This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TTE.2021.3114497, IEEE Transactions on Transportation Electrification

Electrification potential of fuel-based vehicles and optimal placing of charging infrastructure: a large-scale vehicle-telematics approach

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Abstract

As apprehension grows over global warming and urban pollution, Battery Electric Vehicles (BEVs) are experiencing a rise in worldwide popularity. Yet, their market uptake has been slowed down due to high purchase prices and concerns over the limited battery range and the insufficient public charging infrastructure. This work uses a massive real-world dataset, containing the anonymized GPS traces from a fleet of private vehicles, to quantitatively evaluate if range anxiety (*i.e.*,the fear of being stranded due to EV's limited range) is a rational concern. In particular, the fleet's electrification potential is assessed by analyzing the driving patterns of more than fifty thousand vehicles over the course of an entire year. The results reveal the potential of BEVs, which could satisfy the range needs of much of the existing fuel-powered vehicle fleet with no alteration to the owners' routines (except for overnight recharging). Furthermore, the mileage analysis is later used to pinpoint the so-called *Eligible Stops*, corresponding to real charging demand and opportunities. *Eligible stops* are aggregated through clustering analysis, obtaining a ranking of potential charging station sites. Finally, we quantitatively evaluate the effects of the increasing dissemination of charging facilities on the vehicles' EV-switch suitability.

Index Terms

Electric vehicles; electrification potential; vehicle telematics; charging stations.

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Acronyms

BEV	Battery Electric Vehicle
CDH	Charging Demand Hotspot
CDF	Cumulative Distribution Function
CSLP	Charging Station Location Problem
DCD	Driven Cumulative Distance
DVKT	Daily Vehicle Kilometers Traveled
DVKTODR	DVKT Over Double Range
ES	Eligible Stop
EV	Electric Vehicle
GHG	Greenhouse Gas
GPS	Global Positioning System
ICE	Internal Combustion Engine
IDH	Individual Demand Hotspot
IMU	Inertial Measurement Unit
POI	Point of Interest
RCD	Remaining Cumulative Distance
SOC	State of Charge
STOR	Single Trip Over Range

I. Introduction

Greenhouse gases (GHG) emissions are one of the main cause for the steep increase of our planet's temperature. Government and policy makers have set goals and taken measures to minimize air pollution and achieve climate neutrality [1], [2]. However, while sectors such as agriculture and industry have substantially reduced their carbon footprint in recent years, emissions in the transport sectors have been constantly increasing since 2013 [3], and currently account for approximately 27% of the total [4], [5]. Changing the current mobility paradigm by encouraging the uptake of EVs can substantially help in reducing transport's environmental impacts. Thanks to the high energy efficiency of the electric powertrain, EVs can substantially lower pollution (when combined with a non-carbon-intense electricity generation mix [6]): it is enough to consider that, in 2019, the electricity generation to supply the global electric vehicle fleet emitted 51 Mt CO2-eq, about half the amount that would have been emitted from an equivalent fleet of internal combustion engine vehicles, corresponding to 53 Mt CO2-eq of avoided emissions [7]. While the global stock of electric cars has been expanding at a 40% year-over-year rate, the market share of electric cars still only accounts for 2.6% of the total [7]. Amongst the greatest obstacles to pervasive EV uptake we can find the high purchase price, the limited driving range and the perceived lack of charging stations [8]–[10]. While one-time purchase subsidies and annual national tax breaks on vehicle registration have proved effective in breaking down the purchase price barrier [11], the other two obstacles are very difficult to overcome as they are directly tied to the range anxiety phenomenon, i.e., the fear of running out of battery during the day.

This paper wants to understand if range anxiety is only a perceived threat, and how to optimally locate the charging infrastructure to significantly reduce the fear of not finding a recharge point.

Main Contributions

The main contributions of this paper can be summarized as follows:

- this work leverages big-data analytics to answer meaningful mobility questions, analyzing the anonymized driving patterns of thousands of private vehicles. To the best of the authors' knowledge this is the first time (together with [12]) that the driving patterns from such a large fleet of private vehicles (observed over an extensive time interval) have been analysed to produce meaningful assessments on electric mobility.
- the paper proposes a unique and consistent framework to estimate the electrification potential of private fuel vehicles, to optimally solve the charging stations problem and to evaluate the impact of building such stations on the electrification potential.
- the paper provides a solution to the Charging Station Location Problem, rooted in empirical observation and pinpoints the locations with greatest demand density. The proposed method does not require selecting candidate locations a-priori, can work on very large scales and is geographically unbounded, as it uses clustering analysis at its core. The results produced from the clustering analysis are actionable and the obtained clusters have consistently meaningful geographic extensions.

This work stems from the preliminary results presented in [12], where the electrification potential was evaluated under the assumption of frequent public charging availability. In this study, no such assumption is made, and the actual effects of incremental charging stations dissemination are evaluated in Section VIII. Since range anxiety is the result of unawareness, this study (the first of its kind to use a comprehensive massive dataset of driving patterns from private fuel vehicles, observed over an extended one-year time-frame) can help facilitating EV uptake by increasing the understanding of real range requirements. .

Structure of the Paper

The paper is organized as follows. Section II introduces the problem setting and illustrates the existing contributions in the different aspects treated in this work. Then, Section III describes the dataset used for the analysis. Section IV details the data cleaning and preprocessing steps undertaken to make the data as reliable as possible, and describes the dataset mileage features. Section V is focused on evaluating the potential of vehicles with respect to the electric mobility paradigm shift. The concept of Critical Day is introduced and is used to segment the fleet based on the amount of disruption the transition to an electric powertrain would bring to the owner's routines. Section VI describes how to locate the charging demands based on the driving patterns. In Section VII the ideal locations for the charging stations placement are identified and in Section VIII the impact that such stations could have on the previously mentioned vehicles categorization is quantified. Finally, Section IX contains an analysis of the effects of the charging-time improvements EV-Suitability and charging station location.

II. Problem setting

A. Electrification Potential

To get a better understanding of the most common driving patterns and, thus, to assess whether or not electric vehicles would be able to comfortably accomplish such journeys, the literature has focused on analyzing the habits of drivers over extended observation periods of time. Needel et al. [13] demonstrated that even an electric car with a rather limited battery capacity of 19.2 kWh (2013 Nissan Leaf) would be able to satisfy the range requirements for 87% of the vehicle-days in the United States. By analyzing the data collected in two medium-sized Italian cities from $28{,}000$ private cars over the course of one month, De gennaro et al. [14] observed that only approximately 25% of the monitored fleet has traveled over a distance greater than $100\,\mathrm{km}$ in a single take. Such distance can be easily covered even by short-range BEVs, as of 2021. Using one-year GPS traces from vehicles belonging to 255 Seattle households, Khan et al. showed that

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a BEV with $160\,\mathrm{km}$ of range could satisfy the needs of 50% of one-vehicle households and 80% of multi-vehicle ones, assuming overnight charging and the possibility of using traditional ICE vehicles or public transport four times during the year (in order to satisfy long distance trips). In [15], five weeks of driving data (GPS traces) from a sample of 166 motorists in Sydney were analyzed. The study shows that less than 1% of the home-home tours exceeded the $170\,\mathrm{km}$ range; thus a simple home-charge set-up could satisfy almost the entirety of the daily journeys. [16] explores the impacts of BEV range limitations in Switzerland and Finland, using a simulation model based on national travel surveys. The study suggests that more than 95% of all national trips can be achieved by a low-range BEV and overnight charging. The authors explore the effect that policy packages can have on the electrification potential and highlight how ensuring that households have access to appropriate charging infrastructure is essential for increasing the BEV-potential.

