machine Learning (ML) model for the vehicle selection procedure in a holistic Spatial-Temporal Model (STM) that accurately simulates the most typical stochastic behaviour within the transportation and electricity networks. The methodology assesses traffic behaviour, evaluates the grid impact of charging processes, and extends the analysis to flexibility services, particularly the provision of primary frequency regulation. The methodology is applied to the Lombardy region in Italy, adopting the 2030 e-mobility scenario defined by policymakers as a reference. This framework selects EVs diverting from linear probabilistic extraction models based on penetration rates by exploiting behavioural patterns and the socio-economic characterisation of EV drivers. Relying purely on open-source data, the work demonstrates the frequency regulation potential of EVs fostered by smart charging algorithms, which increase the power band available for grid services. The results of the procedure provide actionable insights for grid operators and urban planners, bridging the gap between transportation and electrical infrastructure.

1. Introduction

A decisive shift towards policies attempting to reshape the behaviour of consumers for *net-zero* [1] human impact was promoted in recent years by governments and agencies alike. The main course of action taken was the progressive move towards the electrification of domestic and industrial consumption. For the former applications, the main feasible instruments for this change have been identified as the electrification of domestic appliances, mainly heat pumps, and the light-duty transportation sector. Although these phenomena can be considered marginally endogenous, they are mainly underpinned by the significant endeavour of governments to subsidise key consumer industries to achieve their agendas, such as those schemes in place for EVs and recharging infrastructures [2,3]. Taking as an example the European Union (EU), specific acts and rules have been approved with this goal: the guiding one can be recognised as the Fit For 55 (FF55) package [4], a set of proposals to review and update EU legislation and to implement new initiatives to ensure that EU policies are in line with the climate goals agreed by the Council and the Parliament. The FF55 plan was then adopted by each Member State and translated into national-specific goals ("National energy and climate plans"). In Italy, these were formalised and put into law with the 10-year PNIEC (2021–2030) [5].

In the first quarter of 2024, electric car sales grew by around 25% compared with the first quarter of 2023, similar to the year-on-year growth seen in the same period in 2022. Moreover, by the end of 2024, the market share of EVs was projected to reach up to 45% in China, 25% in Europe, and over 11% in the United States, amounting to about one in five cars sold worldwide according to IEA data [6], pushed forth by competition among manufacturers, falling battery and car prices and ongoing policy support. Furthermore, observing the IEA outlook, the price gap between electric and conventional vehicles has been steadily declining over the years, with China being the one market in which this figure was already negative as of 2022 (i.e. an EV was cheaper than an equivalent conventional model). However, not all outlooks seem as promising. For example, Bloomberg NEF 2024 EV Outlook [7] reports a slowdown of EV sales in most of Europe. As this shift brings forth a novel demand pattern, characterised by its non-uniform distribution across both time and territory [8], effective and adaptable tools must

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Abbreviations	
BEV	Battery Electric Vehicle
CP	Charging Point
ECDF	Estimated Cumulative Distribution Function
EU	European Union
EV	Electric Vehicle
EVT	Electric Vehicle Trip
FCR	Frequency Containment Reserve
FF55	Fit for 55
GL	Generalised Logistic
GIS	Geographic Information System
KPI	Key Performance Indicator
MC	Monte Carlo
ML	Machine Learning
MPN	Netherlands Mobility Panel
NHTS	National Household Travel Survey
OD	Origin-Destination
OSM	OpenStreetMaps
PDF	Probability Distribution Functions
PFC	Primary Frequency Control
PS	Primary Substation
STM	Spatial-Temporal Model
SOC	State of Charge

be developed to support strategic investments, grid reinforcement, and infrastructure deployment [9]. From a planning perspective, the need to replicate spatially and temporally the behaviour of electric fleets is recognised and approached with Spatial-Temporal modelling [10–12]. This is done by integrating real-world data into Geographic Information Systems (GIS) to assess the impact of mobility. Although based on real measured data, this type of approach relies on limited datasets biased by a specific class of drivers (such as the New York autonomous taxi fleet [13]) or limited spatially, where analyses are conducted only on a single municipality. Eitel and Stolle [14] estimate the impact on the electrical grid by fitting an EV distribution to the currently installed recharging infrastructure. The study does not model actual trips. Conversely, agent-based traffic simulations represent a recognised methodology to improve on the data availability and granularity. Yi et al. [12] exploit an open-source framework to model all trips that take place on a typical day, in which synthetic drivers are generated starting from a population sample and socio-demographic characteristics are given. Daily driving profiles are assigned to each individual to simulate traffic for the entire study area. While such an approach generates a rich database with detailed information on energy expenditures, state of charge, and time scheduling of each vehicle, it resorts to synthetic data. Novosel et al. [15] employ the same tool for a national-scale analysis of EV impact.

Synthetic drivers and driving patterns are generated using sample population data and can be guided by statistical considerations and travel surveys are often useful to make the analysis more adherent to reality [16]. One downside is the computational burden and the complexity of calibrating a model in an increasingly complex framework [17].

Modelling vehicle movement in a given area is just one challenge in analysing the impact of EVs on transmission and distribution networks. Once traffic flows have been simulated, factors such as mode choice and EV penetration must also be considered. One such approach involves customised surveys. For instance, Langbroek et al. [18] compare the travel patterns of EV and conventional vehicle users in Greater Stockholm, focusing on the number of trips and the modal share of cars in total travel distance. They find that EV users make significantly more trips than their non-EV counterparts. Similarly, Danielis et al. [19] use a stated-preference survey from 2018 to examine the growing confidence of younger Italian drivers in the EV range, suggesting that future incentives will have a larger impact on adoption rates than technological advances. They also find that most EV trips are shorter than those taken in conventional vehicles. Alternatively, the same issue is addressed using ML models trained on public datasets. For example, Jia et al. [20] analyse EV owner characteristics from the 2017 National Household Travel Survey (NHTS) [21], which provides extensive individual data on drivers and trips. They develop a comprehensive estimation model for EV adoption that incorporates vehicle, personal, and household factors, training and comparing several ML models to predict regional EV penetration in the U.S. Similarly, Javid and Nejat [22] develop a Multiple Logistic Regression model applied to the 2012 California Household Travel Survey and validated on data from a survey conducted in the Delaware Valley region. One common limitation in the literature, concerning the goal of estimating which trips are electric within a traffic framework, is the lack of representation of trip characteristics in the adoption models. Miconi et al. [23] compare four ML models trained on public data at both regional and provincial levels, alongside data from a personalised 2019 survey of 300 people. Their analysis identifies the most significant variables influencing adoption. Li et al. [24] conduct a systematic literature review to identify factors influencing consumer intentions to adopt battery EVs and propose key variables for developing an effective model of vehicle adoption. Table 1 summarises the methods used in the relevant literature.

Lastly, once the EV flows are assessed, it is possible to evaluate the impact of charging processes on the grid and to extend the analysis to the flexibility services offered. Such a flexibility provision could transform e-mobility charging processes from a mere incremental load into a resource that enhances the operation of the electric grid. Currently, literature predominantly focuses on load shifting applied to demand peaks [10] and the coupling of EVs' electricity demand with electricity production from photovoltaic [13]. Seo et al. [25] investigate the capability of EV fleets in supporting the German balancing market for grid stability was investigated. Temporal energy level stochasticity was modelled through Markov chain and a Monte Carlo (MC) behaviour model.

These challenges ultimately lead to the research questions: *"How can the impact of private transportation electrification be quantitatively assessed from a temporal and spatial perspective during the planning phase?"* and *"How will this incremental demand affect the existing network, and can it serve as a viable decentralised storage solution to provide grid-oriented services?"* Building on previous works [11,26], this paper proposes a GIS-based approach that develops an STM to estimate the impact of e-mobility on the distribution network in the Lombardy Region (from here also simply Region), based on a scenario for 2030 published by policymakers. Specifically, the goal is to study the available power bands for the provision of Frequency Containment Reserve (FCR) by the EVs requesting a charge within the territory, supposing a unique aggregator managing the recharging infrastructure in the Region.

