Data-Based Assessment of Plug-in Electric Vehicle Driving

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Abstract. The limited driving range of electric vehicles (EV) is one of the biggest deployment challenges for electromobility. We use GPS driving data from a fleet of about 1,000 conventional private vehicles collected over two years to simulate energy consumption of electric cars. We estimate how much energy is required for EV charging at home and at a secondary parking location (e.g., at work) and to what extent energy from solar panels during sunlight hours can be used for charging.

Keywords: Electric vehicle · GPS driving data · Energy demand · Photovoltaics

1 Introduction

Electric vehicles (EVs) are a crucial element of our society's mobility strategy as they provide independence from fossil fuels, can lead to a reduction of CO_2 emissions, and lay the foundation for technology leadership, job creation, and economic growth [1, 2]. From the perspective of the automotive industry and utility companies, the transition toward EVs opens up new challenges and opportunities within the emerging EV value chain. For drivers, electrification seems to be the most viable trend in the long run on the pathway to sustainable petroleum displacement [3].

However, both supply side actors (including EV, battery, and automotive component manufacturers) and demand side actors (drivers and governments) face significant barriers that hamper a rapid mass-market adoption of EVs. The industrial success depends, on the one hand, on the competencies of new business players to meet the demands of the new emerging ecosystems (particularly battery pack producers), and, on the other hand, on the availability of the EV-enabling infrastructure. Both factors ultimately determine range, the ease of re-charging the car, and thus the degree to which the consumers' requirements regarding personal mobility will be satisfied. In fact, the popularity of electric cars in the years to come is likely to depend much more on improvements to their performance and on the success in overcoming the lack of infrastructure than on the oil price [4]. Although the developments to date suggest

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significant potential, the actual global uptake on EV sales is not yet impressive. Main reasons include high acquisition costs, the poor charging infrastructure, and the limited driving range [5, 6]. Moreover, EVs represent a new source of demand for electricity and may require the addition of electricity-generation capacity and substantial upgrades to transmission and distribution infrastructure. So, for instance, [7] predicts that widespread use of EVs will increase electricity demand modestly – in the order of 10–15 %. Reduction of this demand can be achieved by using distributed resources of renewable energy, like solar panels on a rooftop. This is where the motivation of our research emerges.

In this paper, we provide estimates on the two critical factors of electric mobility: range and electric load for two likely-to-come charging topologies (charging at home and at work). Based on the real-world driving data collected from vehicle sensors of conventional cars - specifically, Global Positioning System (GPS) based location data - *we aim at (i) estimating the share of the trips that can be driven fully electrically, (ii) examining the electricity demand change, and (iii) assessing the demand change in the situation when EVs charge from the solar energy during sunlight hours.*

To reach our goals, we assess energy demand of the simulated EVs based on the real-world car motion patterns and examine two charging scenarios: (a) charging at home, and (b) charging at home and at a secondary parking location (e.g., work). Parking locations of each car are found using a density based clustering algorithm. A comprehensive physical car energy consumption model is employed to derive state of charge during the trips. The underlying assumption in our model is the use of range extenders, so that all actual trips are taken into consideration.

Analysis of car motion profiles is an emerging stream of the EV feasibility analysis and infrastructure planning research. The idea is to use high-resolution data from gasoline vehicles collected through GPS and derive individuals' driving patterns. Recently, [8] analyzed start and end locations from the data including GPS coordinates and speed profiles of 79 drivers in Michigan over 5 nonconsecutive days to simulate a plug-in hybrid electric car and provide information on the likely state of charge of the battery at the time of arrival. [9] statistically investigated daily driving distances of 484 car owners in the United States and concluded that even short-range EVs can be satisfactory for a significant fraction of the population. In general, these approaches help to segment vehicle buyers by the range needs. Driving profiles associated with 255 households were analyzed by [10] to address the EV household needs in Seattle for one- and multiple-vehicle dwellings. [11] recorded usage data of 76 cars in a one–year period in the city of Winnipeg, Canada, and used this data in a simulation model to predict EV charging profiles and electrical range reliability. [12] evaluated GPS based travel surveys and found that 10 % of drivers could reach all destinations electrically when charging at home. [13, 14] used GPS driving data from the cities of Modena and Firenze in Italy to estimate the percentage of urban trips that could be covered electrically. We go beyond the state of the art by comparing two realistic charging scenarios, using a larger sample over a longer period of time in Europe that may reveal different driving characteristics and thus produce different results regarding the range and electricity demand. The experimental part of our research uses the data from 985 cars with internal combustion engine in North Italy collected over two years from 2007 to 2009 at a 2-km granularity. Moreover, in contrast to the datasets used in the reported studies, our data cover different kinds of areas (not only urban, but also suburban and rural).