These and other studies ([17]–[22]) are already an important indication of the fact that BEVs could comfortably supplant conventional Internal Combustion Engine (ICE) vehicles without substantially affecting their owner's routines. However, all the cited studies draw their conclusions from the analysis of either small sample sizes (in terms of number of monitored vehicles and/or in terms of observation time-frame), or from surveys, or a combination of both. The surveys, in particular, are based on manual records: individuals are asked to describe quantitatively and/or qualitatively their trips, for example by keeping a daily diary. The estimation of the covered distance, the stop time and the stop location are, in this case, based on human book-keeping, and thus subject to human error. Thus, there exists a literature gap with respect to the size and quality of the dataset used for the analysis.

B. Charging Station Location Problem

Particular attention has also been given to the Charging Station Location Problem (CSLP), the problem of determining the optimal siting of charging stations for electric vehicles. This issue is multidimensional by nature and, as such, it has been addressed from multiple perspectives: from the point of view of the driver, of the electricity supplier, of local authorities and so on. We will particularly focus on the demand-based approaches, that aim to maximize the charging demand

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satisfied by the charging stations. We chose to explore a demand-only perspective because we want to investigate the effects of charging stations placement on the amount of captured demand when only demand maximization is considered: the addition of other constraints can only negatively affect the efficacy of the charging stations, in this regard. Most of the literature treats the problem as a classic facility location problem, with a set of candidate locations and different objectives and constraints. A part of the literature uses flow-based models ([23]–[25], where the demand is represented as a flow passing along the routes of travel [26]. The idea is that, for certain types of services, users may be willing to briefly stop their travel and use the service, before proceeding to their final destination. This method has proven effective for the placement of traditional fuel stations, fast food restaurants and other fast services. Due to charging speed constraints, flow capturing models applications have been substantially limited to the placement of fast charging stations. For this reason, and because flow-capturing models entail an alteration of the driver's behaviour, we did not consider such approaches for our analysis.

Another research branch considers parking as a proxy for charging opportunities. Dong et al. [27] use data coming from recorded driving activities of 275 volunteer households in the Seattle metropolitan area. The objective is that of minimizing the number of missed trips under a budget constraint (a trip is considered missed when its distance is greater than the remaining battery range). Furthermore, the authors explore the effects of charging station placement on the percentage of missed trips. Shahraki et al. [28] propose an optimization model based on taxi travel patterns to capture public charging demand and select the locations of public charging stations to maximize the amount of vehicle-miles-traveled (VMT) being electrified. Chen et al. [29] use data from a fleet of $30{,}000$ taxis to locate the charging stations. Only the dwellings with a duration of 30 minutes or more are considered to be valid for recharging. In [30], the demand is deduced from operational taxi data from about 800 vehicles. The authors assume that parking is a good proxy for the charging demand, but do not make any consideration about the stop duration or the actual charging need of the vehicle.

Since the aforementioned studies adopt a classic discrete facility location approach, they are constrained to consider only few selected candidate sites and, as a consequence, they usually focus on finding the optimal location of charging stations within a restricted territory (a province

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or a region). Fewer studies use, instead, clustering analysis to determine where to optimally position the charging stations. Ip et al. [31] propose a model that quantifies the road information into data points, which are later aggregated into 'demand clusters' by hierarchical clustering analysis. Jianmin Jia et al. [32] generate the EV trips from cellular signaling data, collected during one day from 118 thousand cellphones. The study first estimates the origin and destination of the trips based on the user's dwell time, then it simulates the trips to estimate the driven distance, finally it uses the trips with distance greater than 20 km to discover the charging demand locations. The final results of the clustering analysis are not directly usable, as they indicate stations with non-uniform service radius ranging from 4 km (40 minutes by walk) to 13 km (more than two hours by walk). Andrenacci et al. [33] estimate the demand from conventional fuel vehicles that have been equipped with an on-board acquisition device. The analysis only considers one week of samples, does not take into account the duration of the stop and does not consider the actual charging need of the vehicles. [34] use the location of facilities, population and popular attractions to determine where to optimally place large-scale charging stations, using a k-means clustering analysis.

All the cited studies rely on either surveys / questionnaires ([35]), limited fleets of monitored vehicles ([27]), observation over a limited time and space ([33]), monitoring of fleets of taxis ([28]–[30]) having radically different charging needs from private vehicles ([36]), and cellular data from which to attempt to deduce the travel by car ([32]). Again, there exists a literature gap with respect to the size and quality of the data used for the public charging station placement. Additionally, only few studies are based on unbounded clustering analysis, and the few clustering approaches are either missing necessary considerations about the stop duration and charging need of the vehicles ([33]), or produce excessively large and sometimes inconsistent charging station clusters[32].

C. *Effects of charging station placement on Electrification Potential*

Due to the range anxiety phenomenon, the lack of public charging stations is perceived as one of the fundamental factors affecting the purchase of an EV. The fear adds a psychological component to the demand, which is hard to quantify [37]. Thus, charging stations dissemination is of fundamental importance for the cars' electrification process, if we consider the huge psychological relief in knowing that a charging station is located nearby: it's like a safety net and fallback option [37], which mitigates the fear of getting stranded on the side of the road. The psychological effects of charging stations were demonstrated in a field trial of the Tokyo Electric Power Company [38], where a higher use of the company's EVs was observed when a new charging station was located within their service area, even if such station remained largely unused. This sense of reassurance can be the key for convincing potentially interested and motivated customers to buy an electric vehicle.

A. Melliger et al. [16] have analyzed simulated trips generated using travel surveys and assessed that, once home-chargers are widely available, the effects of installing charging stations at public sites are minor (a change $\leq 1\%$ of BEV-potential). Similarly, pilot projects all over the world have consistently shown that the use of public charging stations is low in comparison to that of charging stations at homes [37].

To the best of the authors' knowledge, no existing study has ever used an extensive dataset of driving patterns from GPS devices to assess the effects of optimal charging station placement on electrification potential within a single, cohesive framework.