The reference studies adopt an MC simulation to characterise the fuel type information of passenger cars, which is missing in the OD matrix. Based on a fixed penetration rate and a provincial share of EVs [27], the algorithm randomly selects a coherent share of EVs from the trips dataset. Improving on the existing procedure, an ML-based mode choice model enriches the existing methodology to identify the most likely EV Trips (EVTs) based on trips and drivers' features. The resulting hourly demand profile is the direct consequence of this selection, along with the peaks, identified by specific behavioural patterns in the traffic model. By incorporating behavioural and socioeconomic factors within a physics-based, bottom-up traffic model, the present method provides a deeper understanding of traffic dynamics. This enhancement allows for a more refined, case study-specific analysis, particularly during critical hours, ensuring a more accurate representation of demand fluctuations.

This paper is organised as follows. Section 2 introduces the case study setting and the input data required to define the adopted scenario, along with a detailed description of the ML models and the

Table 1
Summary of methods in relevant literature.

References	Survey	ML model	Open datasets
Jia, Shi, Che, Zhang [20]		✓	✓
Langbroek, Franklin, Susilo [18]	✓		
Miconi, Dimitri [23]	✓	✓	✓
Danielis, Rotaris, Giansoldati, Scorrano [19]	✓		
Li, Long, Chen, Geng [24]		✓	

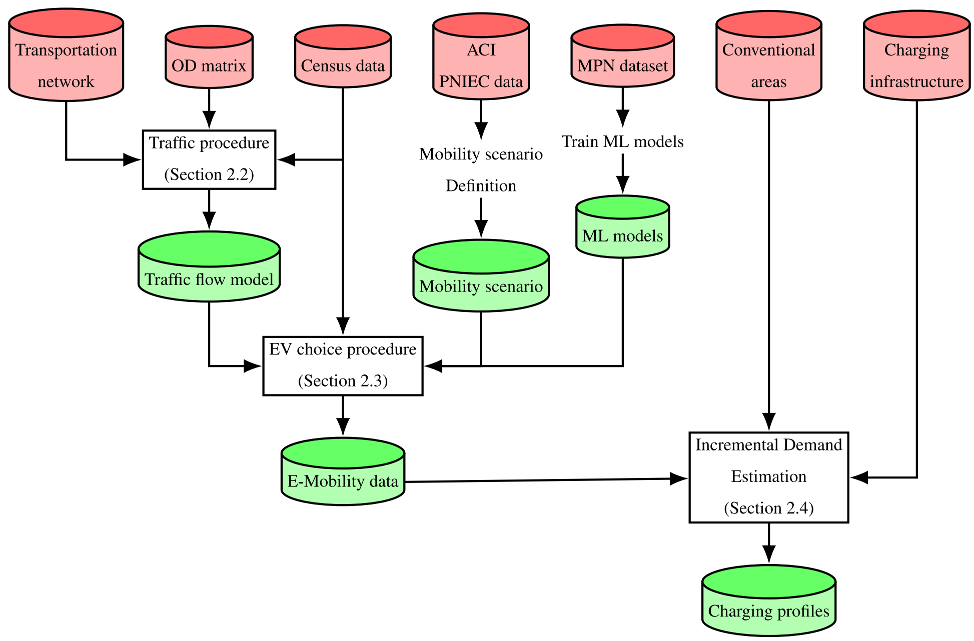


Fig. 1. Information flows and procedures.

methodologies developed to analyse the impact on the grid. Section 3 presents the results, highlighting the unique features introduced by the ML model and providing a brief comparison with the results of the MC simulation conducted on the same scenario. Moreover, it estimates the performance and schedule of the band availability for an EV charging aggregator, providing flexibility for FCR services to the market. Finally, Section 4 presents the conclusions.

2. Materials and methods

The proposed methodology develops an integrated framework to locate EVTs, estimate their energy demand and the impact on the grid, and finally quantify their participation in the ancillary service market. The procedure is structured into three key steps. First, a bottom-up model simulates traffic flows in a given area using geospatial information and open-source traffic data (Section 2.2). Secondly, ML techniques are applied to accurately identify EVTs within the simulated traffic framework (Section 2.3). Lastly, the EV traffic layer is integrated with the existing charging infrastructure at a provincial level, producing a temporal and spatial incremental demand profile and evaluating the bandwidth for FCR (Section 2.4). The approach only considers V1G charging schemes; thus, the profile is strictly incremental and does not entail any discharging of the EVs. The entire procedure is summarised in Fig. 1, where input datasets are highlighted in red and procedure outputs are shown in green.

2.1. Study setting and adopted scenarios

This study focuses on an application in Lombardy, the most populous region in Italy. This region was chosen due to the availability of input and the economic relevance within the Italian context. Specifically, six key data sources are required for this analysis.

First, critical demographic information is obtained from periodic census reports conducted by ISTAT [28]. The agency provides a GIS-based dataset in the form of shapefiles, along with numerous thematic tables containing geo-referenced socio-demographic and economic data for each census section nationwide. Secondly, regional mobility patterns are assessed using the Origin-Destination (OD) matrix developed by the Region. This dataset tracks and periodically updates trips representing daily travel patterns in a standard winter working day. As shown in Table 2, it includes details such as origin and destination zones, provinces, departure times, trip purposes, and traveller roles. Third, the transportation network is modelled using the region's road infrastructure, sourced from OpenStreetMaps (OSM) in GIS format. Carriage roads are represented as a graph, enabling the routing of trips based on their origin and destination. To relate the geographical areas providing the background of the traffic modelisation to the geographical extension of the distribution system, it is necessary to find a bridging dataset. In Italy, the conventional areas provided by GSE [29], represent an estimation of the extent of the territory served by each Primary Substation (PS).

A critical aspect of this study is defining a mobility scenario that characterises the degree of penetration of transportation electrification and the current deployment of charging infrastructure. The first step involves analysing data on EV distribution across municipalities: in Italy, this data is updated annually by ACI [27]. To estimate future adoption, the current distribution is scaled to a 2030 scenario, aligning with national policy targets [5]. Numerically, this projection is derived by applying the national target of 4.3 million Battery Electric Vehicles (BEVs) by 2030. As a result of these considerations, key assumptions in this study are summarised in Table 3.

Additionally, modelling the charging infrastructure is essential for transitioning from a traffic-based model to an energy-based one. This

Table 2
Exemplified structure of Lombardy OD matrix [30].

Index	Origin province	Origin zone	Dest. province	Dest. zone	Time frame	Purpose	Role
1	MI	Milano 7	BG	Bergamo 1	16:00 - 16:59	0	0

Table 3
Summary of the adopted scenario.

	Italy 2024	Lombardy 2024	Italy 2030	Lombardy 2030
EVs [k]	219.5	43.5	4 300	851.9
CP [k]	48.9	9.7	115	23

Table 4
Assumed distribution of CPs in Lombardy [%].

