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Estimating the impact of electric mobility on distribution networks through GIS techniques

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ABSTRACT

This paper presents a novel GIS-based (Geographic Information System) approach, integrated with graph theory algorithms to predict the additional power demand from EVs (Electric Vehicles) on electric distribution grids. The energy consumption of an EV is primarily influenced by distance travelled, which is affected by factors such as traffic congestion and road network design. To consider all these factors, a weighted graph is constructed using the layout of Lombardy's traffic network in northern Italy. The traffic flow patterns are simulated utilizing a regional travel survey that provides the trips between the 1450 different travel zones of the region. The trips are simulated within the roads graph using Dijkstra's algorithm to find the fastest paths. The spatial resolution of the trips' origins and destinations is increased using a further sectionalization of the region and gravity model using GIS-empowered probability density functions. The output from the traffic simulation is overlaid with the service areas of primary substations to estimate the added load from EVs. This integration of the two layers enables the identification of when, where, and to what extent electric mobility will impact the electric distribution grids. The novelties of the research work encompass the following key contributions: modelling a large-scale and real-world transportation network represented in graph theory and integration with the corresponding primary substation service areas, consequently enabling the estimation of added load from EVs with a high spatial–temporal resolution.

1. Introduction

In recent years, the escalating issue of mass production of greenhouse gas (GHG) emissions has garnered significant concerns on a global scale. Recognizing the direct impact of these emissions on climate change and the subsequent adverse environmental consequences, governments worldwide have taken the initiative to develop comprehensive regulative frameworks aimed at minimizing GHG emissions [1].

Among the sectors contributing to GHG emissions, the transportation sector holds a considerable share, accounting for approximately one-quarter of total emissions [2]. In 2021, the road transport sector accounted for 77% of all EU transport greenhouse gas emissions [3]. One promising solution to mitigate these emissions is the widespread adoption of electric mobility [4,5]. This transition to electric transportation is projected to yield a significant reduction in GHG emissions, especially when coupled with the integration of cleaner and greener primary energy sources [6,7].

There are various methods for achieving greenhouse gas emission reductions in the transportation sector and mitigating climate impacts, such as boosting active travel, improving the public transportation infrastructure, and widespread adoption of electric vehicles [8]. Active travel, defined as walking or cycling for transportation purposes, and public transit will favourably influence greenhouse gas emissions, but their acceptance depends on travellers' behaviour and perception of comfort. Consequently, the overall impact of these solutions can be seen as uncertain [9]. Therefore, the promotion of electric vehicles seems to be the most promising deterministic alternative to reduce the emissions of GHG in the transportation sector [10]. For these reasons, authorities in the industrialized world have been actively promoting and subsidizing the trend of EVs over traditional internal combustion engine vehicles (ICEV) [11]. The support comes in the form of tax incentives, purchase subsidies, and other special measures such as free public parking, free use of motorways and free charging [11].

Indeed, this has been the case in recent years, with the sales of EVs in Europe showing a yearly increase of more than 15% in 2022 relative to 2021, reaching 2.7 million. Moreover, 25% of all automobiles sold in Europe were electric, with this percentage varying significantly between different countries. This trend is dominated by the Nordic

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countries, with Norway (88%), Iceland (70%) and Sweden (54%) [12]. The growth and development of the electrical grid should be considered when analysing the long-term prospects for EV usage. The rising trend of EV sales and usage will reach saturation without a growth strategy for the electrical grid. Depending on the scenario, EVs could acquire an 11%–28% share of the world's fleet of roads by 2040. The consequence will be an additional 11%–20% rise in world electricity usage. The difficulty, however, lies in getting the electricity infrastructure to adjust to the rising demand peaks brought on by EV charging habits [13].

The positive impact of EVs on reducing GHG emissions is conditioned by overcoming challenges related to the capacity of the existing electric grid to accommodate a significant number of EVs [14]. The increased number of electric vehicles and the added electric power demand necessitate coordinated planning between transportation and the electric grid [8]. Increased EV penetration will impose a new power demand pattern for the electric grid, which could vary depending on time and geographical location [8]. The additional load could put stress on transformers [15] and feeders [16], increase system loss, cause voltage drops [17], and inject harmonics into the grid [18]. The power system's operation will be significantly impacted by a new peak load comprised of EV charging and the original load profile [19,20]. Therefore, it is crucial to develop spatial–temporal-energy models to simulate the behaviour of EV fleets in both transportation and electricity networks to detect the criticalities imposed by the widespread adoption of EVs. The results from these models could be used to upgrade power systems to host a large number of EVs [20].

Electric vehicles are driven within the transportation network, and their energy is sourced from the electric grid. Building accurate models to predict EVs power demand requires considering the integrated functioning of transportation and the electricity power network [8]. The primary goal of this research is to develop a methodology to estimate the additional power demand imposed by electric vehicles on the electricity grid. The motivation behind developing a temporal–spatial simulation was the requirement for a detailed and high-resolution model that considers the integrated functioning of both the traffic and electric grids. This research aims to fill the gap in conducting a large-scale integrated electric grid and transportation network analysis.

In particular, this research proposes a methodology that integrates GIS datasets with a travel survey to simulate the traffic flow patterns in a large-scale and real-world transportation network. Travel surveys contain information regarding vehicle movement within a specific geographical region. Depending on the precision of the travel survey, it could include detailed data about travel purposes, the geographical location of the start and end of the travel, the initiation time, and the travel medium [21,22].

Nevertheless, travel surveys are typically available in low spatial resolution, where origin and destination pairs may correspond to a wide area. To address this shortcoming, this work develops a gravity model that increases the spatial resolution of the travel survey. Unlike classic gravity models that rely solely on the population as a determinant for a location's attractiveness for a trip [23], our model considers multiple factors to enhance spatial resolution in travel surveys. The results from the traffic flow model provide information about the route choice, distance travelled, and arrival times of the cars to the destinations.

The outcomes derived from the traffic model serve as the basis to project the number of vehicles approaching a specific geographical cell within a designated time frame (e.g., 5 min). In this methodology, the fundamental geographical cells correspond to the administrative area clustering, as delineated by ISTAT. Once the flow of cars is simulated, it is possible to estimate the additional power demand for e-mobility by adopting proper assumptions on those trips that could be undertaken by electric cars.

To model the electric grid layer, this study uses the concept of substation service areas, or areas of influence of each substation. Starting from georeferenced data on HV/MV substations, the Italian territory is divided into polygons that represent service areas of individual substations, which are affirmed by the national regulatory authority and utilized at a national scale [24]. The main goal of these areas is to provide a spatial correlation between distributed resources, and their substation of origin. Even though the areas were not obtained by accurately tracking the MV distribution lines due to their complexity and meshed structure, the correspondence of the areas and distributed resources has been validated by the regulatory authority. This clustering of geographical areas facilitates the seamless integration of traffic and electric grid layers. Combining traffic-electric layers establishes an integrated network of traffic and electric grids. This allows for a more accurate assessment of electric vehicles' charging impact within real-world traffic conditions and facilitates informed decision-making regarding grid management and infrastructure planning.

It is important to emphasize that detailed information regarding the MV grid structure is publically unavailable due to legal constraints, and it is restricted solely to the Distribution System Operators (DSOs). For this reason, the evaluation of the impact on the distribution grid is confined to the primary substations, portrayed by the substation service areas which introduce only a minor approximation in the representation of the electric grid layer.

In summary, the proposed methodology first uses a travel survey to simulate the flow of passenger vehicles in the Lombardy region. The traffic model is recreated using the real layout of the traffic network, preserving the main characteristics of the roads, such as the flow speed, capacity and length. A further division of the national territory in smaller cells by ISTAT and a gravity model is applied to the travel survey in order to increase its spatial resolution, allowing for more certain and accurate estimate regarding the origin and destination of the trips. Then, Dijkstra's algorithm is utilized to obtain the quickest path and obtain the total distance travelled and arrival time of each trip. Given the spatial distribution of arrivals and subsequently charging requests, effectively allows the estimation of the additional load requested for EV charging within each primary substation service area.