The results indicate that about *63 % of distances could be driven electrically* if charging was possible at home only, given that each driver has a home-base parking spot with a socket. With an additional charging facility (e.g., at work), this number rises only modestly to 69 %. The availability of fast charging facilities (i.e., charging 80 % of an empty battery within 30 min) increases the electrically driven share to 71 %. Furthermore, the analysis of *network load* shows that EV charging intensifies electricity demand peaks in the evening hours (in an unmanaged charging scenario), in particular during the working days (Monday to Friday), when drivers return home to charge their vehicle. The introduction of a secondary charging facility can slightly smooth this demand peak without load shifting strategies. Finally, the comparison of charging energy demand with sunlight hours shows that a direct *use of photovoltaic cells for EV charging* at home may be limited. While cars are parked at home, the sun is shining 44 % of the standing time on average. In contrast, secondary charging facilities are used during the daytime with the sun shining 68 % of the parking time (which is an advantage for mostly flat production buildings that inhibit large spaces for PV modules, but a disadvantage for urban areas with high office buildings that offer less roof area per employee).

The remainder of the paper is organized as follows. Section 2 provides description of the data that supports our calculation. The analysis methodology is described in Sect. 3. Section 4 details the results. Conclusions are summarized in Sect. 5.

2 Data Description

We obtained the experimental data from the major European pay as you drive insurance provider. To collect it, combustion engine cars were equipped with an on-board GPS sensor and a GSM module. During vehicle operation, position updates were carried out every few seconds and then aggregated on the device level to reduce costs of transmission and storage. For aggregation, the system calculated traveled distance from incremental position updates and generated new data entries every 2 km. The distance between the points can in some cases exceed 2 km intervals if no position update was available, for example, due to the signal obstruction. In our study, we focused on the data from accident-free cars. The same dataset and a similar data cleansing approach (except elimination of drivers exhibiting many long trips) was used in [15]. As a result, 985 vehicles were considered. For privacy reasons, no driver particulars of any kind were included in the sample. Table 1 outlines the available variables.

3 Data Analysis Methodology

We present an approach that uses GPS data to simulate driving, energy consumption, and charging of EVs. The proposed procedure includes three following steps:

Table 1. Variables available in the GPS dataset [15]

Attribute	Description
Car ID	Car/device ID
Date and time	Date and time on which the dataset was recorded
Latitude, Longitude	Vehicle position in decimal notation
Speed	Vehicle speed at recording time in km/h
Distance to previous point	Distance traveled since last recording point
Time since previous point	Time traveled since last recording point
Panel session	Provides dataset description/dataset purpose:
	0: Dataset recorded on ignition turn-on
	1: Dataset recorded during vehicle operation
	2: Dataset recorded on ignition turn-off
Road type	Road type at recorded location:
	0: Urban, 1: Highway, 2: Extra Urban

1. ***GPS data exploration***. This step converts raw GPS data into driving trajectories. The term 'trajectory' refers to a connected sequence of GPS measurements. These sequences allow for identifying complete trips, which may be described by their length, duration, speed and acceleration. In addition, the parking location and time between successive trips is determined.
2. ***Stay region clustering***. Based on the trip information, it is possible to identify potential charging areas, that may include a home base, a workplace, or commercial sites [16]. We identify the hypothetical home location and a second major parking place of each vehicle by means of density based clustering algorithm.
3. ***EV simulation***. Finally, we simulate energy consumption of EVs during the trips, along with their charging at home and at the second major parking location. This is necessary for determining which destinations are reachable. The energy consumption model reflects one of the most relevant aspects of electric driving: the state of battery charge, which depends on the battery capacity and on the driving pattern.

3.1 Derive Trips from GPS Data

Start locations and destinations of trips are derived from the panel session data. We convert this information into driving trajectories to identify trips, which are described by their length, duration, and speed. A complete trip is a sequence of connected GPS measurements between a start location and destination.

3.2 Detection of Charging Locations

EVs can be charged at any conventional power outlet. Therefore, charging facilities may be installed at many different locations, for example, at home, at commercial sites, or at work [16]. Based on the trip data, it is possible to identify potential charging areas, such as the home location or a secondary parking location (e.g., workplace of a driver or a secondary residence).