BG	BS	CO	CR	LC	LO	MN	MI	MB	PV	SO	VA
11.2	14.8	7.5	2.9	3.4	1.6	2.8	33.2	8.9	3.3	1.4	9.0

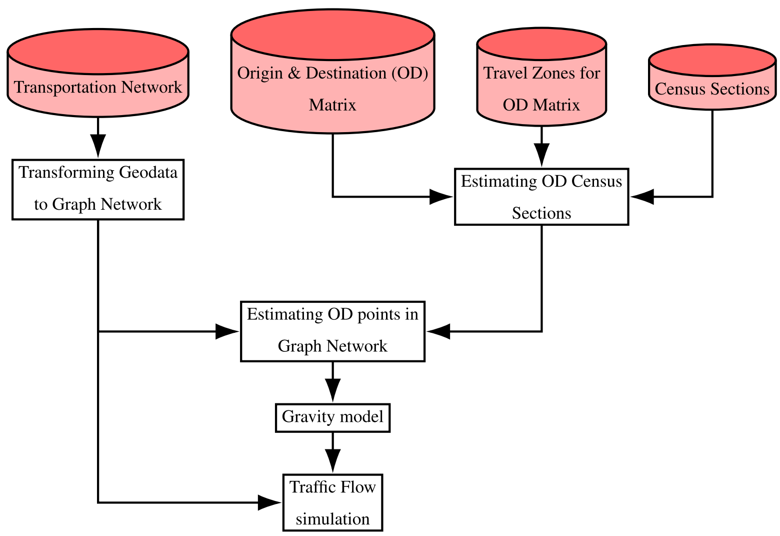


Fig. 2. Summary of the traffic model.

step enables the location and quantification of the constraint on the recharging needs of EVs, allowing for the estimation of the impact on the power system. The number of public charging points (CPs) is projected using the current ratio of those in Lombardy relative to the national total [31]. Based on a conservative estimate of CPs to be installed nationwide by 2030 [32], this study adopts the same proportion for the area under investigation. Their distribution is estimated at the provincial level, and replicates the latest EV ownership distribution data published by ACI [27] (Table 4), which also serves as the basis for the distribution of CPs. The charging infrastructure consists of CPs with nominal power outputs of 7.4 kW and 22 kW, randomly distributed across the region with a 55/45% split [32]. Conversely, all domestic charging is assumed to take place exclusively at a nominal power of 7.4 kW. Table 3 provides a summary of the mobility scenarios adopted in this study, comparing the national and Regional penetration of vehicles and charging infrastructure.

2.2. Traffic model

As introduced above, this study does not focus on the development of a traffic modelisation framework: the traffic simulation adopted in this work is thoroughly detailed in [26]. Nevertheless, a brief rundown is provided to give some context and identify the inputs, sub-routines of the algorithms, and output of this first step. The flowchart in Fig. 2 summarises the procedure.

A bottom-up, GIS-based approach is utilised to analyse mobility patterns. The process begins with the construction of a weighted graph representing the regional traffic network, incorporating factors such as road infrastructure, traffic flow, and congestion levels. Using information on the road network, a graph is created where the weight of the edges is related to both the length and the maximum speed and represents the time needed to cross it. The weighted graph represents the regional traffic network, incorporating factors like road infrastructure, traffic flow, and congestion levels. Starting from census sections that are characterised by socio-demographic information, to achieve finer spatial resolution for trip origins and destinations, the region is further subdivided using a GIS-enhanced gravity model. This method enhances large-scale survey data by distributing travel demand across census areas using predefined attraction factors. Census areas are chosen as the spatial resolution due to their common use in demographic and workforce reporting, and their alignment with amenities data, which is frequently available at this scale. Moreover, census areas offer greater spatial detail than coarser zoning systems, supporting more precise analyses while remaining consistent with the existing data framework. A gravity model is employed to spatially refine mobility data, reallocating trips among census areas according to their relative attractiveness for various travel purposes. The approach relies on probability density functions that account for local characteristics, such as population size, employment distribution, proximity to universities, and amenity availability, which influence the probability of an area functioning as a trip origin or destination. The model assigns probabilities dynamically, adjusting parameters based on trip types, such as commuting, academic travel, leisure, or homeward journeys.

For each input travel processed by the model, relevant data added to Table 2 include the precise location of the origin and destination, the

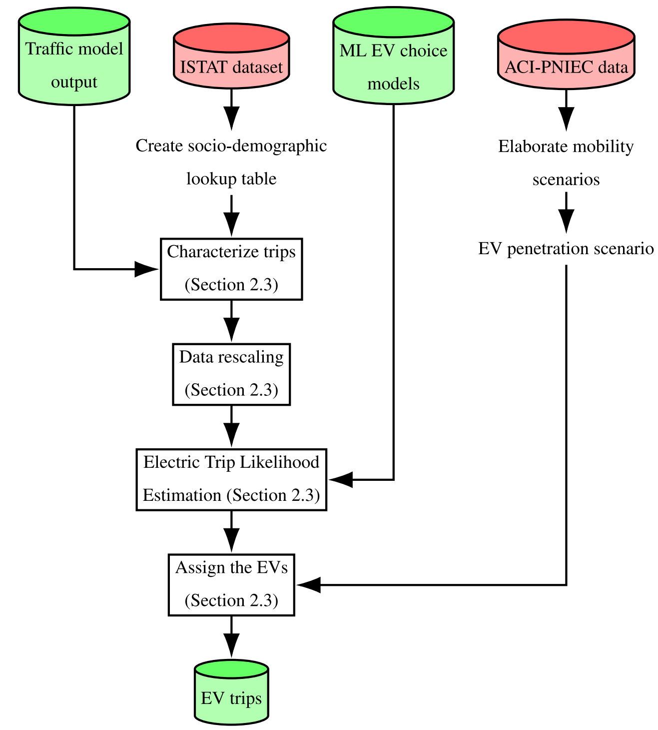


Fig. 3. ML-based EV choice procedure.

total distance travelled, and the estimated arrival time. For each trip, a shortest-path algorithm is run to find the quickest path, subsequently updating a state matrix that portrays the traffic on each street that affects the time needed to cross it for the trips that follow.

The outcome of these elaborations is an enriched dataframe detailing the 8 million trips reported in the OD matrix, comprising trip purpose, duration and distance, and fine-grained spatial and temporal resolution of departure and arrival.

2.3. Machine learning EV choice

This section aims to create an ML model able to relate the trip characteristics to the vehicle choice, using data from public datasets. The model is created by exploiting variables that must be correlated and effective for this section, and, in addition, publicly available. Fig. 3 provides an overview of the procedure designed for the vehicle choice: the public input data is represented in red while the outputs of previous procedures, hereby integrated as inputs, are represented in green. The algorithm carries out a characterisation of the trips based on the mode choice: specifically, the methodology selects among the trips carried out with a private car (the only ones simulated by the traffic model) those which are more likely to be EVTs, based on trip features and drivers' socio-economic characterisation. Lastly, the algorithm will sort the trips by likelihood and label as electric only those that also fulfil the constraint on local EV penetration.

Variables selection and learning datasets

Understanding mobility patterns and assessing the impact of electrification in the private light-duty transportation sector requires a careful selection of relevant variables. However, not all factors discussed in the literature can be incorporated into the analysis, either due to data availability constraints or their suitability for integration within the model. Some variables, such as vehicle and fuel prices or garage ownership, are difficult to obtain and integrate into the framework. Others, like photovoltaic installations, pollution indicators, or driving range limitations, introduce additional complexity, as effective metrics for these factors are challenging to define, and there is no broad consensus in the literature regarding their influence [33,34]. Given these constraints, the selected variables fall into two main categories: those characterising each trip based on its intrinsic properties and those describing the socio-economic profile of the driver. While the first category is typically derived from trip datasets, the latter is not always readily available. As will be demonstrated in the case study, socio-economic attributes may need to be sourced from statistical reports published for the relevant territory. Moving on to the choice of the training dataset for this application, this must include the variables discussed above and should be quite vast, to guarantee a sufficient number of samples for the model training phase. The Federal Highway Administration publishes a very large dataset called the National Household Transport Survey (NHTS) [21]. The dataset records all the selected variables, but the number of EVs is very small, close to 1.33% of the total number of vehicles, therefore, it may not provide a good modelling. On a more qualitative note, a case could be made that the North American and European commuters, given the distances and overall transportation needs, have a different set of factors influencing the adoption of an EV. No combined dataset of trips and drivers' features is published for Italy, and the data available could not be elaborated into a robust dataset for training purposes without major and potentially disruptive statistical assumptions (see Table 5).