The paper is structured as follows: in Section 2, a comprehensive literature review is conducted to analyse prior methodologies employed by researchers in the assessment of the e-mobility impact on electric grids. Subsequently, in Section 3, a detailed explanation of the selected case study is provided. Section 4 outlines the methodologies employed to estimate EVs incremental load. Results and discussion concerning the outcome of the simulation are presented in Section 5.

Nomenclature

Symbol	Description
C	Road capacity
V_i	Flow speed matrix in timeframe i
FC	Flow over Capacity ratio
L	Length matrix
SM	State Matrix
CM	Capacity Matrix
PAR	Peak-to-average ratio

2. Literature review

New technologies, intelligent transportation systems (ITS), GIS, and real-time data collection, have revolutionized transportation research. They provide access to historical and current traffic data, particularly in urban areas via Origin–Destination matrices or travel surveys [20]. Some research works relied solely on travel surveys to derive the pattern of travel in specific areas to estimate the power demand from EVs. For instance, in [25], the authors used travel surveys to generate EV driving patterns, enabling the calculation of energy consumption, plug-in/plug-out times, and their effects on one specific distribution network. The work in [26] investigated the future challenges imposed by electric vehicles in 2040, outlining the differences in rural and urban areas. The driving patterns are acquired using the travel survey in

Germany, constituting 900000 individual trips. In [20], a Monte Carlo simulation and a travel survey were utilized to assess the impact of electric vehicle load on each bus bar under different charging scenarios. This evaluation was conducted for a generic urban distribution network in the UK.

Using GIS tools in combination with travel data is a common approach to assessing the impact of electric mobility. The methodology presented in [27] combines travel surveys with demographic factors in each municipal section of Berlin to generate vehicle-based mobility profiles for estimating energy demand from electric vehicles, assuming a 100% EV adoption rate. Additionally, some studies have utilized GPS-based trip data to simulate traffic flow, although these GPS data are typically collected from a limited number of vehicles, it is necessary to extend it to cover the entire study area. For example, in [28], data collected from onboard GPS devices was used to derive driving patterns for cars in two Italian provinces, with an evaluation of the spatial distribution of electricity demand from EVs. However, the number of samples used to create these driving patterns was limited to 3.7% and 1.8% of the fleet size in the analysed provinces. In a similar vein, researchers in [29] employed GPS-based floating car data from 3% of registered cars in Turin, Italy, to generalize parking and driving habits across the entire city. This expanded dataset was then leveraged to estimate the added load from the e-mobility sector within 258 traffic zones of the city. Furthermore, in [30], an assessment was conducted on the impact of EV charging demand on the entire low voltage grid of Sweden, which was modelled using 1 km^2 square cells. In that case, GIS data and GPS-measured driving patterns were utilized to identify power system violations within the low-voltage grid under different charging scenarios imposed by residential charging.

In the absence of comprehensive travel surveys, GIS tools are a valuable alternative for estimating driving patterns and assessing the impact of electric mobility. In [31] authors examined the impact of EV integration into an urban distribution network. This analysis was carried out on a segment of the distribution network located in Skopje, North Macedonia. Based on demographic and geographical features driven by open-source data, a Gaussian distribution function is fitted to generate the travel distances. Researchers in [32] developed an approach that overcomes the availability of travel surveys to create activity-based vehicle mobility profiles. They demonstrated the model's applicability in assessing the added load from e-mobility in municipal sections of Berlin, Germany. Another large-scale study made extensive use of GIS data to initially estimate the distribution of various EV types within 25 km^2 square grids covering Thailand. Then, the added EV load is calculated by assuming an average distance and energy consumption rate for each EV type within transformer service areas, which are represented using Voronoi diagrams [33].

Few studies have delved into the simulation of transportation networks in conjunction with electric networks to understand the impact of electric vehicles. For example, [34], the authors assessed the spatial–temporal distribution of EVs' power demand in a 77-node transportation network within a Chinese city, accounting for factors such as speed, distance, traffic congestion, and temperature. Another study, [19], integrated a 30-node transportation system with a 33-bus electric distribution network to evaluate EV charging demand at varying penetration rates. This integration involved creating a two-way transportation network using graph theory and implementing the shortest path algorithm for trip routing. In [35] introduced a two-layer optimization model for routing decisions and assessing the impact of electrifying long-range semi-trucks on local marginal prices. The model utilized standard test networks, specifically the 24-node Sioux Falls network for transportation and the 5-bus PJM network for the electric grid.

This literature review offers an overview of current approaches in the field and highlights existing research gaps. Many studies often rely on travel surveys or GIS data to evaluate the impact of EV charging, focusing either on specific network segments or broader perspectives. However, there is a significant research gap in developing methodologies that transcend small-scale networks to encompass real-world large-scale scenarios [8]. Additionally, there is a need to integrate transportation and electric grid modelling to understand their intricate interplay. The transportation networks examined in previous literature are typically limited to test networks or specific segments of larger networks. Given the mobile nature of EV loads and the varying regional characteristics that influence charging patterns, it becomes imperative to encompass a wider geographical area. Furthermore, the lack of a dynamic routing algorithm for large-scale transport networks, considering factors like traffic congestion and road characteristics, is evident in the current literature [34].

The novelties of the research work encompass the following key contributions: (i) Modelling a large-scale and real-world transportation network represented in graph structure which preserves the characteristics of the real traffic network within the study case. (ii) Implementing a fastest path algorithm that accounts for network congestion. (iii) Overlaying the result from traffic flow simulation on primary substation service areas to estimate additional load from electric vehicles.

3. Case study: Lombardy region, Italy

To thoroughly investigate a complex issue such as the integrated analysis of the electric and traffic networks, a real-life case study has been utilized. The aim was to incorporate real-world data as inputs and to illustrate how this information can be used to effectively approach the problem. The Lombardy region, located in the northwest of Italy, has been chosen as the study case. This choice was motivated by several factors, among which the particularity of the region, both in national and European contexts, and the availability of the different datasets for conducting comprehensive research. The regional authorities of Lombardy published an Origin & Destination matrix, which contains detailed travel information. This matrix serves as the foundational dataset for the procedure outlined in Section 4. The Origin and Destination Matrix refers to a data structure that represents the patterns of travel between different origin and destination zone pairs within a given geographic area [36]. The matrix typically includes the number of trips or travellers between each origin–destination pair and may also incorporate additional attributes like trip purpose, mode of transportation, and time of travel. The travel matrix could be analysed and processed to develop accurate models to simulate regional traffic flow. With its high spatial–temporal resolution, the Lombardy travel matrix offers greater certainty in predicting traffic patterns.

Unfortunately, not every region in Italy, or other European countries, possesses an Origin & Destination matrix as comprehensive as the one in Lombardy. Instead, each region may offer varying subsets of data, which can range from highly detailed, as seen in Lombardy, to more simplified versions. Focusing on the Lombardy region, according to Eurostat data [37], almost 10 million residents are hosted, accounting for 16.8% of the Italian population. Lombardy region is the third most populated region in the EU [38] and ranks second in GDP among the European regions [39]. The high population density and economic capacity indicate a higher probability of electric vehicle adoption [27]. The region has the highest number of passenger cars in the NUTS −2 region in the EU, with a count of 6.22 million automobiles [40]. This figure accounts for approximately 15.6% of the Italian vehicle fleet [41].