III. Dataset description

TABLE I: General provinces description

Province	Province population	Municipality population	Province area	Population density	# Registered vehicles
Parma	447,779	194,417	$3447/\mathrm{km}^2$	$131/\mathrm{km}^2$	290,329
Padova	936,887	209,829	$2144\,\mathrm{km}^2$	$438/\mathrm{km}^2$	603,290

In recent years, thanks to global IoT connectivity, telematics devices have become increasingly widespread. Through a GPS module and an IMU, the telematics device (often referred to as a Black-Box), installed directly on-board of the vehicles, periodically collects the spatio-temporal data about the vehicle travels, which is then transmitted, stored and finally processed for a multitude of purposes: smart fleet management, road safety, Pay-How-You-Drive insurance and so on. Such data contains a wealth of empirical observations that can be used to better our

TABLE II: Dataset overview before and after preprocessing

Province		Number of analysed vehicles	Penetration	Number of trips and stops $[\times 10^6]$	Total km traveled $[\times 10^6]$
Parma	Original	21,251	7.4 %	30.94	233.65
	Preprocessed	11,860	4.1 %	18.12	163.48
Padova	Original	30,925	5.1 %	45.31	330.22
	Preprocessed	18,364	3.0 %	28.28	238.83

understanding of mobility patterns: a powerful tool for answering to open transport planning and policy design issues.

This paper is based on a massive dataset (the same dataset used in [12]), acquired from a large fleet of vehicles equipped with a Black-Box device. The data spans over a one-year time frame (1st September 2017 – 31st August 2018) and includes the anonymized GPS traces of 52,176 privately owned conventional fuel vehicles, registered in the Italian provinces of Parma and Padova (21,251 from Parma and 30,925 from Padova, representing the 7.4% and 5.1% of the entire vehicular fleet of the two provinces). Each Black-Box collects information in the form of *events* (such as the vehicle ignition or shutdown event, or the periodical sampling event during the travel) with details on the time, the position and the distance covered between samples. We can use the startup and shutdown events to transform sequences of events into *trips* and *stops* (the building blocks of this work), thus moving to a higher degree of abstraction. The *trip* object is represented by origin and destination locations (each with its latitude and longitude coordinates), the start and end timestamps and the amount of kilometers traveled cumulatively during the trip. A *Stop* is strictly connected to a *trip* through a 1:1 relationship (a stop always precedes/succeeds a trip), and is characterized by a stop location, a duration and the relative timestamps.

IV. Preprocessing and preliminary analysis

This section summarizes the steps undertaken to ensure the consistency and reliability of the analyzed dataset. Additionally, a short description of the dataset's statistical features is provided, for a general overview of the most widespread driving habits.

A. *Data cleaning*

The dataset has been meticulously examined and cleansed from acquisition errors, which might otherwise compromise the result of the analysis. Through this preprocessing step, we make sure that the movements of the vehicles have been fully captured during the observation period.

The preprocessing consists of:

1) Removing the Black Boxes considered to be malfunctioning, due to a high number of incomplete or invalid trips and stops [1].
2) Performing consistency checks to maintain a one-to-one mapping between trips and stops.
3) Collapsing anomalous 0 distance trips into the adjacent stops.
4) Amend the remaining invalid trips and stops.
5) Removing the vehicles that have been active for less than 10 months.

Steps 1 to 4 are related to the intrinsic inaccuracy of GPS acquisition devices, since these provide very coarse information when the signal is weak. Step 5, instead, is performed to guarantee that the vehicles in the examined sample have been observed extensively enough to understand how they are operated under different circumstances during the year, thus ensuring consistent results. This is especially important for our dataset, since Black Boxes can either be acquired or uninstalled during the observation year.

Following the application of these criteria and adjustments, 30,224 out of 52,176 vehicles (58% of the original sample) are considered satisfactory, as we can reliably trace their movements for an extensive amount of time. Further details on the cleaning and filtering procedure can be found in Table II.

B. *Statistical properties of trips and stops*

As a preliminary step to the electrification potential analysis and the CSLP, we now shortly review the general statistical properties of the dataset (as summarized in Table III). As mentioned

[1]Invalid trips and stops are identified via data pre-processing as those not presenting the needed event chain from vehicle ignition to vehicle shutdown or having non-meaningful duration

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TABLE III: Statistical features of the datasets

	Trips						Stops		
Province	Duration Mean [hh:mm:ss]	Duration Median [hh:mm:ss]	Duration Std. [hh:mm:ss]	Distance Mean [km]	Distance Median [km]	Distance Std. [km]	Duration Mean [hh:mm:ss]	Duration Median [hh:mm:ss]	Duration Std. [hh:mm:ss]
Parma	00:15:26	00:11:09	00:15:47	9.3	4.5	18.6	05:13:30	00:58:15	20:46:27
Padova	00:15:19	00:11:08	00:15:26	8.7	4.2	16.9	05:12:21	01:04:46	19:00:25

in Table III, the two building blocks of our analysis are *trips* and *stops*.

In general, *trips* tend to cover very short distances (Figure 1), with an average distance traveled of approximately $9\,\mathrm{km}$. The trips exceeding $50\,\mathrm{km}$ only represent the 2% of the total. However, these account for 20% of the total distance traveled during the entire observation time-frame. This statistic is already an important indication of the exceptional nature of lengthy trips, compared to the average use of personal vehicles.

Moving on to *stops*, the relationship between stops' start time and their duration is telling of the nature of the stops themselves (Figure 2): predictably, most of the long stops (having $duration \geq 7\,\mathrm{h}$) are concentrated around the evening hours (when returning from work) or during early morning (when arriving at work). Brief stops are very frequent across the entire day, while stops with $3\,\mathrm{h} \leq duration < 7\,\mathrm{h}$ are most common in the morning and around lunch time.

V. Paradigm Shift: evaluating the potential of electric vehicles

Given the assortment and complexity of human behavior, we can expect vehicles to be used in a variety of ways, accordingly. Consequently, some of the analyzed vehicles will be more suited than others to being replaced by BEVs (depending on the distances driven, the dwell time in between trips and so on). In this section, we establish the framework that allows us to assess the electrification potential for each of the analyzed vehicles.

A. Fundamental assumptions

In order to evaluate the ease of transition from an ICE powertrain to an electric one, we have to lay some fundamental assumptions concerning human behavior, battery range limitations and

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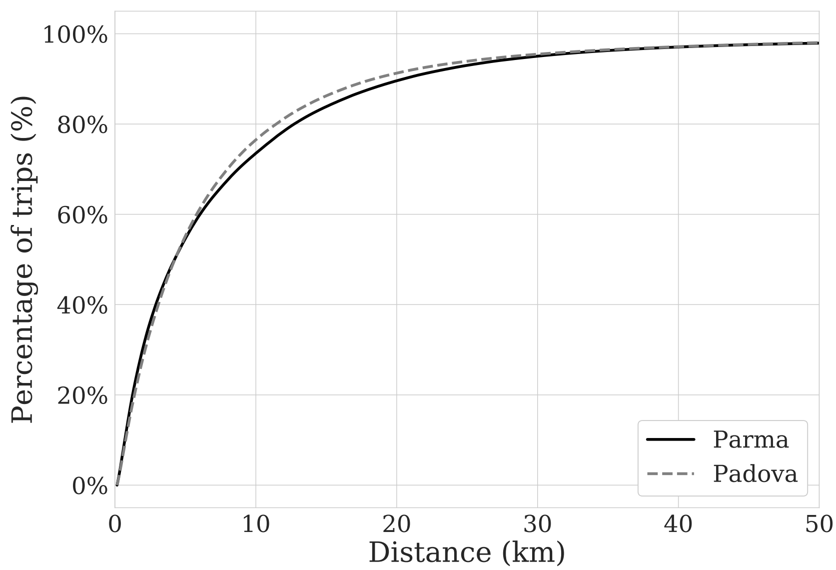

