

European electric vehicle fleet: driving and charging behaviors

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Abstract—The electrification of vehicles would be a reality in the coming decades. Statistical results on real electric vehicle usage data is a key point in the development of the electro mobility. A large collection of electric vehicles and charging points have been monitored during three years and the results about the driving and charging patterns are shown in this work. These results may help to develop future policies on, for instance, charging infrastructure location, end-users incentives, or to allow different type of economic analysis such as an evaluation of the electric vehicle integration in the grid, smart-charge impact...

I. INTRODUCTION

With growing concerns over climate change, the quality of air in urban areas and trade imbalances associated with the EU's dependence on imported oil, there is a drive towards alternative fuel sources for transport in Europe, championed by the European Commission. In general terms, mobility or transport data has been always expensive to gather and to analyze. The difficulties are even larger with the introduction of the electro mobility: there are few electric vehicles (EV) running around our cities or countries.

There are some studies which deal with the topic of the description of electrical driving and charging patterns. By means of sample travel surveys, Pasaoglu et al. (2013) aim to build a database of load profiles for EVs based on car-use profiles of current conventional fuel powered vehicles in six European countries. Pearre et al. (2010) also use data from 484 instrumented gasoline vehicles in the US to infer the range requirements of EVs. Other studies analyze the current existing EVs and charging infrastructure: Van den Hoed et al. (2013) give detailed analysis on the actual charge patterns on the public infrastructure in the city of Amsterdam with approximately 520 monitored CPs, while Ashtari et al. (2011) recorded vehicle usage data of 76 vehicles in a one-year period in Winnipeg (Canada) in order to predict plug-in vehicles charging profiles. In this lies the great importance of the data gathered for the analysis presented in the current paper. To the authors best knowledge there are currently no other studies with such amount of real, mature and representative data regarding electric mobility with a great variety of EV fleets and charging point (CP) locations within different regions in Europe.

During an extensive data collection period of three years, a heterogeneous fleet of electric vehicles and charging points have been monitored and their dynamic behavior has been registered. This fleet is distributed across ten European countries (Figure 1).

The aim of this work is to give some insights on into the behavior of early electric vehicle users. This data contains a great amount of information that could be used by users, manufacturers, utilities and regulators to enhance their knowledge about the electro mobility and to reach a large deployment of EVs. In the following sections the data collection is described, the users' behavior in terms of driving and charging is statistically illustrated and finally a set of four patterns are described.



Figure 1. Demonstration region location

II. DATA COLLECTION PROCESS AND SAMPLE CHARACTERIZATION

During three years (from 2011 to 2013) static and dynamic data on both electric vehicles and charging points have been reported by the different demonstration regions on a monthly basis. Each of the mentioned elements has a unique identifier also reported in every recorded associated event. Note that there is not a mandatory relationship between registered EVs and CPs, i.e. monitored elements interact with other running EVs or charging infrastructure not being monitored within the project.

Table 1 describes the sample size, indicating the registered number of CPs and EVs, which reported data on trips and charge events via on-board logging equipment. A total amount of more than 140,000 trips and more than 230,000 charging events were registered during the data collection period. The EV fleet comprised cars, transporters, bus and motorcycles and both pure battery and plug-in hybrid electric vehicles. This paper focuses on the pure battery EVs and passenger vehicles (cars) which represent 81% of the total. On the charging point side, the 95% of them were slow-charge and these are the ones included in this work.

Table 1. Sample characterization

	Registered		Total uses
Charging points	2,672	Charge events	129,726
Electric vehicles	689	Trips	94,488
		Charge events	77,620

There are some key variables to identify patterns and detect differences among the monitored elements. Within the EV fleet, the ownership (private owner, private company or municipality) and the use (private use, business use, renting or captive fleet) were specified. The majority of the vehicles (63%) are owned by private customers and nearly 62% of the EVs are used for business purposes. Within the CP, the location is the key descriptive variable and the most prevalent location is the street accounting for 64% of all installed infrastructure. There were also CP monitored located in households, public access and office parking.