The Dutch yearly survey on mobility, published by the Netherlands Mobility Panel (MPN) [35,36], does fit the requirements. This dataset is made up of thematic surveys divided by the nature of the questionnaire, related to a person or a household: the entries are correlated by a unique ID linking drivers and households. It is thus possible to associate each trip with the demographic characteristics of either the person or the household: for example, while age and gender are personal features, income is reported in the household data. The range of questions allows to have a significant number of variables from which to choose, also including some such as trip duration and purpose. Finally, reflecting on how good a fit this dataset would be for these purposes, it must be noted that the trip habits of Dutch drivers and the extension of the territory could be considered comparable to that of this Lombardy case study.

Rescaling: transfer learning

The selection of a learning dataset carries the concern related to its adaptability to other scenarios: likely, the distances that characterise trips in the learning and target datasets are different, reflecting the drivers' attitudes. While this cannot be solved in a deterministic way, a data rescaling step [37,38] is implemented on both datasets to address the issue.

The first and most basic approach could be to rescale the datasets based on the ratio between attributes sampled at a particular percentile, or some combination of mean and median. This clearly cannot be a generalised approach, since these figures are impacted by the particular distribution of the trip distances. A second scaling factor could be pinpointed as some features of the regions, for example, the surface, population density, and topography. This would constitute a quick but rather limited solution, as it would in no way consider complexities such as the structure of the road network (which is reflected in the traffic). A more generalised approach, integral to the distribution of the values itself, must be found. Cao et al. [39] deal with some practical applications of data scaling (data normalisation), comparing the outcome of three techniques. Firstly, two conventional techniques are applied, Min-Max and Z-score, which were found to be sensitive to the normalisation interval, to the number of samples and outliers. The authors propose another algorithm, called Generalised Logistic (GL) scaling, which scales v to v' by applying:

$$v' = P_X(v), \tag{1}$$

where $P_X(\cdot)$ is the computed Estimated Cumulative Density Function (ECDF) of X since the distribution is not a priori of the analysis. This algorithm is robust to outliers and may be applied to instances with a small number of samples. Adopting this technique, both learning and target datasets' *distance* and *duration* variables are rescaled.

Table 5
Summary of trip characterisation required for the ML.

Trip characteristics	purpose, distance, duration, mode, departure time, day of the week
Socio-economic features	gender, status of employment, education, age, household income

Table 6
Machine Learning training: accuracy results.

	Outward trips		Return trips
Indicators	Three purposes	One purpose	One purpose
Logistic regression	0.64	0.63	0.65
Support Vector Machines	0.49	0.51	0.61
Random forest	0.76	0.74	0.70
Naive Bayes	0.61	0.60	0.60
K-nearest neighbour	0.58	0.55	0.48
Xgboost	0.68	0.67	0.59
GradientBoos	0.661	0.71	0.62

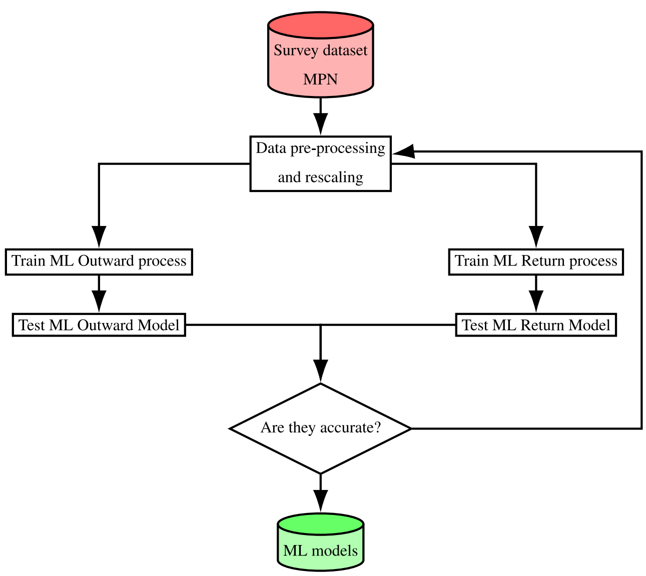


Fig. 4. Flowchart of the model training and testing.

Machine learning model

As the flowchart in Fig. 4 shows, two ML models are trained on the separate datasets of outward and return trips, discriminated using the *purpose* variable: this precaution allows better accuracies in the testing phase compared to the training of one single model. Several supervised machine learning algorithms were designed, tested, and compared to achieve the objective, using the *accuracy* metric to evaluate their performance. The learning dataset differentiates trips based on their mode choice, thus, the ML models are trained with the aim of assigning to each entry a likelihood of being an EVT. The procedure uniquely evaluates learning trips carried out by the respondent as a driver of a private vehicle during a weekday.

As introduced, the ML models are trained on outward and return learning trips separately, filtered by the "purpose" variable. Tests are conducted to assess whether distinguishing outward trips by purpose (*Work*, *Occasional*, *Study*) improves learning accuracy. Results suggest training two separate *Random Forest* models for outward and return trips, with purpose-based characterisation slightly enhancing the accuracy indicators, as shown in Table 6.

Socio-economic characterisation of the trips

For those trip datasets that do not present any driver socio-economic feature (as is the case of this study), it is necessary to further characterise the trip dataset before implementing the ML model. This lack of information is addressed by creating Probability Distribution Functions (PDF) for each variable at a census section level: each trip is then assigned a particular coded classification (based on its departure section) by random extraction from each of the variable distributions. Moreover, all the features should be mapped in a way that fits the coded classification of the learning dataset. These further steps enforce a correspondence to the data structure of the learning dataset.

At this point of the procedure, the trips in the target dataset are coherent with the learning one and characterised by all the necessary variables: trip features (such as distance, time frame and duration) and the socio-economic features of the driver. The two ML models can be applied to the trip datasets, split into return and outward trips: the datasets will be enriched by the likelihood of being carried out with an EV. Table 7 shows an example of a characterised trip.

Algorithm 1 Geographically Constrained Selection of EVT

Input:
- Trips datasets with likelihood scores of being EVT.
- Mobility scenario mapping available EVs for each city EV_{city}.

Output: Trips' datasets labelled as EVT.
for each city c in the list of municipalities **do**
  $availableEV \leftarrow EV_{\text{city}}[c]$ ▷ EVs available in the city
  $tripList \leftarrow$ List of trips departing from c
  Sort $tripList$ in descending order based on likelihood score
  for each trip t in $tripList$ **do**
    if $availableEV > 0$ **and** t is not already labelled as EVT **then**
      Label t as EVT
      $availableEV \leftarrow availableEV - 1$
    else
      break ▷ No more EVs available in this city
    end if
  end for
end for

Assigning the electric vehicles

After the ML procedure has classified the trips on a likelihood of being an EVT, it must perform a geographically bounded selection of those which, according to the assumed scenario, are actually to be considered as such. The algorithm detailed in 1 effectively moves the model to a deterministic scenario in which a finite number of EVs are circulating: the geographical constraint is imposed on the departure municipality of the relevant vehicles. Considering one city at a time, the pool of potential EVTs leaving from such a city can only be as large as the number of EVs estimated for the city itself: the most likely EVT is labelled as such only if there are EVs available and not yet chosen.

The resulting framework, which will be subject to the recharging process framing, comprises one scenario labelling as EVs the most likely trips.

Table 7
Exemplified structure of a trip after the ML implementation.