According to the European Air Quality Index, the Lombardy region, especially the city of Milan, is one of the most polluted areas in Europe [42,43]. The region of Lombardy is home to numerous industrial facilities and small to medium companies, which are highly dependent on road transport for economic sustainability [44]. In terms of air pollutant emissions, data from the INEMAR Emission Inventory of Lombardy 2017 [44] reveals that industrial and non-industrial combustion plants, along with road transport, contribute to over 73% of particulate matter emissions and more than 76% of nitrogen oxide emissions in the region.

Table 1
An overview of Origin & Destination Matrix.

Origin zone	Destination zone	Travel start time	Work	Study	Return home	Leisure
…	…	…	…	…	…	…
Milano 8	Milano 10	7:00–8:00	22	14	4	2
…	…	…	…	…	…	…

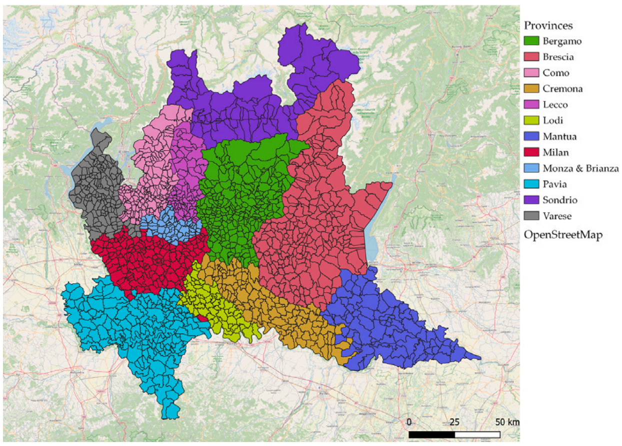


Fig. 1. Travel zones within Provinces.

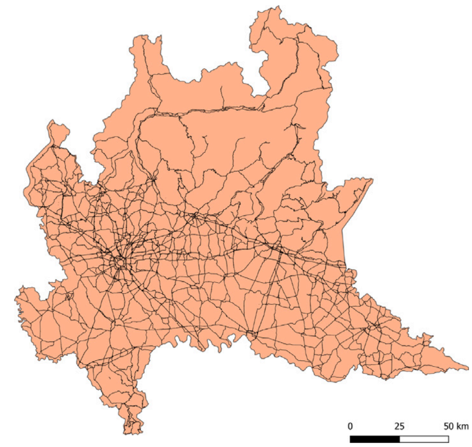


Fig. 2. Transportation network.

Notably, the emission levels of carbon dioxide, nitrogen oxides, and particulate matter in road transport significantly exceed the European Union average [44]. These environmental problems stemming from road transport could be the main drivers for officials to mandate legislative acts to speed up the transformation from ICEs to EVs, especially in polluted regions.

The current status of electric vehicles in the Lombardy region is not significant. E-mobility accounts for 0.38% of total cars [41]. The low penetration rate of EVs in Lombardy may not have a considerable impact on the electric grid yet. However, with EVs' inevitably increasing adoption rate, the infrastructure planning for the electric grid is crucial.

3.1. Origin & destination matrix

The car flow patterns in the traffic model are derived from the origin & destination matrix of the Lombardy region, which serves as the primary database for the analysis [45]. It is a complete travel dataset for various means of transportation that provides a statistical overview of the trips within the Lombardy region. It is the officially endorsed commuter dataset supported by regional authorities for widespread adoption. The passenger vehicle trips which are of interest for this paper are obtained by a comprehensive model that aggregates commute questionnaires from the most recent national census, socio-economic factors on the municipal level, online questionnaires about movement within the region, as well as in-person questionnaires conducted within public entities and enterprises. The dataset provides information about the start time interval of each travel, the travel reason, the medium and the start and destination zone. The trips are categorized into four main groups regarding travel reasons denoted by Work (W), Study (S), Return home (H) and Leisure (L). In the Lombardy region, the travel matrix is obtained at a zonal resolution, dividing the region into 1450 zones. Fig. 1 shows the positioning of the travel zones with black-coloured borders within the provinces of the region.

For a given reference working day, the original travel matrix contains 7936824 individual trips. The two columns of the origin and the destination zones in the matrix represent the municipality areas where the trip could either start or end. The trip initiation time is available within the 1 hour time intervals and for each travel reason, an integer number indicates the frequency of trips between 2 zones. (See Table 1.)

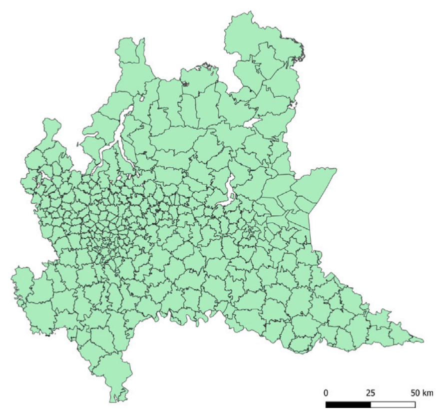


Fig. 3. Conventional areas belonging to the HV/MV substations.

3.2. Transportation network

To obtain the road network, corresponding shape files were downloaded from OpenStreetMap for Lombardy. A shape file is a standard geospatial vector data format containing geometric information (such as points, lines, and polygons) and the attributed data. The road network data in the shape file is represented as Linestrings, which are sequences of connected points. Each point in the line string has coordinates that correspond to the actual geographical location of the road segments in real life. The shape file for the road network in Lombardy consists of a total of 867,258 Linestrings representing different road segments. One specific road or street could be represented as one or more Linestrings. However, for the purpose of the traffic model, certain road types, such as pedestrian walkways or bicycle paths, are not relevant. Therefore, a filtering process is applied to retain only the roads that are suitable for driving passenger cars. This ensures that the traffic model's road network consists of roads relevant to vehicular traffic. Fig. 2 depicts the positioning of main roads within the study area.

The roads in the OpenStreetMap are categorized into seven main groups. Each type is featured with one maximum flow speed and

Table 2
Road types and their characteristics.

Road type	Nominal flow speed (km/h)	Capacity
Trunk	90	510
Motorway	95	460
Primary	65	320
Secondary	45	120
Tertiary	30	80
Residential	25	60
Living Street	25	60

one maximum capacity. Capacity for a road is defined as the maximum number of vehicles that can pass a cross-section of the road within a given time period [46]. In this study, the time interval for capacity determination is 5 min. Table 2 describes the road types and corresponding features.

3.3. Primary substations

In order to model the local distribution grid, as pointed out in the introduction, in Italy, the conventional areas of influence for each HV/MV substation are made publicly available by GSE (Gestore Servizi Energetici) which is the Italian public body in charge of managing renewable sources and energy efficiency [24]. The distribution grid of Lombardy is fed by 332 primary substations. The depicted conventional area in Fig. 3 accurately considers the geographical disparities between metropolitan and peripheral areas. In metropolitan areas, the higher load density leads to a greater number of substations, resulting in smaller conventional areas. Conversely, in peripheral areas, lower energy demands lead to a dispersed distribution of HV/MV substations, causing the conventional areas to be larger.

4. Methodology

The methodological approach of our study is comprised of four levels. First, the input data is used to create the representative graph network for the transportation system and estimate the origin and destination section for each trip in the travel matrix. In the second step, a gravity model is developed to enhance the detail of the raw travel matrix, and promote higher attractiveness to certain sections of each travel zone for being the trips' origins or destinations. Then, the output from the previous levels is used to simulate the traffic flow within the graph network, acquiring a tempo-spatial representation of the vehicles' arrivals and potential energy demand. Finally, the additional loading of primary substations is determined based on the results from the traffic flow simulation. The overview of the procedure is illustrated in Fig. 4. In the following subsections, the procedure for each step is described.

4.1. The road graph

The framework of the graph network utilized in this study is constructed using the shapefile containing the road network data for the Lombardy region. As stated before, the shapefile for the transportation network contains Linestrings representing each road within the study case. Each Linestring is composed of a set of consecutive points. A straightforward method is to transform the Linestrings into a graph network, whereby the points along each line string are assigned as nodes, and connections (branches) are established between them. However, employing this approach would result in a complex and extensive graph, posing significant computational challenges when applying the fastest path algorithms. A solution is proposed to reach the minimum possible size of the graph for the transportation network. In this solution, the points are categorized based on their connection state in the network.