All the gathered data have been studied with the aim of describing EV consumer profiles and building accurate driving and charging patterns. In order to gain knowledge of the vehicle performance in different situations factors such as geographical location, EV ownership, EV usage or CP location have been taken into consideration. Following, some of the main findings are presented; firstly, results derived from the analysis of

data belonging to electric vehicles and secondly from data corresponding to charging points. Finally, a sequence analysis to identify and characterize charging, driving and parking patterns is carried out.

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III. DRIVER BEHAVIOUR

A. Distances run

Electric car range is one of the most important concerns among potential purchasers. It was found in a study for 6 EU member states that daily driven distances among ICE vehicles vary from 40km to 80km, distances that can be comfortably covered by EVs (G. Pasaoglu et al. (2012)). Actually, for a fully charged standard battery of 16kWh, the average mileage of the electric vehicle is around 100km.

In our fleet 75% of the cars run a daily distance shorter than 47km. Table 2 shows the mean distances per trip, the daily driving distance and the distance since last charge by EV ownership and use. Longest distances belong to renting EVs (a daily average of 66.5km), who also drive further between charging events. On the other hand, captive fleet usage EVs drive significantly shorter trip distances (3.1km per trip).

Table 2. Travelled distances

		Trip distance (km)		Daily distance (km)		Distance since last charge (km)	
		N total	Average	N total	Average	N total	Average
Owner	Municipality	46,954	4.4	46,954	40.5	5,331	27.6
	Private company	37,406	7.7	37,406	31.3	6,966	31.2
Use	Business use	20,374	8.1	20,374	29.3	5,007	30.6
	Captive fleet	41,956	3.1	41,956	33.1	3,986	19.6
	Private use	10,732	7.4	10,732	34.3	1,959	32.7
	Rental	4,998	14.9	4,998	66.5	1,345	52.4

Note: this information is not available for private owners.

Correlated with the distance between charges, the time between charges arises. The distribution of this variable seem to illustrate periodic patterns with peaks every 24 hours, which means that, independently to the use and owner, the car is charged every day, two days, ...

B. Battery usage

The state of charge (SOC) of a battery provides indications on how range anxiety affects the users, helps understanding charging and trip patterns and gives information about range mileage limitations. It has been seen that the average state of charge before starting a charge event is around 60%, which means that users do not tend to drain their battery storage limits connecting the vehicle as soon as they have the opportunity and not only when battery levels are low. Table 3 depicts, for every studied type of EV owner and EV use, the average initial SOC and the percentage of registrations with an initial SOC smaller than 20%, both for charge and trip events. It can be seen that renting cars tend to drive more often with very small storage levels, nonetheless, the average percentage of users starting a charge or trip event with a battery storage level lower than 20% is, in general, very low (less than 5%).

Table 3. Travelled distances

		Charge			Trip		
		N total	Average Initial % SOC	Initial % SOC<20	N total	Average Final % SOC	Final % SOC<20
Owner	Municipality	7,885	63.8	3.50	39,620	74.5	0.90
	Private company	10,350	61.5	4.10	5,187	75.2	1.10
Use	Business use	7,138	62.7	3.90	5,187	75.2	1.10
	Captive fleet	5,870	64.2	2.30	34,622	75.5	0.50
	Private use	3,212	58.6	4.80			
	Rental	2,015	62.5	7.10	4,998	67.2	3.40

Note: this information is not available for private owners.

Furthermore, for a wider EV penetration and in order to estimate the future distribution grid impact the energy consumption from the grid during the charging process has been also analyzed. The average consumed energy for each charging event corresponds to 7.08kWh, but this result is highly influenced by the variables studied: municipality fleets consume 5.52kWh in average, private companies 6.85kWh and private owners 8.82kWh.

IV. CHARGING BEHAVIOUR

In this section, data belonging to charge events is analyzed. This type of analysis is very useful since the identification of charging patterns can help to optimize the use of the charging infrastructure and to estimate the future impact on the power system: the EV users charging schedule will have consequences on the electric load profile. These data is analyzed from two different points of view: analyzing differences among a set of owners and usages and analyzing patterns by charge point location.