Ind.	Sect.	Educ.	Income	Gender	Empl.	Age	Purp.	Dur.	Dist.	Time	Likelihood
10	100 175	2	4	1	1	5	1	15	20	6	0.9

2.4. Charging processes impact on the electric grid

This section discusses the opportunities provided by this procedure for the modelling of the impact of e-mobility and related services on the grid. The procedure relies on that presented and detailed in [11], which constitutes the main reference for the following analysis.

Unconstrained energy demand and charging infrastructure

The first step in the analysis of the impact of EVTs on the distribution network is the estimation of the energy needed related to the distance travelled by the EV and the pertaining energy consumption. This was approached in a rather simplified way, as shown in Eq. (2), multiplying the distance by a constant factor:

$$\Delta E^{consumed} = c_{spec} \cdot d \tag{2}$$

where c_{spec} is the average specific consumption of an EV in $\frac{\mathrm{kWh}}{\mathrm{km}}$ and d is the distance in km deriving form the traffic model. As in the reference papers, c_{spec} is set at 0.2 $\frac{\mathrm{kWh}}{\mathrm{km}}$.

After each EVT is characterised by its energy consumption (demand), the modelling of two drivers' behaviours is introduced to enhance the simulation of charging requests. First, as EVs that have travelled a long distance are more likely to require a charge than those that have completed a short trip, a probability p is assigned to account for the likelihood of drivers recharging upon reaching their destination. Secondly, while in longer trips the energy required for charging is likely to match the energy used, if a vehicle is selected to charge after a shorter trip, it is reasonable to suppose that the charging process will last longer than the energy expenditure for the last trip. This is accounted for in Eq. (3) with a scaling factor sf representing the relation between the consumed energy in the last travel, $\Delta E^{consumed}$, and the energy to be recharged ΔE^{EV}.

$$\Delta E^{EV} = sf \cdot \Delta E^{consumed}; \quad sf \geq 1 \tag{3}$$

The probability of requesting a recharging is not one, and it is modelled by a curve, similarly to the approach adopted by Venegas et al. [40], where the probability is a function, among other variables, of the State of Charge (SoC). In this case, the piecewise linear curves which assign the probability of requesting a recharge p, detailed in Eq. (4), are strictly a function of the energy spent. Furthermore, the energy multiplier sf is characterised by a piecewise linear curve.

$$\begin{cases} p = 1, \quad sf = 1 & \text{if } e_{\text{spent}} \geq \text{ub} \\ p = \frac{1}{\text{ub}-\text{lb}} e_{\text{spent}} - \frac{\text{lb}}{\text{ub}-\text{lb}}, & \text{if lb} < e_{\text{spent}} < \text{ub} \\ sf = -\frac{10}{\text{ub}-\text{lb}} e_{\text{spent}} + \frac{10 \cdot \text{ub}}{\text{ub}-\text{lb}} & \\ p = 0.02, \quad sf = 10 & \text{if } 0 \leq e_{\text{spent}} \leq \text{lb} \end{cases} \tag{4}$$

where *ub* and *lb* indicate the thresholds selected as a percentile of the ΔE^{EV} for the whole set of EVTs. The dynamic thresholds of the piecewise curve, adapted based on the distribution of energy needs, ensure that the probability of requesting a recharge aligns with the specific scenario. However, the need to charge does not represent a sufficient condition to effectively gain energy. Dealing with the real infrastructure system, as this can be saturated at peak hours due to the finite number of public CPs. This does represent the bottleneck for the provision of ancillary services, as results will show. The matching between arrivals requesting charging and available chargers is performed on a provincial scale. The availability of a CP at each time-step of the simulation can be "free" or "busy" while the EV state can range between "not connected", "connected", "charging". The charging will start only when a charger is available in the considered area, delaying the charging start instant. This analysis, consistent with the traffic modelling, provides a 5 min temporal granularity.

A *smart charging* strategy performing a modulation of the load is applied only to the outward trips; conversely, the "return home" trips are charging at home only in 55% of instances (extracted randomly), simulating the case of an EV driver without the infrastructure for domestic charging. An additional 15% of the return trips not yet selected choose to recharge at an available public CP.

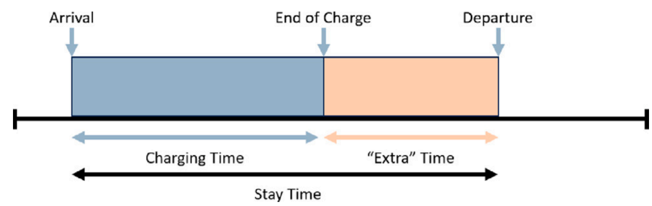


Fig. 5. Stay times representation.

Bands enhancement

The resulting EV-related incremental load profile shows power peaks and valleys directly induced by drivers' habits. To mitigate power fluctuations, the procedure implements a *load shifting* strategy. The underlying idea is to postpone charging sessions beginning in time windows when the load profile is above its average to hours of *valley profile*, achieving a smoother incremental load profile. Each car, with a travel purpose different from "return home", will remain at the destination location for a stay time st_{EV} defined by a normal distribution function, subject to the purpose of the trip itself, as in Eq. (5):

$$st_{EV} \sim \mathcal{N}(\mu_r, \sigma^2) \tag{5}$$

where μ_r is the average number of stay hours different for each reason of the travel r8. Referring to the nomenclature reported in Fig. 5, the departure time of an EVT, dt_{EV}, is dependent on both the outcome of the traffic modelisation (the ***arrival*** time at_{EV}) and the stay time st_{EV}.

Assuming constant charging power, recharging time ct_{EV} is defined once the matching between vehicle and charging infrastructure is performed (Eq. (6)). Moreover, since the modelled recharging processes involve AC-slow charging stations, non-linearities in the estimation of the charging time are neglected.

$$ct_{EV} = \frac{\Delta E^{EV}}{P_{nom}} \tag{6}$$

Consequently, knowing the *arrival* time at_{EV}, the *end of charge* and *departure* timeframes, eoc_{EV} and dt_{EV} respectively, can be computed as per Eqs. (7)–(8).

$$eoc_{EV} = at_{EV} + ct_{EV} \tag{7}$$

$$dt_{EV} = st_{EV} + at_{EV} \tag{8}$$

As charging time is independent of the stay time, a continuous check between the end of the charging process and the departure instant must be performed. In case this is not verified, the new charging end is set to be equal to the charging limit time frame, and the EV's battery is not fully charged.

Since the *load shifting* procedure is designed to be neutral on the user side (i.e. flexibility purposes must not affect mobility needs), a charging process can be postponed only if it will be completed before

Table 8
Average stay time as a function of travel's purpose.

Stay times μ_r [h]			
Work	Study	Return	Leisure
8	6	11	4

the departure time dt_{EV} and no car is waiting that specific charging point to be free to charge. The power profile that the aggregator may exploit, resulting from the previous considerations, is constrained by mobility patterns and user habits. As a result, the extra time, depicted in Fig. 5, represents the real source of flexibility, enabling the smart charging algorithm to reduce peak power demand without any impact. As only V1G is modelled, the decreasing band is solely obtained by decreasing the power provided to the recharging EV.