Table 3
Point types and descriptions.

Point type	Description	Occurrence
Start	The first point in the point list of a Linestring.	$1 \leq$
End	The last point in the point list of a Linestring.	$1 \leq$
Junction	It connects one Linestring to the other Linestring(s).	$2 \leq$
Internal	It only connects the internal segments of a Linestring.	1

Table 3 provides information about the types of points and their respective occurrence frequency in the dataset. The occurrence value indicates the frequency of a point with specific coordinates appearing in the Linestrings throughout the whole dataset. In other words, it represents how many times a particular set of point coordinates is repeated among the points of the Linestrings in the dataset. If a specific coordinate point is repeated three times, it indicates that three Linestrings in the dataset share that point and they are connected through that particular point.

Internal points exclusively link internal segments of a Linestring without connecting to another Linestring. Reducing the graph's size necessitates the identification of the internal points of the Linestrings. Specifically, internal points have a frequency of 1 and are neither start nor endpoints. This can be achieved by first excluding the first and last elements of Linestring point sets, and then, examining the occurrence frequency of remaining points. To create the graph with the minimum size object the procedure is to establish a connection between points of a Linestring if points are start, end or junction type (see Fig. 5).

Algorithm 1 Create Nodes and Branches from the Linestrings

for each Linestring i in the dataset **do**
  Establish the first point $P_0^{L_i}$ as a node $N_0^{L_i}$
  for each point in the Linestring i **do**
    if the point j is a junction **then**
      Establish the point $P_j^{L_i}$ as a node $N_1^{L_i}$
      Establish a branch between $N_0^{L_i}$ & $N_1^{L_i}$
      Measure the length of the Linestring i from $N_0^{L_i}$ to $P_j^{L_i}$
      Set $N_0^{L_i} = N_1^{L_i}$
    end if
  end for
  Establish the last point $P_n^{L_i}$ as the node $N_1^{L_i}$
  Establish a branch between $N_0^{L_i}$ & $N_1^{L_i}$
  Measure the length of the Linestring i from $N_0^{L_i}$ to $P_n^{L_i}$
end for

The branch length of the simplified graph is determined based on the geometry of the Linestrings before the simplification process. It is essential to emphasize that branch length is a specific attribute associated with each branch, and it differs from its geometric length. This attribute can be compared to other line characteristics, such as its name, maximum speed, or road type. Algorithm 1 summarizes the graph creation and simplification from the input data. The graph network comprises 567,193 branches and 446,427 nodes. The dataset initially contained approximately 1.8 million internal points, which were filtered out during the processing phase.

4.2. Gravity model

The routing algorithms used for traffic purposes require input in the form of points with coordinates to calculate the paths between start and destination locations. Uncertainties could arise as the origin & destination zones could contain numerous potential start or destination points. To address this, a gravity model is developed using the census section layer; this allows for a significant increase in the granularity of the model compared to the raw data reported in the origin & destination

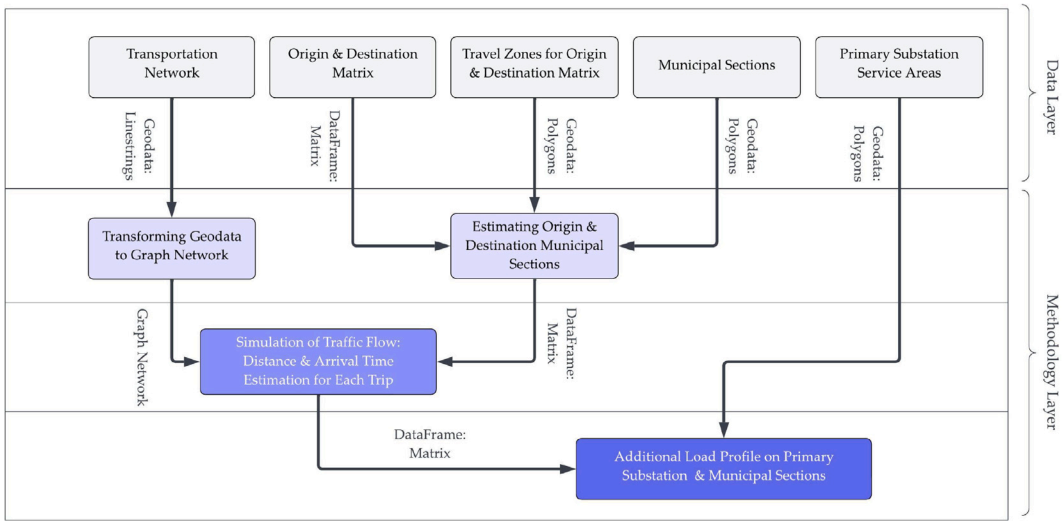


Fig. 4. Overview of the input data and the developed methodology.

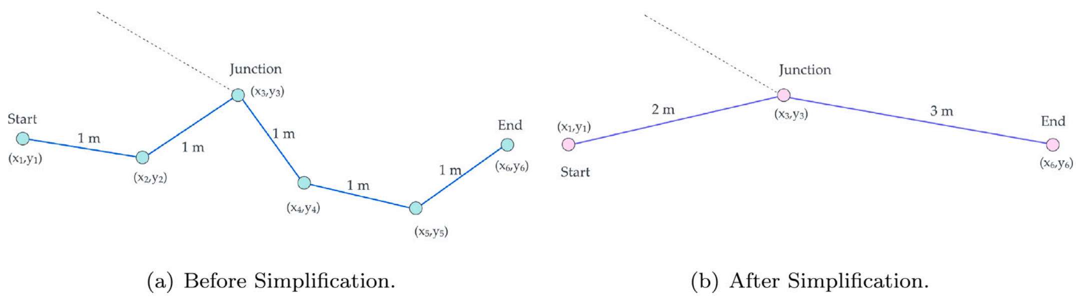


Fig. 5. Graph simplification.

Table 4
Factors affecting origin/destination estimation.

Factors	Description
Population	Population of the section
Number of workers	Number of workers in the section
Parking area	Availability of parking area
University areas	Presence of university campuses
Workers around	Proximity of parking areas to workers
University around	Proximity of parking areas to university campuses
Number of Amenities	Count of amenities (e.g., bars, restaurants, shops) in the section

matrix. Gravity models are mathematical representations used to estimate the flow of trips or movements between different locations within a transportation network [23,47]. The census sections are divisions within municipalities (travel zones) which have similar characteristics. Not only do census sections increase the spatial resolution by dividing Lombardy into 52832 sections, but also the information available for each section, such as population, workplace area, university area, and the number of workers numbers is used to build probability functions for the gravity model to estimate the start and end section of each trip within the corresponding zones.

The gravity model takes the travel matrix as an input and based on the trip's purpose, estimates the start and destination census sections within the start and end zones. For each travel reason, one or more factors have been selected that are likely to influence the start or destination section. For example, consider a work trip arriving at zone Milano 1. A criterion for selecting a destination section for that trip could be the number of workers present in each section of Milano 1 zone, i.e. the sections with more workers will have a higher probability of being selected as the arrival section for the trip. Table 4 shows the factors chosen to estimate the origin and destination sections of the trips.