Fig. 1: Empirical CDF of trips distance

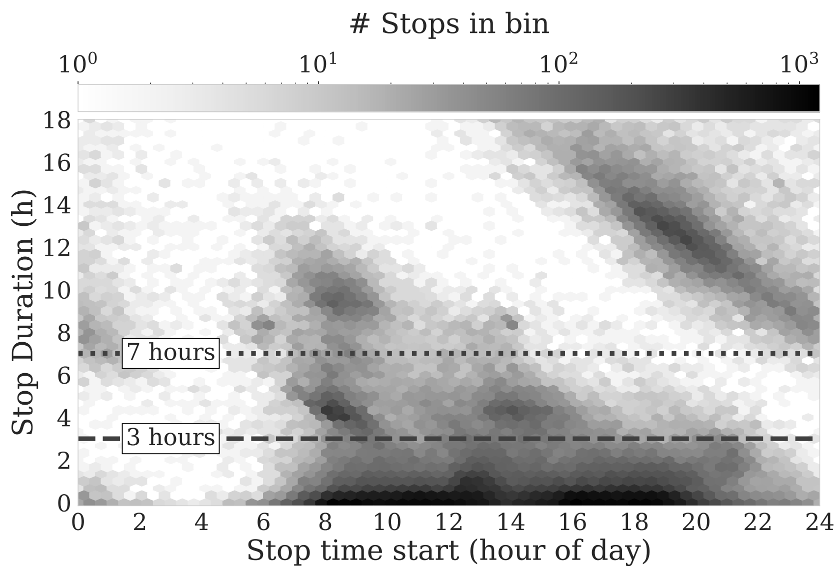

Fig. 2: Hexbin histogram of stops duration

charging patterns.

- *Vehicle range*: for the purpose of this study, we decided to focus only on BEVs (and not on Hybrid electric vehicles). We then modeled our vehicle according to the battery capacity and discharge rates of commercially available mid-range BEVs, establishing a range autonomy

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of $200\,\mathrm{km}$ (from [39]).

- *Driving habits*: when exploring the transition to BEVs, we assume that the drivers have to accomplish the same trips performed with their conventional fuel vehicles, without explicitly adapting to the limitations of the new battery-powered ones. This is, obviously, a conservative assumption, as (in real life) owners may adjust their plans to compensate for the new constraints (the modification of travel behaviour in response to EV adoption is explored in [40]–[43]). Adapting, however, comes with a cost, since being forced to change plans to make up for the technological limitations of BEVs certainly represents an additional burden on the driver. We decide, thus, to evaluate how seamless the transition BEVs would be by leaving unaltered the paths and schedules of each of the analyzed traces.
- *Overnight charging*: wall-boxes and residential charging stations are crucial enablers of BEV technology. As such, we always assume that a vehicle can be charged overnight, resulting in a full available range of $200\,\mathrm{km}$ at the beginning of the next day.

The 200 km threshold was set according to the data collection time period (year 2018), and - even nowadays - represents a relevant range threshold as it includes most of the modern compact and subcompact BEVs [44]. Variation of this threshold would further favour the electric vehicles' feasibility.

B. SOC modeling and Daily Vehicles Kilometers Traveled

Following the assumptions of Section V-A, we can model the vehicles' SOC according to the following rules:

- The SOC is 100% (fully charged) at the beginning of the day (i.e., we assume overnight charging).
- The SOC is 0% (fully discharged) after 200 km of cumulative driven distance from the last recharge.

Due to the lack of information about temperature, acceleration, braking, slope and terrain, a more detailed and dynamic SOC modeling could not be developed. However, since we work on a large number of trips, this approximation can be intended as the representation of an average behaviour.

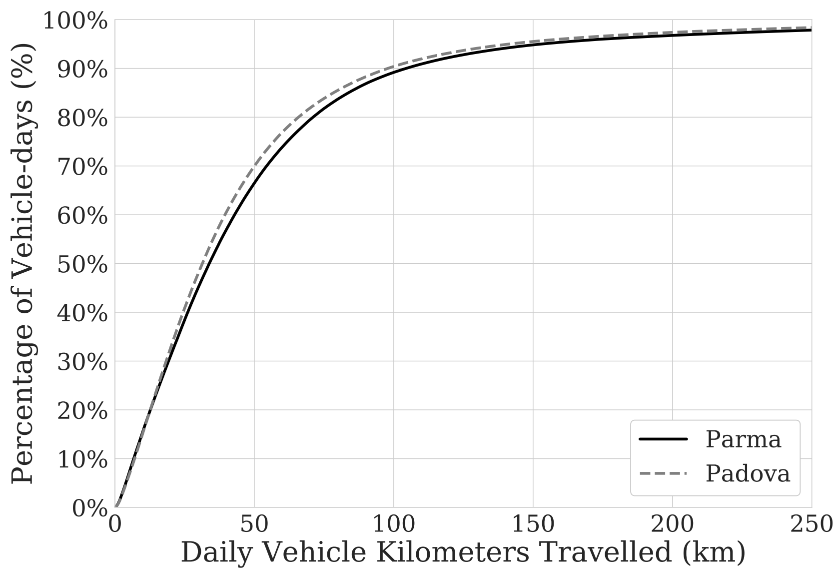

Fig. 3: Empirical CDF of vehicle-days DVKT

With this in mind, we have established that to evaluate whether or not a sequence of journeys could be achieved using a BEV (only considering overnight recharging) we have to analyze the cumulative amount of kilometers driven throughout the day. We define this quantity as *Daily Vehicles Kilometers Traveled* (DVKT).

The empirical cumulative distribution function of the DVKT can be observed in Figure 3. For the most part, personal fuel vehicles are used to cover daily distances that could easily be satisfied by their electric counterparts (97% of the vehicle-days are under the $200\,\mathrm{km}$ threshold). However, we need to pay particular attention to the remaining 3% of the vehicle-days, as they still represent important obstacles to the widespread diffusion of BEVs.