Primary Frequency Regulation (PFR)

PFR acts to slow and arrest changes in frequency via rapid and automatic responses that increase or decrease output from generators available for these services. PFR can be provided by multiple generator types, potentially including an aggregate of EVs. The fleet of vehicles is assumed to provide frequency response based on a droop curve with dead-band [41] as in Eq. (9):

$$\Delta P_{PFC} = -\frac{\Delta f \cdot P_{nom}}{f_{nom} \cdot \sigma} \cdot 100 \tag{9}$$

where ΔP_{PFC} is the power set point of PFR, Δf the frequency deviation, f_{nom} the nominal frequency, P_{nom} the nominal power, σ is the droop value. As determined by the TSO's grid code [42], the intervention was assumed to be triggered whenever the frequency value deviates more than 20 mHz from the nominal frequency of 50 Hz. The modelled aggregator imposes a limit on the power drawn by recharge processes, which does not overtake 90% of the nominal value. The remaining power - 10% - is available to provide the potential for regulation in both directions. If this strategy is not enforced, the CPs can only provide a unidirectional band, decreasing the power delivered to the connected vehicle. As a result, the aggregator can provide flexibility according to two strategies:

- "Decrease Charge Direction", when the frequency of the grid is within the dead-band threshold value and the control action imposed on the pool is to decrease the charging power;
- "Increase Charge Direction" instead results in an increase of the energy uptake as the frequency of the grid is outside the dead band.

For mainly historical reasons, the Italian regulatory framework encompasses no remuneration for the relevant plants that provide FCR services, as it is considered a mandatory service for those wishing to be eligible for the connection to the grid. To simulate the available bands for flexibility services, the analysis is run considering an existing European framework, although not in place in Italy. This work does not perform an accurate business case study of an aggregator but rather evaluates the potential for flexibility and its tempo-spatial characterisation across the whole Lombardy region, accounting for all the resources within its territory.

For this purpose, a market-based capacity compensation scheme is assumed, inspired by the FCR (Frequency Containment Reserve) coordination mechanism implemented in Central Europe [43]. Remuneration is proportional to the minimum offerable band, $band_{min}$, which represents the smallest level of power flexibility that can be reliably provided over a four-hour window. Eq. (10) defines this band as a function of the electric vehicles connected to the CPs, capturing the aggregated capacity potentially available for grid services. The focus on the minimum band is essential, as the reserve service can be activated at any moment during the window, and non-compliance is subject to significant penalties. For this reason, only the capacity that

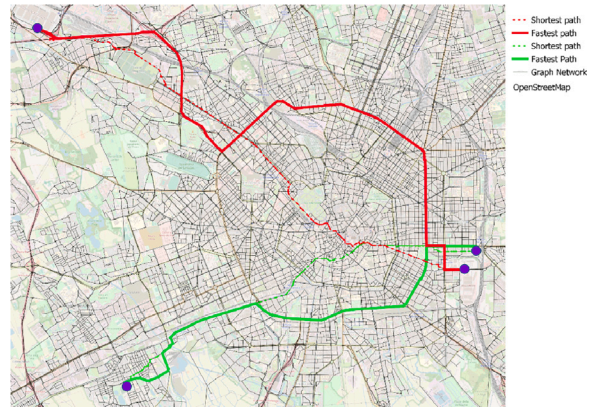


Fig. 6. Routing procedure for two different travels.

can be guaranteed throughout the entire period is considered eligible for bidding. Furthermore, since flexibility must be symmetrically available in both directions (i.e., increasing and decreasing charging), simulations that involve only the "Decrease Charge Direction" are not economically viable and are thus excluded from the analysis. It is important to note that the present study does not address how the service is distributed among individual vehicles. Instead, it concentrates on evaluating the aggregated potential at the CP level, which defines the feasible contribution to grid stability through FCR services.

$$band_{min} = \min(\min(band_{decrease}), \min(band_{increase})) \tag{10}$$

3. Result and discussion

This section presents the results of the case study in the two implementation directions. First, it focuses on the outcomes of the applied ML techniques, including model performances and a comparative analysis of outcomes. Secondly, it demonstrates the application of the enhanced model in the case study described in Section 2. Lastly, it discusses some limitations of the procedure.

3.1. Traffic model output and Monte Carlo selection

The procedure recalled in Section 2.2 produces a layer representing the 8.2 million cars distributed in the census sections of arrival (see examples in Fig. 6 and Fig. 7). This volume of vehicles must undergo a selection procedure, *EV choice* (Section 2.3), which returns the layers of EV arrivals distributed in the territory. While this work details the methodology to perform this selection by adopting ML models, another selection procedure serving the same objective is presented to provide a point of reference. This algorithm, based on an MC simulation, was also adopted in the reference papers [11,26]. The MC simulation is characterised by the explicit parameter of EV penetration rate, tailored to the ratio of ML-selected EVs compared to the volume of all trips modelled. Table 9 compares the similarity in the number of EVs selected by the two procedures.

3.2. ML validation and comparison

The effectiveness of the ML approach is demonstrated through a differential analysis that compares its results with those obtained from an

Table 9
Electric Vehicles selected.

	ML	MC	Overall traffic volume
Number	1 696 743	1 703 955	7 882 984

Fig. 7. Cars arriving in Milan city centre between 7-8 AM.

MC simulation run for the same scenario. The comparison is conducted under the assumption that the same number of cars is distributed over a typical day. The MC simulation relies on a straightforward probabilistic selection based on EV penetration rate at the provincial level and does not incorporate any behavioural information into the selection process. To quantitatively evaluate the differences discussed above, a geo-referenced *arrivals matrix* is computed, representing the metric Δa obtained for each time frame τ as the difference between the arrivals a according to the ML model, indicated with subscript *ML*, and those simulated by the MC model, indicated with *MC*:

$$\Delta a = a_{ML}(\tau) - a_{MC}(\tau) \tag{11}$$

In Fig. 8, two key differences stand out. First, the ML model excels in capturing the spatial distribution of electric trips, showing patterns following the geographical distribution of EVs reported by ACI. This is particularly evident in the higher concentration of trips in provincial capitals, such as Milan, and other major hubs. Secondly, the ML model better reflects the temporal patterns of electric trips, leveraging the temporal characterisation embedded in the training dataset. This accuracy is further enhanced by dividing the ML process into two models: one for outward trips, predominantly occurring in the morning, and another for return trips, mainly in the afternoon and evening hours.

Considering the temporal schedule throughout the day, Fig. 9 demonstrates that while both scenarios exhibit a similar baseline trend, the ML procedure allows for partially decoupling EVT patterns from the general volume of cars travelling at a given hour, highlighting its ability to reflect unique mobility habits. Due to the nature of the MC EV choice procedure introduced above, there is a significant correlation between the EVTs and the overall arrivals, since the selection procedure is purely linear. Conversely, the EVTs selected with the ML procedure diverge from this relationship. This can be appreciated in the plots reported in Fig. 10. To restate this two-fold spatial and temporal enhancement of the trip's characterisation, the volume of vehicles has been analysed in the following way: based on the overall arrivals at the conventional areas, the numerical series have been sorted increasingly, applying the same updated order to both the series of EVT volumes. The first series was rescaled by a factor of 4.6 (see Table 9) for purely graphical purposes, as in Fig. 9. Lastly, the data was smoothed by applying a Savitzky-Golay filter (with a window of width 10 and a polynomial order of 3) to obtain three continuous curves depicting the ranked volumes of arrivals on a geographical basis, the conventional areas. The result of this elaboration, Fig. 11, outlines the strong dependency of the MC selection procedure on the geographical characterisation of the traffic model, showing conversely how the ML chooses to overestimate the volumes on the tail end of the spatial distribution, effectively selecting, in relative terms to the MC, more EVTs in the area which show to be more congested by traffic.