Table 5 shows the influential factors which are adopted to create discrete probability density functions for the gravity model. For a zone with i number of sections:

$$\begin{cases} P_R^{(1,X)} = \sum_{k=1}^{EP_R^X} w_{X,R}^k \dfrac{EP_{1,R}^k}{\sum_{m=1}^{i} EP_{m,R}^k} \\ \vdots \\ P_R^{(j,X)} = \sum_{k=1}^{EP_R^X} w_{X,R}^k \dfrac{EP_{j,R}^k}{\sum_{m=1}^{i} EP_{m,R}^k} \\ \vdots \\ P_R^{(i,X)} = \sum_{k=1}^{EP_R^X} w_{X,R}^k \dfrac{EP_{i,R}^k}{\sum_{m=1}^{i} EP_{m,R}^k} \end{cases} \tag{1}$$

$$\sum_{m=1}^{i} P_R^{(m,X)} = 1 \tag{2}$$

$X \in \{O, D\},\ \ R \in \{W, S, H, L\}$

Table 5
Influential factors for section estimation.

Reason	Origin factors	Destination factors
Work	1. Population	1. Number of workers 2. Parking area 3. Workers around
Study	1. Population	1. University area 2. Parking area 3. University around
Leisure	1. Number of workers 2. Population 3. University area 4. Workers around 5. University around	1. Number of amenities 2. Parking area
Return home	1. Number of workers 2. Number of amenities 3. University area 4. Parking area 5. Workers around 6. University around	1. Population

Table 6
Weights for origin & destination estimation.

Trip reason	Section type	Weights
Work	Origin	$w^1_{(O,W)} = 1$
	Destination	$w^1_{(D,W)} = 0.4; w^2_{(D,W)} = 0.3; w^3_{(D,W)} = 0.3$
Study	Origin	$w^1_{(O,S)} = 1$
	Destination	$w^1_{(D,S)} = 0.4; w^2_{(D,S)} = 0.3; w^3_{(D,S)} = 0.3$
Leisure	Origin	$w^1_{(O,L)} = 0.1; w^2_{(O,L)} = 0.15; w^3_{(O,L)} = 0.15$ $w^4_{(O,L)} = 0.2; w^5_{(O,L)} = 0.2; w^6_{(O,L)} = 0.2$
	Destination	$w^1_{(D,L)} = 0.5; w^2_{(D,L)} = 0.5$
Return Home	Origin	$w^1_{(O,H)} = 0.1; w^2_{(O,H)} = 0.15; w^3_{(O,H)} = 0.15$ $w^4_{(O,H)} = 0.2; w^5_{(O,H)} = 0.2; w^6_{(O,H)} = 0.2$
	Destination	$w^1_{(D,H)} = 1$

Parameter X denotes the section to be an origin (O) or destination (D) section for a trip, $P_R^{(j,X)}$ represents the probability that section j with a given X could be either the origin or destination section of a trip with reason R. EP_R^X is the subset of parameters affecting the trip's origin or destination estimation based on Table 5. $EP_{j,R}^k$ is the value of the parameter k in section j for the trip reason R. The denominator is the sum of the values of parameter k in all sections within the zone. The sum of the probabilities for sections in a zone to be the origin or destination of a trip with a specific reason is 1, as shown in Eq. (2).

The parameters outlined in Table 5 are subject to weighting denoted by $w^k_{(X,R)}$. This weighting mechanism acknowledges that the influence of parameters varies for different travel reasons. (See Table 6.) For instance, in estimating a destination section for a work trip, the number of workers has a more pronounced impact compared to the other two parameters. Despite these variations, the differences in weights are deliberately kept minimal to prevent one parameter from exerting undue influence over the others.

As already pointed out, the application of the gravity model enhances the spatial resolution of the travel matrix. This involves replacing the original origin and destination zones with smaller sections, significantly reducing their respective areas. This adjustment enables the simulation of traffic flow, leveraging routing algorithms within the transportation network.

4.3. Traffic flow simulation

The accurate estimation of the distance is a critical factor in determining the energy requirement of an EV, as the energy is positively correlated with the distance [19]. The graph created in Section 4.1, is used along with Dijkstra's algorithm [48] to determine the distance for the trips of the travel matrix. The weight of the graph for the routing algorithm is set to be the travel time between two nodes as a result the output of Dijkstra's algorithm is the fastest path.

Table 7
Relationship between FC, and speed reduction of roads [46,51].

FC	Speed Reduction
0–0.60	0%
0.61–0.70	10%
0.71–0.80	25%
0.81–0.90	50%
0.91–1.00	75%
> 1.00	90%

A time resolution of 5 minutes is chosen to route each trip for a whole day, starting at 00:05 at midnight. The weight matrix (W_i) for the graph during the ith time frame is acquired by dividing the length matrix over the variable flow speed matrix (V_i) using Eq. (3). The initial weight matrix (W_0) is calculated using the nominal flow speed from the data in Table 2.

$$W_i = \frac{L}{V_i} \tag{3}$$

Using the fastest path algorithm and travel time as weights for the branches, it is possible to integrate the traffic congestion impact on route choice. The important factor in modelling traffic congestion utilizing the variable nature of the flow speed of branches to update the weight matrix for the graph.

It is evident that the number of passing cars could not affect the flow speed of the roads to the same extent for all road types. Thus, to simplify the modelling, the effect on the flow speed of a road is correlated to the car flow over capacity ratio (FC) [46,49,50]. Utilizing the FC allows the determination of the flow speed of the road without taking into account the road type. To better explain this, the FC normalizes the congestion state of the road based on the car flow regardless of the road type. For example, the capacity for the highways is more than a living street, so for the same amount of car flow, FC for highways will be lower than for residential streets.

Based on the data in Table 7, the flow speed of a road is expressed in Eq. (4). The flow speed of a road equals the nominal flow speed (V_n) for the FC value up to 0.6, and then the speed reduction follows a 3rd-degree polynomial function.

$$v = \begin{cases} V_n & 0 \leq FC < 0.6 \\ V_n(0.751\,(FC)^3 - 5.482\,(FC)^2 & \\ \quad + 5.288\,(FC) - 0.3678) & 0.6 \leq FC \leq 1.05 \end{cases} \tag{4}$$

To acquire flow speed in branches in each 5-minute time interval, a state matrix (SM) with 567193 rows and 288 columns is created. Each row indicates one branch in the network, and the corresponding columns represent each 5-minute time window (288 5-minute intervals for a day). Each element indicates the number of passing cars in the corresponding branches and time interval. Capacity matrix (CM) is created from the data in Table 2 expressing the capacity of each branch. The FC_i matrix for the ith time frame could be acquired by dividing the column "i" of state matrix SM_i over CM.

Algorithm 2 summarizes the procedure to route the trips within the graph network considering the congestion. The principal outcomes of the traffic flow algorithm involve the computation of distances for each trip using the fastest path algorithm, along with the overall duration of the trips, thereby allowing the determination of arrival times.

Fig. 6 shows the main stages of the proposed methodology. In the last step, the processed travel matrix is used to determine the additional loading from EVs on each primary substation area.

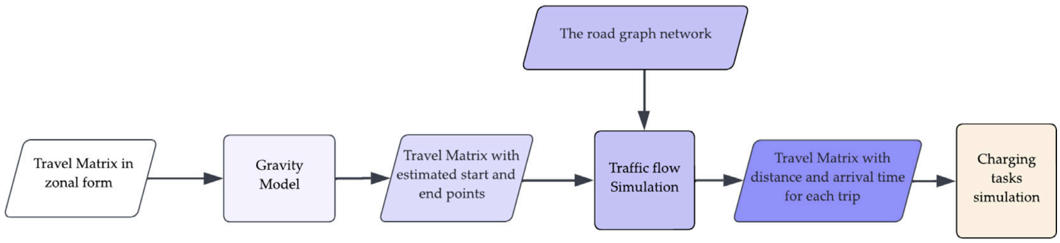


Fig. 6. Different steps of proposed methodology.