C. Critical Days

The vehicle-days having a DVKT greater than the BEV's range (fixed at $200\,\mathrm{km}$) are labelled as Critical Days. As the name suggests, these are the most critical vehicle-days for the EV-switch purposes, as they cannot be accomplished by a BEV without introducing intermediate recharging in the picture (see Section VI). Despite Critical Days being a small minority, a very significant portion of the vehicles has traveled at least once for more than $200\,\mathrm{km}$ (73.1% of the vehicles

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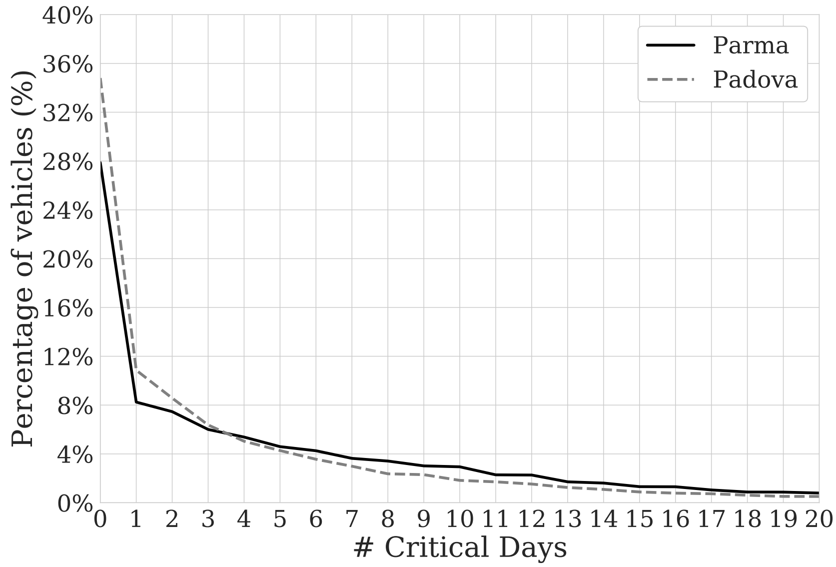

Fig. 4: Number of Critical Days per vehicle

from Parma and 65.2% of the vehicles from Padova, respectively). This means that most of the vehicles are used to cover large distances very few and selected times throughout the year (see 4).

D. Electrification Potential

Using this framework, we can quantify the ease of transition from conventional fuel vehicles to BEVs as a function of the number of Critical Days.

Let the *Critical Ratio* C_R define the percentage of vehicle-days that are also Critical Days

$$C_R = \frac{\textit{Number of Critical Days}}{\textit{Number of Vehicle Days}} \times 100 \tag{1}$$

The *Critical Ratio* C_R indicator represents how much disruption would the switch to a battery-powered vehicle bring in the owner's driving habits. We believe that this indicator is more meaningful than just considering the number of Critical Days, as it describes the disruption with respect to the actual vehicle usage, and not just in absolute terms.

Finally, we can use the critical ratio to define four vehicle categories corresponding to different levels of electrification potential:

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- *Perfectly Suitable*: vehicles with $C_R = 0\%$; they never exceed the 200 km range threshold. Ready to be replaced by BEVs without any adaptation (only night charging).
- *Possibly Suitable*: vehicles with $0\% \leq C_R < 3\%$; they rarely exceed the 200 km range threshold, generally for outdoor day trips / outings associated to holidays or specific rare events. Could be replaced by BEVs with small adaptation
- *Mildly Suitable*: vehicles with $3\% \leq C_R < 6\%$; they sometimes exceed the 200 km range threshold. In this case, switching to a BEV would entail a great degree of adaptation;
- *Not Suitable*: vehicles with $C_R \geq 6\%$; they frequently exceed the 200 km range threshold and, thus, could not be replaced by BEVs.

The threshold were chosen based on the market research of the data owner (a large insurance company), who wanted to investigate effective schemes for EV-tailored insurance policies. In particular the thresholds correspond to the percentage of change/adaptation that the EV owners might be willing to consider if casual and periodic BEV alternatives were included in such EV-tailored insurance schemes.

The outcome of the segmentation for the vehicles of the two Italian provinces is presented in Figure 5 and Table IV. The results depict a very positive picture: 27.9% of Parma's vehicles and 34.8% of Padova's never surpasses the daily range limit across the entire observation time. This fully captures the unexpressed potential of electric mobility: BEVs, in fact, still represents a niche, but they have all it takes to change the urban landscape (even with no public charging infrastructure). We believe that raising awareness about the real driving range requirements through empirical statistics may facilitate the EV uptake and help combating the unjustified range anxiety.

VI. Locating the Charging Demand

Until now, we have not considered the opportunity of recharging the vehicle at a public charging station during the day. Thus, whenever a vehicle crossed the 200 km daily threshold, the

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TABLE IV: EV-switch suitability categorization

	Parma	Padova
Perfectly Suitable	3306 (28 %)	6391 (35 %)
Almost Suitable	4977 (42 %)	7885 (43 %)
Mildly Suitable	1922 (16 %)	2158 (12 %)
Not Suitable	1655 (14 %)	1931 (10 %)

(a) (b)

Fig. 5: EV-switch suitability segmentation for (a) Parma and (b) Padova.

whole vehicle-day was considered as unachievable and was counted as a Critical Day, influencing the C_R score. However, we now want to explore how the public charging infrastructure could modify the electrification potential and determine the optimal charging stations placement. To do so, we will further explore the Critical Days and determine which of them contains one or more charging opportunities (based on the SOC modeling).

A. *Additional assumptions*

When the full battery range is not enough to complete the trips schedule, we need to consider the possibility of charging at a public facility during an intermediate stop. When doing so, we also make the following assumptions (in addition to those of Section V-A):

- *Minimum Charging Time*: it is known that recharge time is one of the main limitations of electric vehicles, especially when compared to their ICE counterparts. Despite the technology improvements over the recent years, it still takes a minimum of 30 minutes to recharge a BEV even when using fast charging is available. For this reason, we will only consider stops

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longer than 30 minutes for the purpose of intraday charging. We don't further distinguish between fast and slow chargers and postpone the sizing issue to future works.

- *Single intraday recharging*: we limit the intraday charging to once a day. This is a realistic assumption, as charging more than once a day would require very careful planning and would likely represent a major hassle for the driver.
- *Updated SOC modeling*: the vehicle will be fully charged (100% SOC) at the beginning of the day and after an intraday charge.

B. STOR and DVKTODR days

Under the assumptions of VI-A, not every Critical Day can be accomplished using a BEV, even with intermediate recharging.

Indeed, our BEV is unable to accomplish any trips with a distance greater than $200\,\mathrm{km}$ in a single take, due to its range limitations. We will call such trips as *Single Trip Over Range (STOR)*. Thus, a *STOR day* is a vehicle-day containing (at least) a *STOR* trip.

Similarly, a *DVKT Over Double Range (DVKTODR)* day is a vehicle-day with a DVKT larger than $400\,\mathrm{km}$. Due to the single intraday recharging assumption, such a trips schedule would be impossible to accomplish with a BEV, as it would require the battery to be recharged (at least) twice within the same vehicle day at public charging stations.

C. Eligible stops and Eligible days

As a final step, we define the criteria to identify the *Eligible Stops*. An Eligible Stop represents both a real charging opportunity (meaning that its duration respects the constraints imposed by the limits of charging technology) and a necessity (as the vehicle needs to use it to complete an otherwise unfeasible schedule). In order to be considered eligible, a stop must:

- Belong to a Critical Day;
- Do not belong to a Single Trip Over Range (STOR) day;
- Do not belong to a DVKT Over Double Range (DVKTODR) day;
- Have a duration greater than 30 minutes;

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TABLE V: Vehicle Days to Eligible Days count

	Parma	Padova
Vehicle Days	3,180,783	4,991,087
Critical Days	102,546	130,129
STOR or DVKTODR Days	30,504	38,706
Tight-schedule Days	17,450	18,444
Eligible Days	54,592	72,979

- Have a Driven Cumulative Distance DCD (i.e., the distance driven within the same day, preceding the stop) $\leq 200\,\mathrm{km}$;
- Have a Residual Cumulative Distance RCD (i.e., the distance to be driven during the rest of the day, following the stop) $\leq 200\,\mathrm{km}$;

Following the definition of Eligible Stop, we can now define an Eligible Day as a vehicle-day containing (at least) an Eligible Stop. These are vehicle-days that, despite having DVKT $\geq 200\,\mathrm{km}$, may still be carried out from an electric vehicle through intermediate recharging (under all the assumptions from Section V-A and Section VI-A). 53% of Parma's Critical Days are also Eligible. The percentage is slightly larger for Padova, which reaches the 56%. Notice that a part of the Critical Days do not fit in any of the aforementioned categories: these vehicle-days are deemed unmanageable for a BEV because they either only contain too brief stops (under the 30 minutes mark), or because their trip chain cannot be broken down in two legs with DCD and RCD $\leq 200\,\mathrm{km}$. Figure 6 schematizes the workflow in an intuitive way, and Table V summarizes the result of the Critical Day analysis.