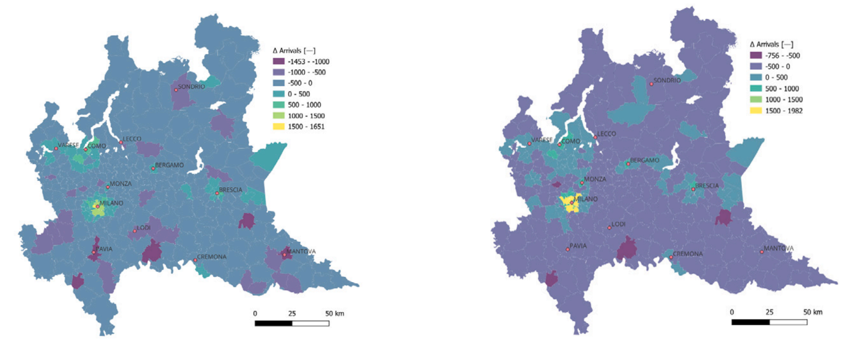
To conclude, in order to improve the clarity and effectiveness of the proposed approach, an explanatory example is provided. Fig. 12 shows the graph resulting from the aggregation of all routes associated with trips that either originate or terminate in Milan. This comparative figure illustrates both the complete mobility network and the subset of routes corresponding to EVTs. By comparing Fig. 12(a) with Fig. 12(b), several previously discussed trends become apparent. First, regarding traffic volume (i.e., the number of vehicles using a given road segment daily), it is evident that in the simulation, eMobility accounts for a portion of the total fleet involved in private light-duty transportation. Second, the electric mobility graph differs significantly from the general mobility network: it is less extensive and is more concentrated around the urban area of Milan and other densely populated centres in the region. This reflects the behaviour learned during the ML training process, which was designed to capture the most probable trips — both in terms of distance (favouring shorter-range travel) and socio-economic context (favouring more urbanised destinations).

3.3. Dumb charging profile and band enhancement impact

The regional aggregated load due to public and domestic (*private*) charging demand is reported in Fig. 13(a): the former shows a significant peak in the morning rush-hours and a more limited one in the evening, representing the impact of drivers returning home. Coherently with the assumptions and the traffic patterns, while the morning peak is made up of public demand (for example, charging at work), the evening one is balanced in its public and private contributions. The peak shaving algorithm produces a more regular power profile, enhancing the power bands the regional aggregated load could potentially provide to the ancillary services market: the morning charging peak of Fig. 13(a) is flattened by 38%, from 292 MW to 182 MW in Fig. 13(b), filling the two power valleys due to the lack of demand in the early morning and afternoon. This modulated profile constitutes a more suitable framework from an aggregator perspective.

Flexibility-wise, the available band is a time-varying attribute, a function of the number of connected EVs and the drivers' needs. The available band is proposed in Fig. 14(a). For each time interval, the power deviation that the aggregator can endure while satisfying all the constraints is reported (see Section 2 for the description of the model and the assumptions). Bearing in mind the above-mentioned drivers, it can be concluded that, for each simulation scenario, the difference between the blue curve and the red curve is the result of the relevance of the second constraint over the first. In other words, it can be easily observed that the available band in "Increase Charge Direction" is a direct transposition of the corresponding load profile trend, as the number of connected EVs is the only bottleneck, and higher charging powers are simply reducing the duration of the process. On the contrary, delaying the full recharge above a certain threshold can be unacceptable both from a user and an infrastructural point of view. Coherently, band difference is accentuated in the middle of the day, when public charging is predominant.

Following Eq. (10), once the value of the available band is set, it is possible to establish for each market session the power deviation the



(a) Arrivals difference Δa at the peak morning time frame

(b) Arrivals difference Δa at the peak return time frame

Fig. 8. EV arrivals difference in Lombardy PSs.

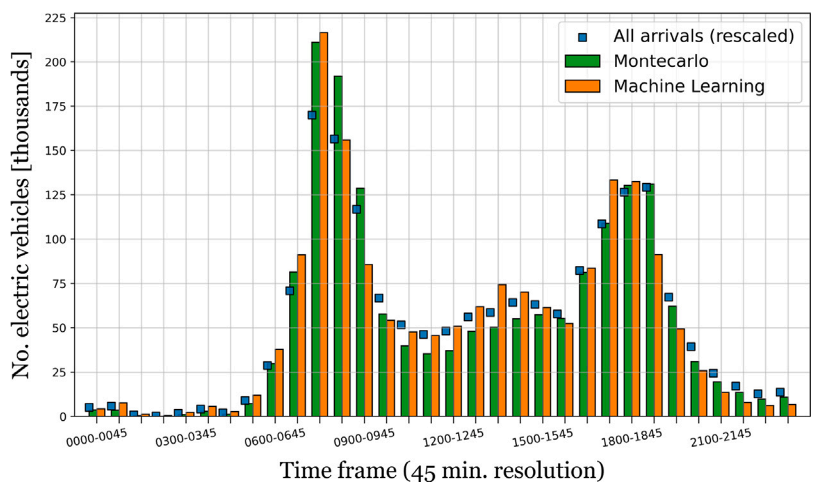
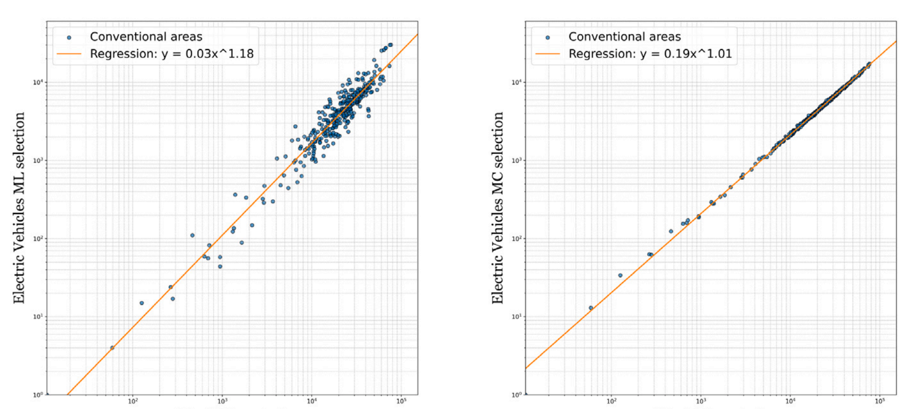


Fig. 9. Arrivals' comparison time evolution (the overall series was rescaled for visual purposes).



(a) Correlation of ML EV selection and overall vehicle volume (Kendall's correlation: τ = 0.883)

(b) Correlation of MC EV selection and overall vehicle volumes (Kendall's correlation: τ = 0.980)

Fig. 10. Comparison of correlation between EVTs and total arrivals.

Table 10
Summary of available bands according to the charging schemes.

	Time slots						
	0–4	4–8	8–12	12–16	16–20	20–24	Daily
Dumb charging bands [MW]	0.34	0.08	10.86	6.57	6.64	5.96	30.45
Smart charging bands [MW]	7.92	2.40	2.13	9.05	9.09	9.41	40

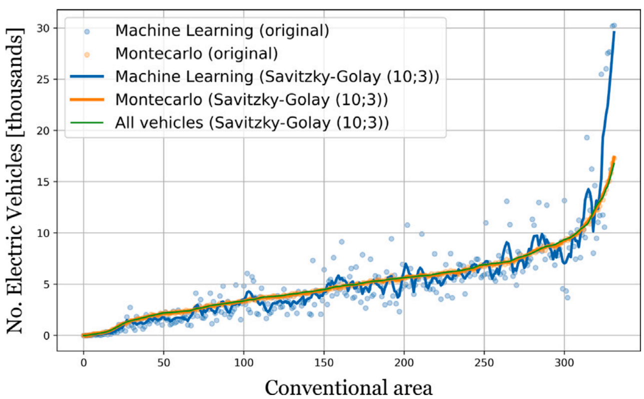


Fig. 11. Sorted arrivals on conventional areas.

aggregator can bid, as summarised in 10. Comparing the simulations with the charging strategies, the effect of the band enhancement technique is evident by observing the increase in the available bands in the outer time frames, which benefit significantly from the valley filling. Conversely, due to the shaving of the peak power, the serviceable power for the provision decreases in the morning hours. Overall, the daily available power bands can be estimated at 40 MW, representing about a 31% increase from the "dumb charging" power band of 30.45 MW.