Numerous studies indicate that charging overnight at home is a typical and convenient method [8, 9, 13, 14, 17]. [18, 19] suggest that the first and the last location during the working day may refer to the driver's home, and that the most stable location during the day may be the work site. [20] assumes that the home location is often the last destination of the day, the location where more time is spent than at any other place, or that a driver is at home at a certain time.

Inference of the home location from GPS driving data can be made using heuristic or clustering approaches [18, 20]. The choice of the appropriate method depends on the nature of the data at hand, as well as on the exact application purpose [21]. For instance, [20] uses hierarchical location clustering and assumes that the largest cluster refers to the driver's home. [22–24] suggest partitioning clustering for finding home bases. [18, 25] use density based clustering algorithms, that were verified with survey participants' home addresses in [26]. The second densest cluster was identified as a workplace.

Clustering algorithm for the home base search must be able to deal with noise (i.e., points reflecting occasional/irregular stops that do not belong to any cluster). In addition, the algorithm has to be able to deal with arbitrarily shaped clusters, because the shape of the potential stay regions is not necessarily circular or convex but depends on available parking sites. We use a popular density based clustering algorithm DBSCAN [27] to find dense groups of parking locations. DBSCAN uses two input parameters: First, the parameter *Eps* defines a neighborhood radius of a parking point, while iteratively including points into the cluster. Second, the parameter minimum number of parking events (*MinPts*) within *Eps* is used to define the cluster density. As a result, the method identifies the home base as a cluster with the maximum overall parking duration. We empirically tested different parameters with the assumption that cars park at home over night, so that *MinPts* = 20 was finally chosen, and *Eps* was incrementally approximated for each vehicle by setting the home base area (respectively its convex hull) to 100,000 square meters. Similarly, the secondary parking location (e.g., workplace or another residence) is a cluster with the second longest overall parking duration.

3.3 Electric Vehicle Simulation

We estimate energy consumption of EVs and derive their charging duration based on the movement patterns of conventional cars. We are aware that driving patterns might be different between a conventional car and an EV with range extender, yet we assume that mobility habits of individuals are rather stable. We assume that real-world data on EV driving that currently becomes available would probably be even more biased as early adopters tend to preferably use EVs as second cars and thus that current driving habits are a sufficient approximation of future electric mobility patterns.

Information on the length and the average speed of trip sections is used to estimate energy consumption during the trips based on the realistic energy consumption model for cars [28]. The model reflects one of the most relevant aspects of electric driving: the state of charge (SOC) of the battery, which depends on the battery capacity and the driving pattern from which the energy consumption of the vehicle is derived. Hereby, rolling resistance [29–31], aerodynamic drag [28, 29, 32], and acceleration [30] are taken into account. With high granularity of the driving data, acceleration can be derived from the speed. However, due to the distance of about 2 km between the pairs of consecutive GPS measurements in our data, such an approach would be rather inaccurate. A comparison of driving cycles [33] indicates that especially in urban areas cars accelerate and decelerate more frequently. Therefore, we use driving cycles (i.e., series of speed points versus time) for the estimation of acceleration and deceleration by replicating speed profiles from a database of driving cycles [34] that was built within the ARTEMIS project [35]. The ECE-15 and EUDC driving cycles refer to the urban and extra urban driving patterns respectively. The EMPA T130 is used for highway driving. We assume that with a negative total tractive effort caused by deceleration, 50 % of energy could be recuperated when braking [28].

The amount of charged energy depends on the state of charge, on the available charging power, and on the time a vehicle parks at the charging location. Only parking locations with a minimal parking duration of 15 min were considered for charging in our study. According to [36], 80 % of the of the total required charge will be provided in a linear way while the remaining 20 % require thrice the charging time.

4 Results

We compare scenarios where EVs are charged (a) only at home, and (b) at home and at a secondary parking location. We use parameters for our energy consumption model that roughly resembles a BMW i3. For our GPS driving dataset, we calculate an average energy consumption of 14.3 kWh per 100 km by applying the model from [28]. This slightly exceeds the official energy consumption of 12.8 kWh per 100 km according to the manufacturer, most probably due to the optimistic consumption statements that are based on the ECE test cycle [30]. For charging the simulated EV batteries, we assume a charging power of 3.7 kW (16 A) [30].

4.1 Shares of Electrically Drivable Distances and Gasoline Savings

Scenario 1: Charging at home. We found that *77 % of destinations could be reached electrically if the EVs are only charged at the estimated home charging facilities*. This corresponds to 63 % of mileage that could be driven electrically. In Fig. 1a) we provide a distribution of electrically driving shares, which indicates how many cars could reach what portion of mileage electrically. The remainder could be reached by means of a range extender, e.g., the commercially available one for the BMW i3 [30].