Algorithm 2 Traffic flow

for each trip within the travel matrix starting from 00:05 **do**
    Run the fastest path algorithm for the trip.
    Determine passed branches $[x_m, \dots, x_n]$, where $x_j \in [0, 567192]$.
    Determine the time slots during the trip $[t_m^{x_m}, \dots, t_n^{x_n}]$, where $t_j^{x_j} \in [0, 287]$
    Add 1 to the elements in rows $[x_m, \dots, x_n]$ and columns $[t_m^{x_m}, \dots, t_n^{x_n}]$ in SM.
    for each 10 trip in the ith time interval **do**
        Calculate $FC_i = SM_i \ / \ CM$
        Determine new flow speed matrix V_i using (4)
        Update weight matrix W_i using (3)
    end for
end for

4.4. Charging requests simulation and load estimation

The origin and destination matrix lacks information about the fuel type of passenger cars used for the travels, necessitating the establishment of a selection procedure to distinguish between EVs and ICEV vehicles. To address this, a specific penetration rate is established, assuming that a certain proportion of trips (e.g., 2.5%) are conducted using EVs. Consequently, an equivalent share of trips from the travel survey is selected, forming an electric trip set that represents the specified penetration rate.

Three main outputs of previous stages namely, arrival time, destination and distance are used to estimate the additional EVs loading. It is assumed that the charging procedure will start upon arrival for the trips in the electric trip set. The trips designated as EV trips will request an amount of energy equivalent to their consumption during the journey. The average energy consumption rate is assumed equal to 0.2 kWh/km [33,34], and depending on the destination of each trip, the requested energy will be aggregated into the power profile of the corresponding substation. The subset of trips that will require charging, i.e. conducted by an electric vehicle, is selected with a probabilistic approach directly correlated to the penetration of EVs. The result of this procedure is the additional charging profile requested in each cell of the region. Then, the additional load of each HV/MV substation is obtained by aggregating the cells that geospatially fall within its service area. Moreover, for the charging scenarios, a charging power of 6 kW, typical for residential chargers, is set for return home trips. Meanwhile, for leisure, work, and study trips, it is assumed that individuals will utilize public chargers with a higher power capacity, equal to 22 kW. This distinction in charging power reflects the varied charging infrastructure commonly associated with different trip purposes. Fig. 7 illustrates the EVs charging demand estimation.

The proposed approach also enables more sophisticated simulations of e-mobility evolutions. It allows for the creation of scenarios wherein specific classes of trips (e.g., short trips in urban areas, and long trips in rural areas) exhibit varying probabilities of transitioning to electric vehicles. Additionally, the simulation encompasses fast-charging solutions. These aspects constitute the ongoing focus of the research group's current endeavours. These assumptions are motivated by the notably limited integration of fast charging processes within the Italian context and the absence of comprehensive travel-related information conducive to a more plausible identification of conversions to electric vehicles. As of 2023, electric vehicle penetration in Italy stood at approximately 0.5% [52]. Consequently, this paper primarily emphasizes the approach utilized for simulating and routing individual trips, while maintaining a uniform distribution in the e-mobility penetration model. This simplification facilitates the evaluation of simulated outcomes and serves as a proxy for future investigations.

5. Results

In this chapter, the outcomes of the traffic model are examined and validated through a comprehensive comparison with real-life data. The performance of the gravity model is subsequently demonstrated through insightful figures. Moreover, we showcase the temporal–spatial distribution of the electric vehicle load across the Lombardy region. Finally, an assessment of the additional EV demand is provided for each substation in Lombardy, allowing the evaluation of the necessity for upgrades and effectively contributing to the future planning of the distribution grid.

5.1. Traffic model outcome

The model was applied to the Lombardy region, simulating all eight million trips outlined in the previously presented origin and destination matrix. Each journey was linked to an initial and a terminal node through the utilization of the gravity model. To inspect the performance of the gravity model a comparison has been drawn between distribution parameters from Table 5 and the number of cars arriving at each section within the zone 'Milano 6'. Milano 6 zone is one of the municipalities situated near the city centre of Milan, the capital of Lombardy. With a total population of approximately 92,000 residents, it encompasses an area of 15.5 square kilometres. The zone hosts university campuses and different commercial and working places. The zone is divided into 520 census sections.

Fig. 8(a) to (d), shows the normalized distribution of four influential parameters, and (e) to (h) presents the total number of arriving cars in each section at four different times. Results from the gravity model show that sections with the availability of parking areas host cars more than the other sections all over the day. However, sections with higher study areas and worker numbers are chosen as destinations during the morning. During the late afternoon and evening, the distribution of cars is more sparse rather than concentrated in some sections, which are mostly return-home trips determined by the population parameter.

To validate the outcome of the traffic model, it is necessary to visualize the results and compare them to real-life data. Modelling a perfect transportation system for an area as large as the Lombardy region is complex. So many factors are neglected, such as driver's route choice preference, different car sizes, traffic queues, and traffic lights. However, as the main goal of developing a traffic model for this study is estimating the energy consumption of the EV fleet, the developed model represents enough accuracy. First, some comparisons are drawn

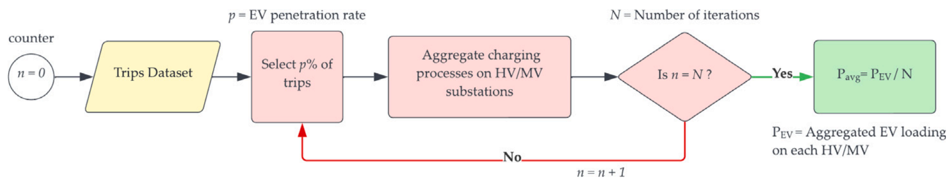


Fig. 7. Flowchart of EVs charging load estimation on the primary substations.

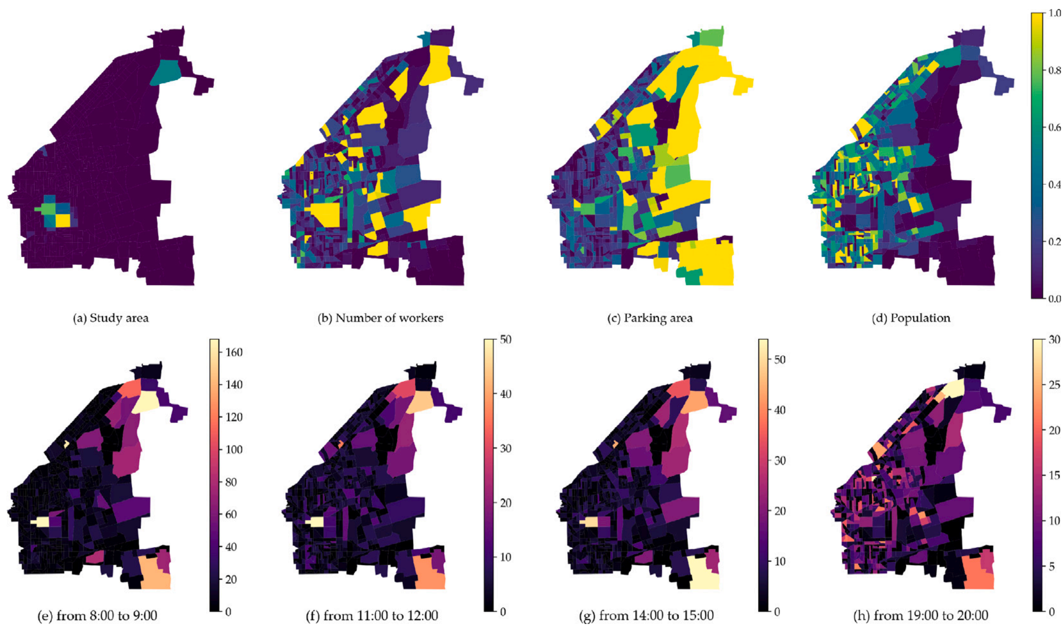


Fig. 8. (a) to (d) Normalized distribution of four parameters of the gravity model, (e) to (h) number of arriving cars at each section in 4 different times.

between the results from our model and Google Maps, to evaluate to which extent the developed model corresponds to real-life records.