VII. Optimal placement of charging stations

Based on the mobility patterns described in the previous section, starting from the locations of the Eligible Stops, we now address the problem of placing the charging infrastructure. In particular, in this work we concentrate on the siting of the stations, while neglecting the sizing which is the topic of ongoing work. Hence, a charging station is defined as a location with one or more charging poles, with possibly different power outputs.

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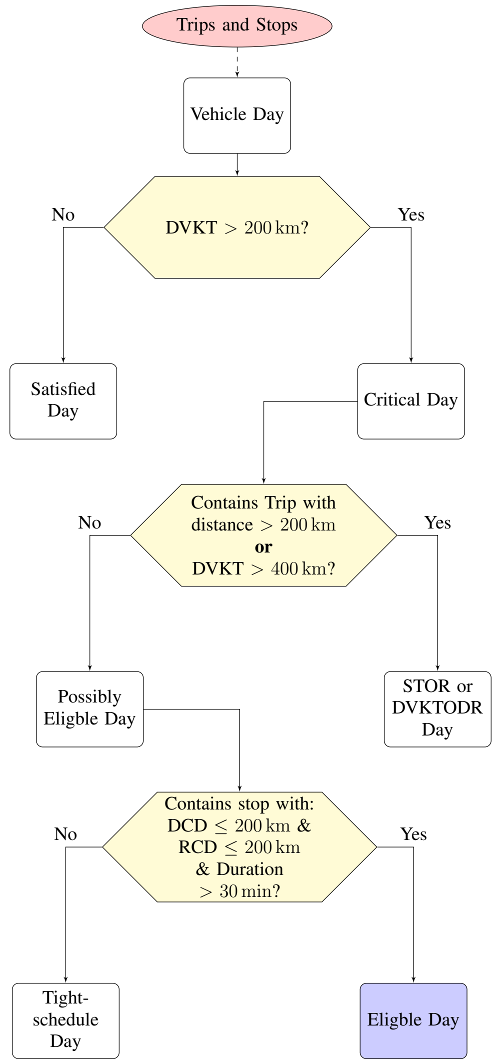

Fig. 6: Workflow to identify Eligible Days from a vehicle's daily trips and stops

We have previously illustrated how the Eligible Stops are meaningful proxies for the actual charging demand. Thus, We use such stops to identify the Charging Demand Hotspots (CDHs), i.e., agglomerates of vehicles' Eligible Stops, which are employed to model hypothetical charging needs that could be satisfied by a charging station placed in the centroid of the clusters made by each CDH. We proceed with a two-steps clustering analysis as follows (see Algorithm 1):

1) For each vehicle, we cluster its Eligible Stops into its Individual Demand Hotspots (IDHs). As the name suggests, an IDH is a cluster containing one or more Eligible Stops belonging to the same vehicle and located in the same area.
2) We cluster the IDHs into Charging Demand Hotspots (CDHs)

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Algorithm 1: Charging Demand Hotspots clustering

Input : Eligible Stops ES from all vehicles V
Output: Charging Demand Hotspots CDH
begin
  $CDH \longleftarrow \emptyset$`// Charging Demand Hostpots`

  $IDH \longleftarrow \emptyset$ `// Individual Demand Hostpots`

  `/* Cluster ES of single vehicle` v `into its IDHs */`
  foreach $v \in V$ **do**
    $IDH[v] = Cluster(ES[v])$
  end

  `/* Cluster all IDHs into CDHs */`
  $CDH = Cluster(IDH)$
end

We use a Mean-Shift clustering algorithm with a flat kernel of size $350\,\mathrm{m}$ for both steps. Mean-Shift was a satisfactory choice because it does not require the knowledge of the number of clusters a-priori and because of its simplicity (one needs to set only the kernel size). While the algorithm does not guarantee clusters to have identical spatial dimensions, the results were always consistent, producing clusters of approximate radius $400\,\mathrm{m}$, a reasonable service radius for a charging station. Thus, we didn't enforce any constraint on the maximum radius of the CDH, so that each point belongs to one of them. The sorted lists of the top charging station locations are provided as the output of the clustering process, as shown in Table VI and Table VII, while their position on the map can be observed in Figure 7. These figures help to visualize how spread over the territory the top locations are, extending over much of northern Italy, often hundreds of km away from the provinces under study.

The outcome of the clustering analysis reveals, in fact, a non-trivial result: several top ranking candidate locations are not in close proximity to the analyzed cities of Parma and Padova, and many of them do not even belong to such provinces. This observation has major impacts on the way urban planners and local authorities should tackle the placement problem: when planning the public charging infrastructure they should, in fact, not only consider the needs of local inhabitants, but also (and especially) consider the needs of those living possibly many

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kilometres away, who come and go to the planners' territory as part of their mobility patterns. Notably, charging demand is more densely arranged around Points Of Interests (POIs) like airports, shopping malls, amusement parks and holiday destinations. Furthermore, some of these locations, such as the car park in the city center of Novara, the amusement park Gardaland and the airport of Bologna, are present in both top 20 locations lists of Parma and Padova. Since such sites attract much of the demand, they should be given priority when planning the siting of the stations. Additionally, installing the stations at visible and well-known locations would further alleviate the range anxiety phenomenon, as awareness of their placement increases.

It is worth to highlight that, as mentioned in Section II-B, the selection of the best candidate sites has been carried out with the only objective of demand maximization. However, if desired, additional constraints / objectives could be added to the proposed framework by weighting the stops (or the clusters) accordingly.