Our calculations indicate that the average driver could save 669 l or 59 % of required gasoline per year, if an electric engine was used instead of an internal combustion engine. Differences between electrically drivable mileage and gasoline savings indicate that variations in driving style (in particular long distance trips with higher speed) have to be taken into account when quantifying electric driving potential.

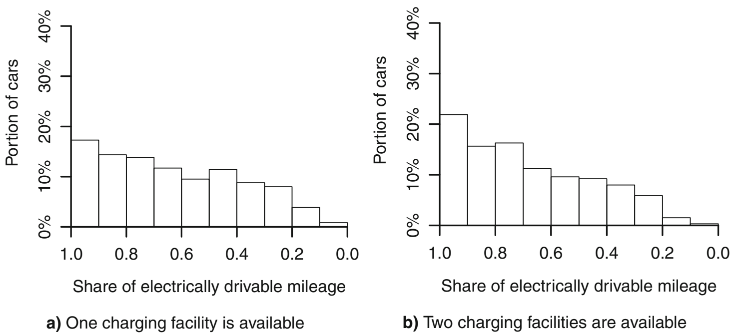

Fig. 1. Share of electrically drivable mileage

Scenario 2: Charging at home and at a secondary charging facility. In this case, *the percentage of reachable destinations rises to 83 %* and the share of electrically drivable mileage rises to 69 %. Figure 1(b) shows the corresponding distribution. The average driver could now save 741 liters or 64 % of required gasoline per year.

4.2 Grid Impact of Electric Vehicle Charging Demand

Recent studies have shown that future electric mobility can have a significant impact on the electric grid. With greater EV shares, the electricity demand grows. However, the main challenge in providing energy for electric mobility lies in increasing peak demand [37]. In particular, in the home charging scenario, demand for vehicle charging is typically higher during peak times in the evening [13, 14]. However, additional charging facilities at work can have a smoothening effect [11]. In this section, we calculate the grid impact of two considered charging scenarios.

Scenario 1: Charging at home. In our simulation, the average vehicle requires 5.3 kWh of energy per day when charging at home. In Fig. 2(a) we show how much energy is required at what time of the day. We can see the peaks at noon and in the evening, when people arrive home. In Fig. 2(b) we compare the weekdays and weekends and see that in general energy demand is lower during the weekend. In particular, demand peaks in the evening are considerably reduced.

Our estimates yield an *increase of electricity demand by 49 % in the EU domestic sector*. To calculate this, we used the average electricity consumption per household and year, which was 3’928 kWh in 2013 according to [38]. Divided by 365 (the number of days in year), it is 10.8 kWh per day. According to the report of the European Commission [39], the residential sector consumes 29.7 % of final electricity. Thus, the *overall increase of electricity demand would be about 15 %*.

Scenario 2: Charging at home and at a secondary charging facility. Average energy requirements for charging per car and day rise to 5.8 kWh in this case, including 4.6 kWh demand at the household side and 1.2 kWh at the secondary location. The EV *grid impact at home is decreased by 13 %* compared to Scenario 1. In Fig. 3(a) we

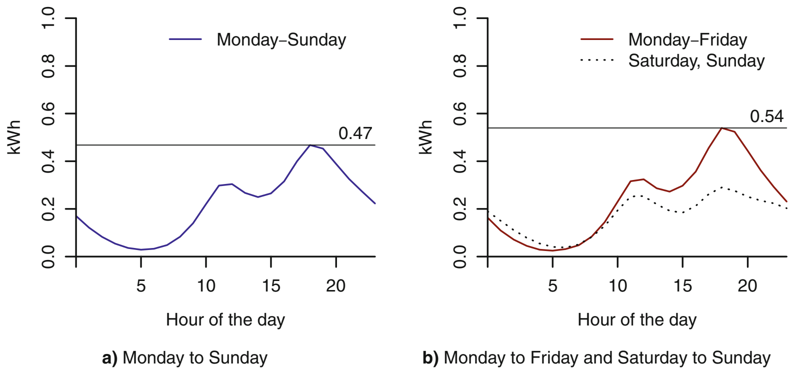

Fig. 2. Average energy needs when charging at home during the day

compare the daily energy demand at home and at the secondary charging facility. At the secondary facility, the peak energy demand is between 7 and 8 AM. The availability of a secondary charging facility also slightly reduces the peak charging demand in the evening. Figure 3(b) shows that daily energy demand is lower during the weekends and that the peak demand in the evening is smoother.