The examples from Google Maps are for a particular day in Milan City. The behaviour of the traffic flow could be very different based on weather, date, time of year etc. So, the differences between the model developed by us and the indicators of Google Maps could not be concluded as a flaw in the model. The model works almost accurately both spatially and temporarily. It should be noted that the traffic indicators for Google Maps and this study are different.

The interpretation of traffic conditions on Google Maps is qualitative, providing indicators such as green for no delays, orange for medium traffic, and red for traffic delays, with darker shades of red indicating slower speeds [53]. However, there is no specific numeric relationship between colour and speed reduction. In contrast, our traffic model employs a more quantitative approach, using the flow-over capacity ratio as an indicator. As outlined in Table 7, an FC higher than 0.8 corresponds to a 50 to 90% speed reduction, while a ratio between 0.6 and 0.8 represents a 10 to 25% speed reduction. The traffic model is capable of capturing traffic patterns both spatially and temporally. Fig. 9 illustrates this by comparing traffic congestion at three different times of the day. Our model reveals two instances of congestion during a typical workday, primarily in urban areas and on main roads—first in the morning when people commute to work or study, and later in the afternoon when they return home.

Fig. 10 provides insights into the morning rush hour traffic, displaying the incoming trips to census sections between 8 to 9 am. The model provides the spatial–temporal distribution of the incoming trips within each census section across Lombardy. This information proves valuable for transportation planning and the effective management of charging infrastructure within the region. Fig. 11 illustrates the fastest paths chosen by trips to the Milano 6 zone. Unlike the shortest paths, the fastest paths show a preference to choose main roads over secondary or tertiary routes.

5.2. Temporal–spatial estimation of EV load

The output of the gravity and traffic flow model provides the means to estimate the destination, required energy, and arrival time for each trip. With this information and a specified penetration rate for electric vehicles, the additional EV load on each primary substation service area is calculated.

For a comprehensive overview of the electric vehicles' load impact, Fig. 12 illustrates the total added load arising from EV charging processes across Lombardy. The figure reveals two prominent peaks, the first between 8:00 and 9:00, which are primarily attributed to the charging from workplaces and study areas. The second peak is due to the return home trips, which peak between 19:00 and 20:00. The result of the analysis shows that having a 2.5% penetration rate, the total power demand could increase up to 240 megawatts during the evening and 170 megawatts during the morning.

Fig. 13 shows the peak load magnitude in each primary substation, marked by a unique ID, and the colour of the bars indicates the peak

(a) Flow over capacity ratio at 9:00.
(b) Google Maps traffic indicator for 9:00.
(c) Flow over capacity ratio at 18:00.
(d) Google Maps traffic indicator for 18:00.
(e) Flow over capacity ratio at 22:00.
(f) Google Maps traffic indicator for 22:00.

Fig. 9. Comparison of results from traffic model with Google Maps at different times of day. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

load occurrence time frame. The figure reveals that the peak load in substations occurs either during the morning or in the evening. However, the number of peaks in the evening is more than double those in the morning. In contrast, the magnitude of peaks in the morning is higher.

Fig. 14 illustrates the average additional loads in 4 different 1 hourly time frames. EV charging between 8:00 and 9:00 impacts the substations mainly in urban areas which encompass workplaces. Concentration of workplaces in urban parts and having 22kw chargers, results in a higher average and peak load during the morning. The average load from 11:00 to 12:00 and 14:00 to 15:00 is significantly lower than the 8:00 to 9:00 time frame. Between 19:00 and 20:00, the average additional is as high as 3 MW, mainly due to the return home trips. In contrast to the 8 to 9 time frame, the EV charging load involves a higher number of substations. The dispersed distribution of the population and residents across Lombardy, as opposed to being concentrated mainly in urban areas such as workplaces, contributes to the observed patterns in electric vehicle charging demand.

The peak-to-average ratio (PAR) in a load profile signifies the relationship between the highest load value and the average load value over a specific time period. This metric provides insights into the temporal dynamics of load profiles during peak periods, with a higher peak deviation suggesting a more concentrated peak occurrence. Analysing power profiles for substations reveals that, on average, morning peaks exhibit a higher PAR compared to afternoon peaks. Morning peaks, driven by workplace charging at 22 kW, are characterized by high magnitude but shorter duration. In contrast, evening peaks, with a more flattened shape, may coincide with the base load's evening peak, posing a risk of grid congestion due to their lower PAR and longer duration. To better show this, Fig. 15 displays the load profile of one of the substations, despite having a higher magnitude during the morning, the peak load in the evening is more persistent.

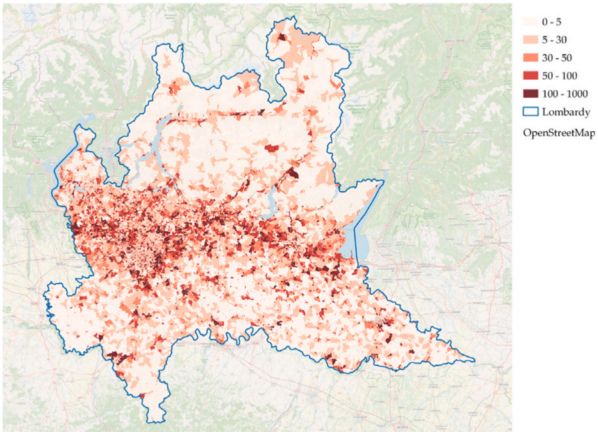


Fig. 10. Cars arriving in census sections between 8:00 to 9:00.

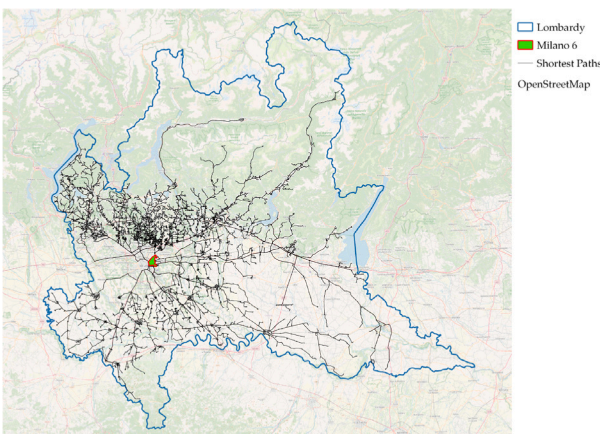


Fig. 11. Fastest paths chosen to travel to zone Milano 6 from other provinces excluding Milan province.

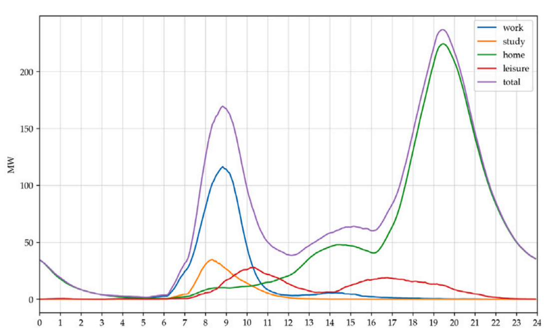


Fig. 12. Overall profile of additional EV load.

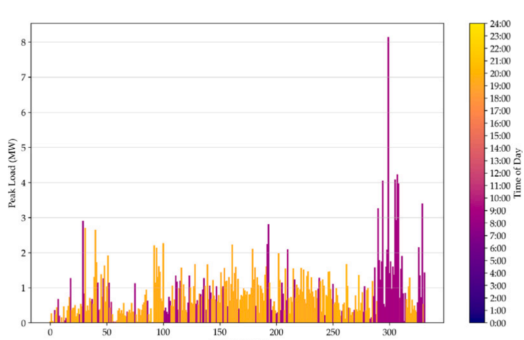


Fig. 13. Magnitude and occurrence time of peak loads in primary substations.