VIII. Impact of public charging infrastructure on Electrification Potential

We are now interested in analyzing how the electrification potential segmentation of Section V might be affected by the charging stations placement. We imagine to place an increasing number of charging stations (corresponding to CDHs) and we consider an Eligible Day to be satisfied whenever at least one of its Eligible Stops is part of the considered clusters. In the case of Parma, the first 20 Parma CDHs account for 7.9% of all the IDHs. However, the number of number of Perfectly Suitable vehicles increases only from 28% to 29%. Even if we considered all Eligible Days as satisfied (corresponding to the scenario in which the maximum number of charging stations has been built, see Figure 8a), the category of Perfectly Suitable vehicles would only reach the 42.5%. Similar figures are also obtained for Padova's fleet, confirming the validity of our previous statement (Figure 8b). The implication is that, even if we scattered many charging stations all around the territory, approximately half of the vehicles would still have (at least) one Critical Day which a BEV could not cover (under working assumptions). This suggests that even as we expand the public charging infrastructure, electric vehicle owners will occasionally have to reschedule their trips to accommodate for the charging necessity. Thus,

TABLE VI: Top 10 public charging locations for Parma's dataset

Ranking	**Name**	**Description**	**# of IDHs**
1	Bologna Airport	Airport	454
2	Centro Torri & Euro Torri	Shopping Malls	371
3	Fidenza Village	Shopping Mall	351
4	Milano San Donato	Metro Connection	240
5	Lerici	Seaside Car Parking	227
6	Mantova Outlet Village	Shopping Mall	218
7	Parma Esselunga	Supermarket	217
8	Marina di Massa	Seaside Car Parking	216
9	Parking Toschi	Multi-storey Parking in Parma city center	206
10	Parking Saba	Multi-storey Parking in Verona city center	204

TABLE VII: Top 10 public charging locations for Padova's dataset

Ranking	**Name**	**Description**	**# of IDHs**
1	Asiago	Mountain car parking	709
2	Adigeo	Shopping Mall	667
3	Gardaland	Amusement Park	532
4	Parking Saba	Multi-storey Parking in Verona city center	498
5	Outlet Noventa	Shopping Mall	468
6	Centro Giotto	Shopping Mall	268
7	Lido di Jesolo	Seaside Car Parking	255
8	Le Piramidi	Shopping Mall	245
9	Fiera di Primiero	Mountain car parking	238
10	Ipercity	Shopping Mall	235

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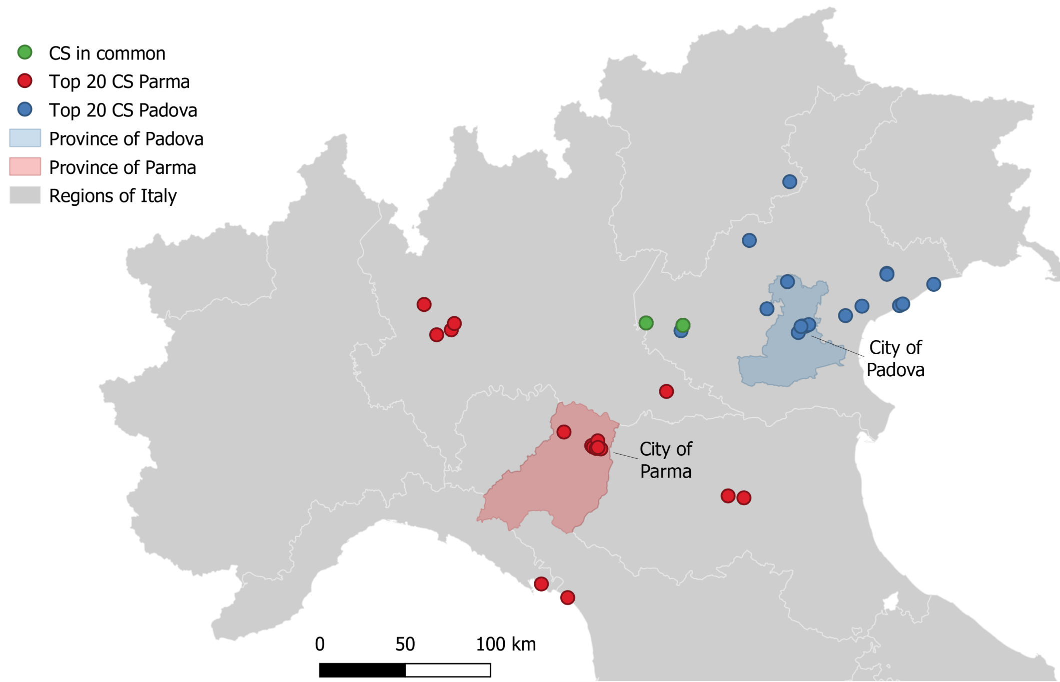

Fig. 7: Top 20 locations for Parma and Padova dataset

charging stations alone are not enough to satisfy the actual need of many potential BEV owners, due to the sparsity of their charging demand, the technological limits of BEVs (range limitation) and their driving habits.

Alternatively, fuel-powered vehicles might still be needed in these few selected occasions. As we already observed in 4, most of the drivers exceed the battery range in very few selected occasions. Using an ICE vehicle instead of an electric one on these limited instances (for example through rental services) increases the electrification potential substantially: 3 days are enough to expand the class of Perfectly Suitable vehicles by approximately 24% in both provinces (Figure 9). We deduce that well planned car sharing services could be one of the keys to facilitating the adoption of BEVs.

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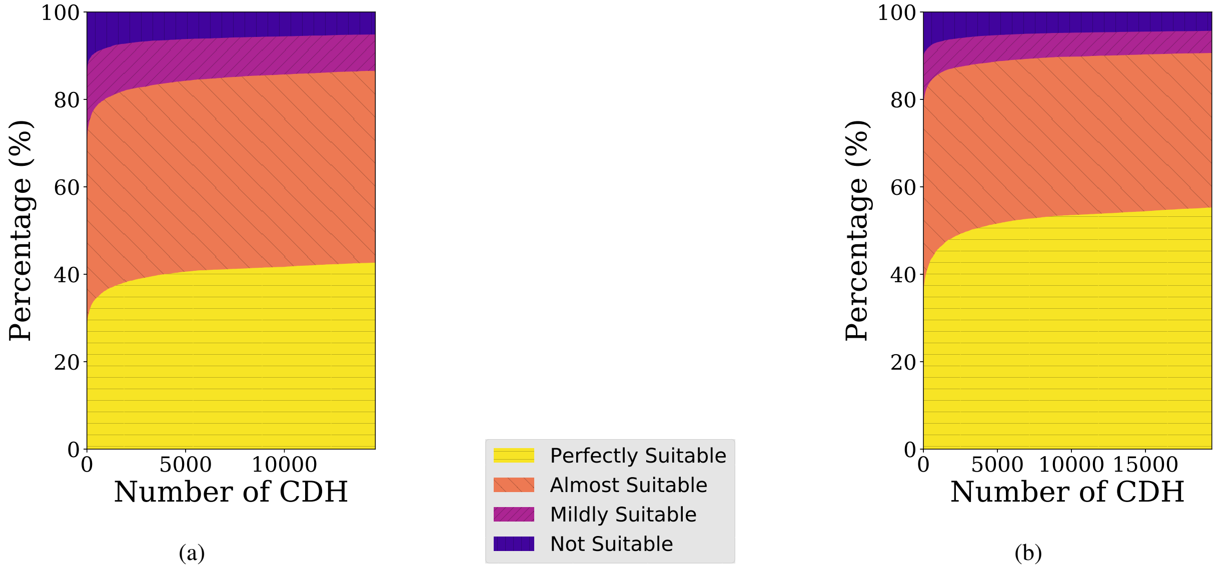

Fig. 8: Impacts of stations on vehicle categorization for (a) Parma and (b) Padova