The charging infrastructure seems to be limiting the potential full exploitation of the additional charging demand. Looking at the evolution of the number of available CPs throughout the day in Fig. 15, it is clear that the morning public charging demand meets a bottleneck in the infrastructure.

4. Conclusions

This work presents a novel approach that enriches the identification of EVTs in the context of a simulated day of traffic by integrating an ML model, exploiting the characterisation and recurrent pattern of EVTs and EV drivers. The implementation of the procedure for Lombardy's 2030 scenario, elaborated according to policymakers' projections, returns a selection of 1.7 million EVs out of the overall passenger car traffic. This framework of daily e-mobility is investigated to study the potential for grid flexibility services provided by EVs, assuming for this purpose that a unique aggregator is responsible for managing the entire recharging infrastructure. Recharging demand is quantified with a linear dependence on the distance travelled, and a dynamic piecewise curve assigns the probability of requesting a charge. The EVTs that are effectively recharged are selected based on the probability and the availability of CPs. The incremental recharge demand is aggregated at a PS level and modulated with a peak shaving algorithm. The analysis of these profiles allows for the estimation of the bands in scenarios of Smart and Dumb charging strategies. This study finds that the implementation of a smart charging strategy increases the available band by 31% and decreases the morning peak demand by 38%.

Future developments of the work will focus on developing a framework to build *trip chains* in the datasets [44–46], thus improving the accuracy of the energy modelling. The critical limitation resides in the manipulated nature of the traffic data (in the form of the OD matrix), which is processed in a way that reduces every entry in the form of a departure-destination trip, such as Home-Work (H-W) and, conversely, Work-Home (W-H). This effectively averts any attempt at building a comprehensive trip schedule for the whole population surveyed. Building a trip chain would allow tracking each vehicle and its consumption, providing detailed information to achieve a deeper modelisation of the recharging patterns and needs. In this work, the outward and return trips are effectively decoupled, thus, the nomenclatures EVTs and EVs serve the same purpose and are adopted simply to help the visualisation of the results achieved in terms of trips or single vehicles. Furthermore, the learning dataset plays an important role in the quality of the ML models trained and, thus, the accuracy of the EV selection process. Despite the rescaling efforts, the application of the ML models on case studies significantly different from that of the learning dataset may introduce some distortions. Additionally, while this work focuses on estimating the aggregate capacity available for grid services, it does not delve into the operational distribution of FCR among individual vehicles. Determining the real-time allocation of a known setpoint — based on optimal dispatch strategies and local constraints — is recognised as a crucial next step in bridging the gap between theoretical modelling and real-world implementation.

CRediT authorship contribution statement

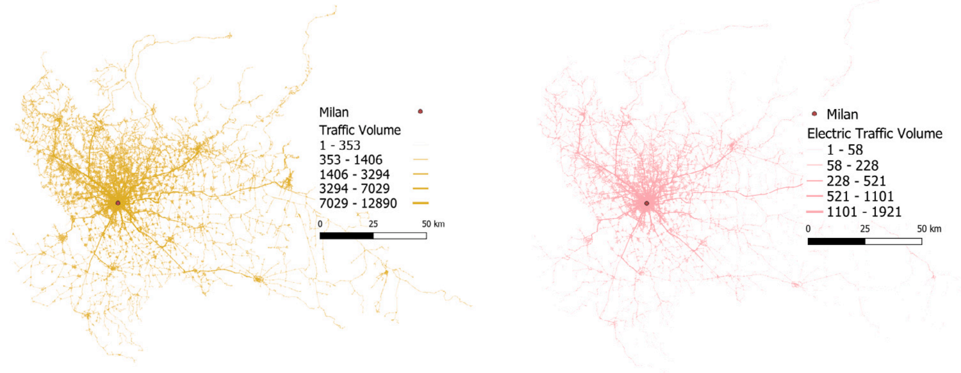
Corrado Maria Caminiti: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Davide Fratelli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matteo Spiller:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Aleksandar Dimovski:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Marco Merlo:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

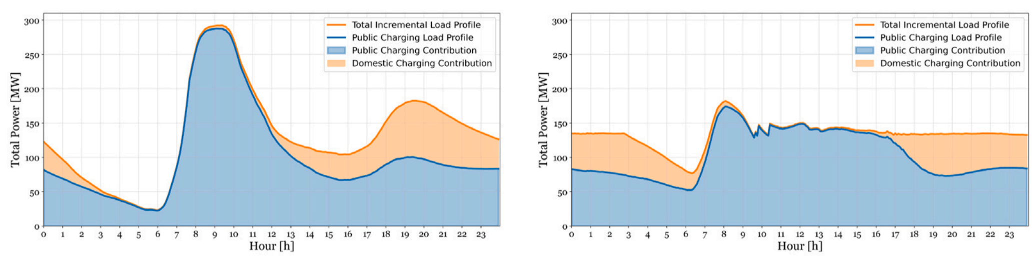
Data availability

Part of the data is owned by Netherlands Mobility Panel and available upon request for scientific purposes.



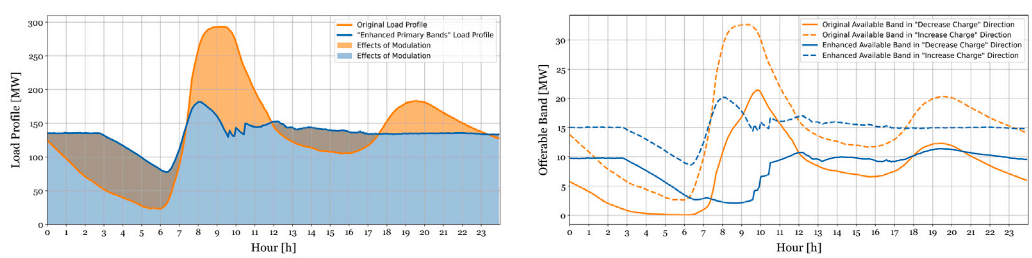
(a) Light-duty transportation mobility graph of Milan (b) eMobility graph of Milan

Fig. 12. Time evolution of the incremental demand in the two scenarios.



(a) Incremental e-mobility related demand (b) Modulated incremental demand

Fig. 13. Time evolution of the incremental demand in the two scenarios.



(a) Effects of Modulation algorithm (b) Modulated incremental demand

Fig. 14. Time evolution of the available bands in the two scenarios.

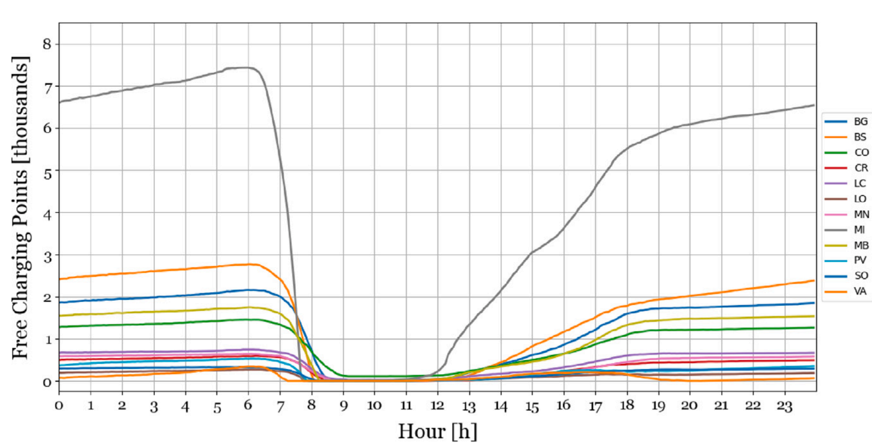


Fig. 15. Available CPs throughout the day.

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