The procedure proposed proved effective in simulating traffic flow across a large area, providing estimations regarding the potential impact of emerging charging requests on the electric grid. The outcomes include detailed incremental power profiles associated with each HV/MV substation. The calculated outcome effectively supports the planning procedures for both the DSO, aiding in the design of electric grid reinforcement, and the e-mobility operator in optimally locating charging stations.

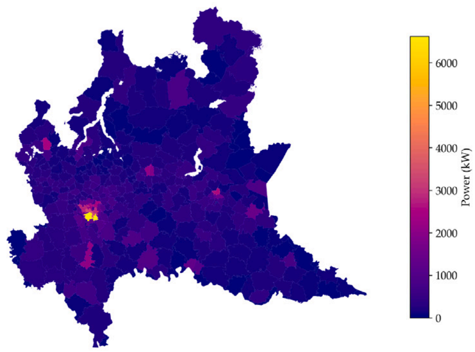
6. Conclusion

To identify infrastructural criticalities and future planning of distribution systems, it is essential to employ accurate models that can estimate potential power demand arising from the electrification of transportation. In addressing this, we bridge the gap in electric vehicle impact assessment by transitioning from small-scale test networks to large real-life cases. The main strength of this approach is that it uniquely considers the integration between transportation and electric grids, providing a holistic approach to accurately estimate the additional power demand resulting from the electrification of urban private cars.

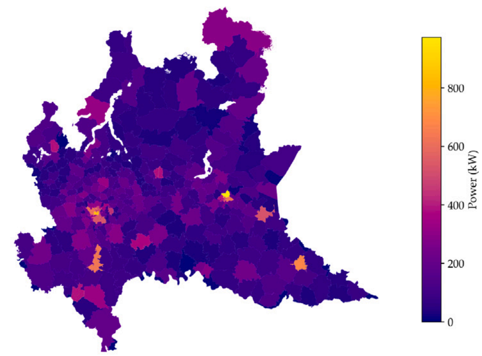
The traffic flow model utilizes a regional travel matrix as its primary dataset, containing nearly 8 million trips for a typical working day. Adopting a gravity model to enhance the spatial resolution of the trips' origins and destinations, and a detailed graph representing the road network, the passenger vehicle trips are simulated to obtain a traffic simulation of a standard day in Lombardy, qualitatively validated with the aid of Google Maps. Using the trips' destinations, distance travelled by each car and arrival time, as well as the EV penetration level, each spatial cell is assigned an additional EV charging profile. Then, utilizing the accurate service areas of each substation in Lombardy, the cells are aggregated to obtain the substations' load profiles. This approach differs from previous studies that employed unrealistic partitioning methods, such as Voronoi diagrams [33].

The results of the simulation reveal two main peaks in additional load for EV charging. The first peak occurs between 8:00 and 9:00 am, primarily attributed to charging sessions at workplaces. In contrast, the second peak takes place between 19:00 and 20:00 and is predominantly associated with home charging activities. The analysis indicates that morning peaks in EV charging exhibit a higher magnitude than evening peaks. Morning peaks are concentrated in substation areas covering workplaces, while evening peaks, although of lower magnitude, are observed in a greater number of substations due to the dispersed distribution of residential areas throughout Lombardy. Based on the results, the EV power demand for Lombardy could reach up to 240 MW in the evening and 170 MW in the morning, with individual substation peaks ranging from 2 to 8 MW.

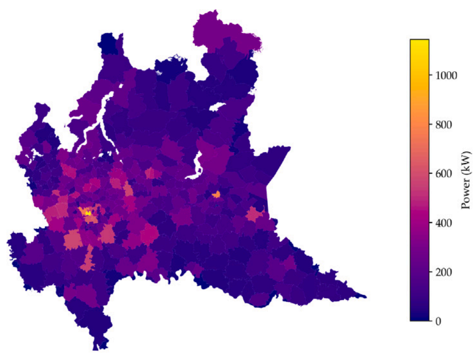
For future improvements, three main strategies can be pursued. First, transforming individual trips into trip chains would allow for a more accurate depiction of passenger car usage, as this is a limitation of the dataset used as input. This approach facilitates the creation of a better charging behaviour model since the energy consumption of the last and upcoming trip could impact the charging behaviour. However, the travel surveys generally present individual trips between zones, creating trip chains might change the traffic flow pattern compared to real-life conditions. Secondly, incorporating public transportation vehicles, electric bikes, and scooters into both the traffic and electrical layers could yield more comprehensive results, as it would help overcome the limitation of considering only passenger EVs and the additional load would not be trivial. The main challenges that come with incorporating electrification of public transport is to access the details regarding their routes, terminal stations and schedules. Finally, diversifying the assumption of a single electric vehicle type to include various models with unique energy consumption patterns could enhance accuracy. In this case, specific statistics regarding the mix of electric cars in the region of interest should be gathered in advance.



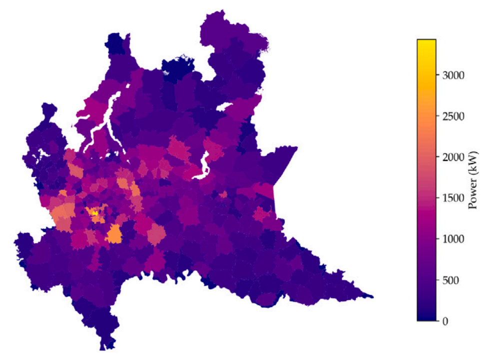
(a) Between 8:00 and 9:00.



(b) Between 11:00 and 12:00.



(c) Between 14:00 and 15:00.



(d) Between 19:00 and 20:00.

Fig. 14. The average additional load from EVs.

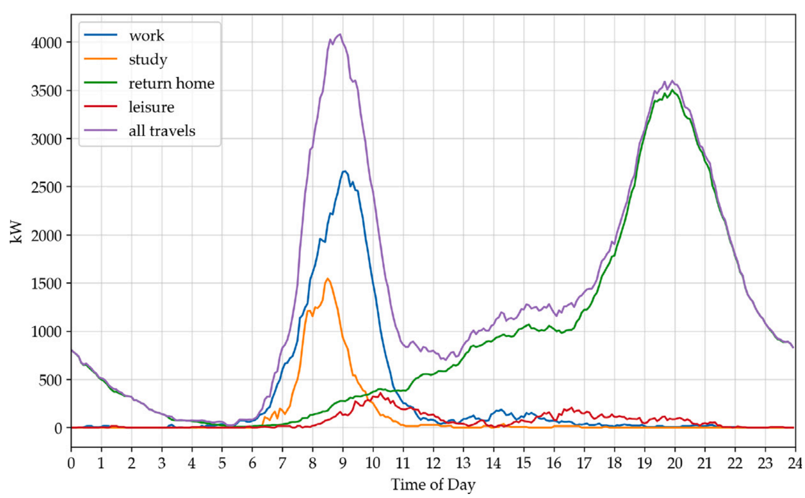


Fig. 15. An example of additional EV load on one substation.

Abbreviations

BEV	Battery Electric Vehicle
EV	Electric Vehicle
HV/MV	High Voltage/Medium Voltage
ICEV	Internal Combustion Engine Vehicle
GIS	Geographic Information System
GHTS	German Household Travel Survey
LOR	Lebensweltlich Orientierter Raum
ISTAT	Italian National Institute of Statistics
DSO	Distribution System Operator

CRediT authorship contribution statement

Ghaffar Yousefi: Writing – original draft, Software, Methodology, Investigation, Formal analysis. **Aleksandar Dimovski:** Methodology, Conceptualization. **Lucio Radaelli:** Software, Methodology. **Marco Merlo:** Supervision, Project administration, Methodology, Formal analysis.

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

The data sources all are referenced.

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