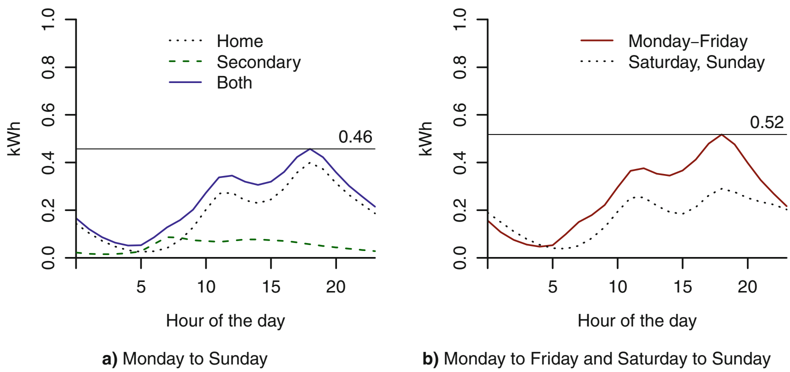

Fig. 3. Average energy needs when charging at home and at a secondary parking location during the day

4.3 Comparison of Charging Times and Sunlight Hours for Electric Vehicle Charging with Photovoltaic Panels

The introduction of EVs increases the utilization of local power generation from photovoltaic panels [40, 41]. Still, the increase is limited because there is a small correlation between photovoltaic power production patterns and plug-in hybrid electric vehicle charging patterns [42]. Analysis of GPS driving data enables us to provide an assessment of the potential of using energy from photovoltaic cells at home for EV charging without temporarily storing electricity. We use hourly historic irradiance data for the considered geographic region and time period, as provided by the MACC-RAD service [43] to determine average sunlight hours at the home bases.

Scenario 1: Charging at home. Our simulation shows that *about 47 % (44 %) of the time EVs charge (park) at home at sunlight*.

Scenario 2: Charging at home and at a secondary charging facility. About *72 % (68 %) of the time cars charge (park) at the secondary parking location at sunlight*, while 48 % (44 %) of the time they charge (park) at home at sunlight. This leads to the conclusion that solar panels can be particularly useful at secondary charging locations where drivers park during the daytime. The use of photovoltaic energy at home is also promising. However, the use of solar energy increases the importance of EV charging strategies that control flexible loads and keep the electric grid stable [44].

4.4 Impact of Charging Power on EV Reachability and Daily Energy Demand

In our assessment, we use the typical charging power values for the European EVs, which are 3.7 kW (16 A), 7.4 kW (32 A), and 50 kW (125 A) [30, 45]. As can be seen from Table 2, faster charging increases not only destinations reachability and electrically drivable shares, but also daily energy demand and evening demand peaks.

Table 2. Comparison of charging times for the average driver

Charging site	Home			Home and Secondary		
Power	50 kW	7.4 kW	3.7 kW	50 kW	7.4 kW	3.7 kW
Reachability	79 %	77 %	77 %	85 %	83 %	83 %
Driving Share	65 %	64 %	63 %	71 %	69 %	69 %
Daily Energy	5.6 kWh	5.4 kWh	5.3 kWh	6.3 kWh	6.0 kWh	5.8 kWh
Demand Peak	0.58 kWh	0.54 kWh	0.47 kWh	0.53 kWh	0.50 kWh	0.46 kWh
(Time)	(5–6 PM)	(6–7 PM)	(6–7 PM)	(5–6 PM)	(6–7 PM)	(6–7 PM)

5 Conclusion

In this paper, we use real-world GPS driving data from conventional vehicles, a density based clustering algorithm, and an energy consumption model to estimate the potential of electric driving. Our study shows that drivers who would replace their combustion engine car by an EV with an optional range extender could reach about 77 % to 85 % of destinations fully electrically. They could also cover about 63 % to 71 % of their mileage electrically, depending on the availability of charging facilities at home and at a secondary charging facility, and depending on the time required to charge the battery. By comparing parking and charging times with sunlight hours, we observe that there is sunlight about 44 % of the time when cars are parking at home and about 68 % of the time when cars are parking at their secondary charging facility. These results have some direct implications for future assessment of electric mobility, including the assessment of EV battery pack parameter requirements, charging facility parameter requirements, as well as the potential of using privately owned photovoltaic systems for EV charging.

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