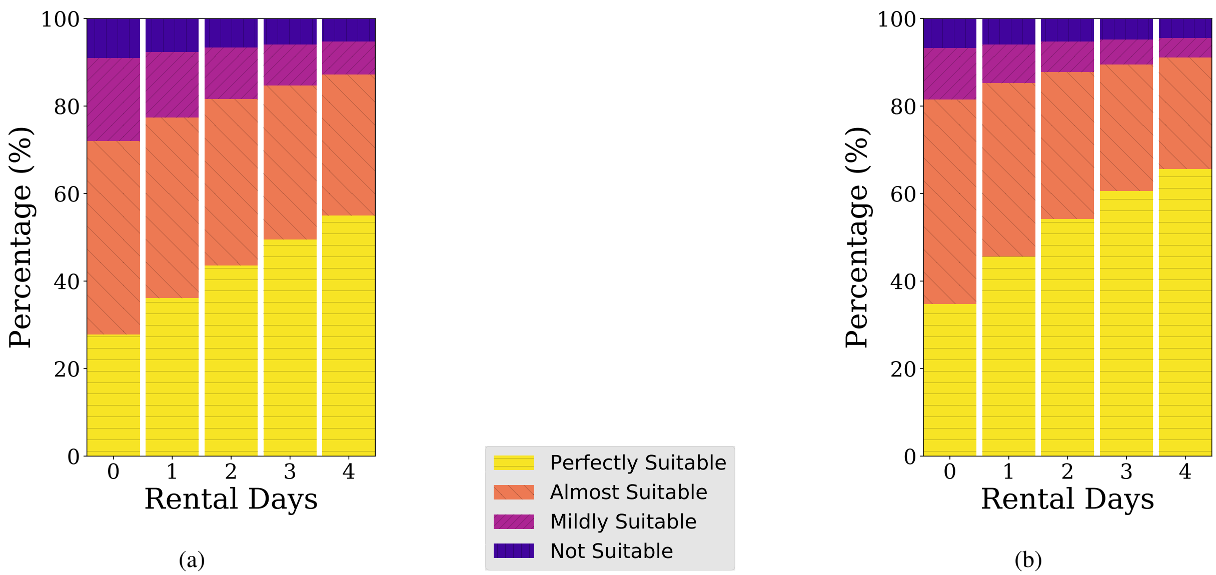

Fig. 9: Impacts of occasional replacement of BEVs with ICEVs on vehicle categorization for (a) Parma and (b) Padova

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IX. Effects of charging-time improvements on EV-Suitability and charging station location

As technology evolves, new and improved charging systems will become increasingly available on the market. Recent research demonstrated that 10-minutes fast-charging times are achievable through a physical constraint-triggered charging control strategy for lithium-ion (Li-ion) batteries [45]. Since the proposed approach is general and modular, we can adapt it to this new scenario by simply modifying the current minimum charging time hypothesis to accommodate for future improvements. Therefore, let us repeat the analysis for the city of Parma, using a 10-minute minimum charging time.

As a result of the threshold reduction, the number of eligible days increases by an additional 6.2%, passing from 53.2% to 59.4% of the critical days. Four motorway service areas (Autogrill) are now present amongst the top 20 candidate sites (see Figure 10). This suggests that motorway service areas should be fitted with the newest charging technologies (10 minutes charging time) once these become available.

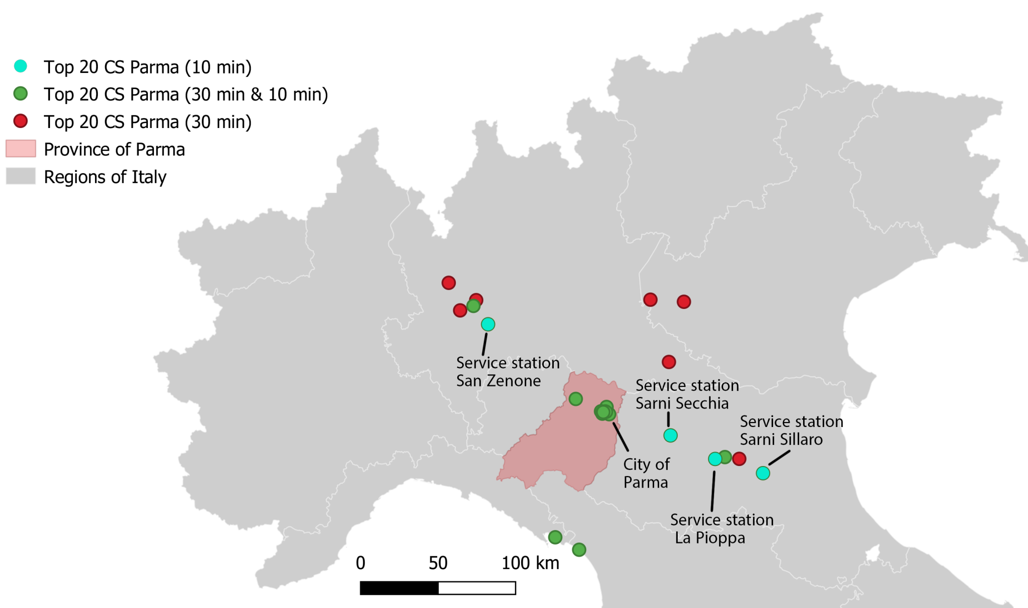

Fig. 10: Top 20 locations for Parma when considering a 10 minutes and a 30 minutes minimum charging time threshold

Ultimately, however, the impact of charging stations is still limited by the territorial dissemination of the charging needs: the new top 20 charging stations would only increase the Perfectly Suitable vehicles by a 1.5% (as opposed to the 1% improvement obtained with a 30-minute threshold - Section VIII). Thus, even when faster charging times are considered, the conclusions of the study are similar.

X. Concluding remarks and Future Works

This study demonstrated the potential of big-data acquired from telematics devices for gaining important insights into human behavior and for solving complex planning problems. In particular, thanks to an in-depth analysis of mobility patterns extracted from massive spatiotemporal datasets, we were able to estimate the amount of disruption caused by the transition to electric mobility and to segment the analyzed fleet accordingly. Over one quarter of traditional ICE vehicles currently in circulation could be conveniently switched with medium-sized BEVs, without any adaptation to the drivers' scheduled trips and without the need for intermediate recharging. Another 40% of the vehicles have a very low Critical Ratio, since they exceed the battery range very rarely and sparsely during the year. Furthermore, we showed how GPS traces can help us to realistically model the spatial distribution of the charging demand and, as a consequence, optimally decide where to place the main public charging stations. A novel way of identifying the stops compatible with a charging opportunity is defined and a clustering analysis is performed to produce a list of the top public charging sites. Finally, the potential impacts of the charging stations placement on the electrification potential are evaluated.

Future works will evaluate the EV-switch convenience in economic terms and will consider the likelihood of overnight recharge by factoring in demographic and geographic considerations. Further the problem of properly sizing the charging stations will be investigated.

Acknowledgments

The work of F. Zinnari and M. Tanelli was partially supported by the project YOU-SHARE, funded by Fondazione Cariplo.

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