A. Charging profile for different electric vehicle owners and use

Figure 2 shows initial charge times for a subset of different EV owners and usage. The distribution of start charging times for private owners who use their EV for private purposes show more frequency during the afternoon, mainly when the work day is finished. On the other hand, the distribution of captive fleets belonging to municipalities shows a bimodal distribution with peaks in the morning and late in the evening. Finally, for private use EVs owned by private companies, the initial time for charging the vehicles seems homogeneous (except from early morning hours), showing a much flatter distribution than in the other cases. After a wider analysis, it is concluded that charge start time is clearly related with EV ownership and use.

Charging times length distribution plays an important role into charging infrastructure deployment. It mainly depends on the CP location, the CP power, the battery technology and the storage level of the EV. Analyses show that the average plug-in time of electric cars is 4h and 53min.

Another important issue to be considered for the electrification of the fleets is the utilization and effectiveness of the installed charging infrastructure. A good indicator for studying this new problem could be the percentage of the plug-in time which is indeed used to charge the EV, depicted in Figure 3. Among all types of EV owners and use, the average connection time is approximately 5h, from which the EV is actually being charged an average of 2h 20 min. That is, on average an EV is being charged approximately 48% of the time that it is connected to the charging point. It can be observed that longer parking times without charging the vehicle are given from midday until the end of the day. This kind of analysis can help to optimize the charging infrastructure utilization by including, for instance, penalization fees for long parking times without grid consumption.

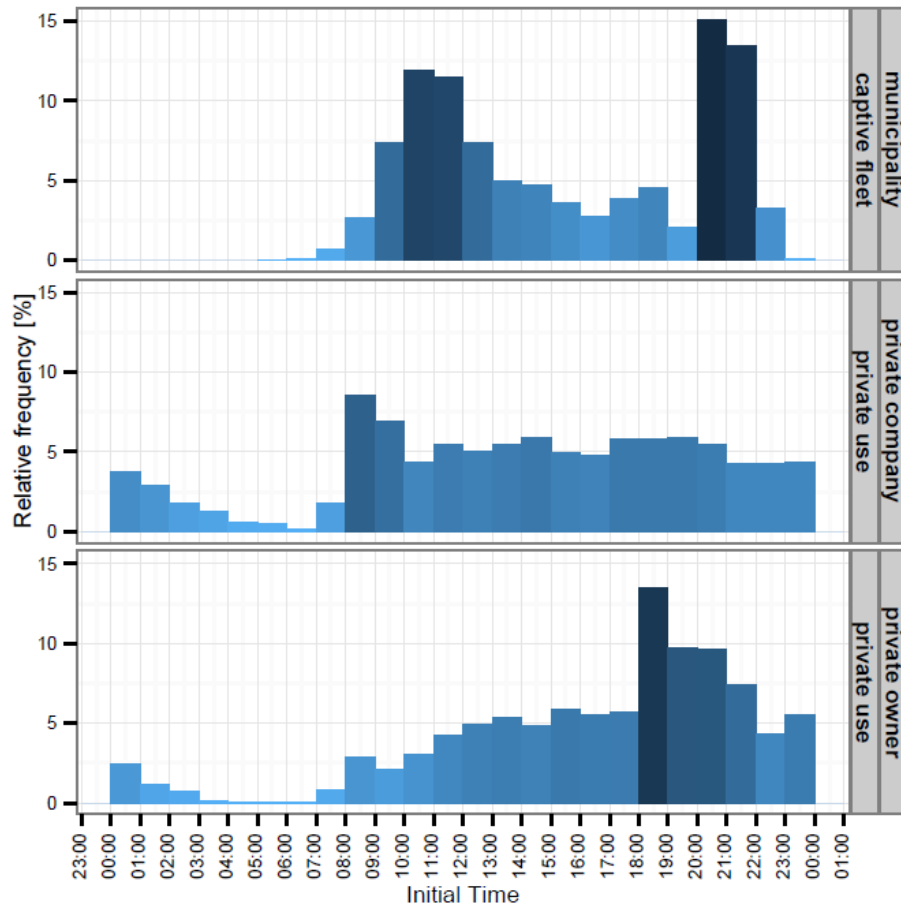


Figure 2. Histogram of relative frequency, charge start time by EV ownership and use.

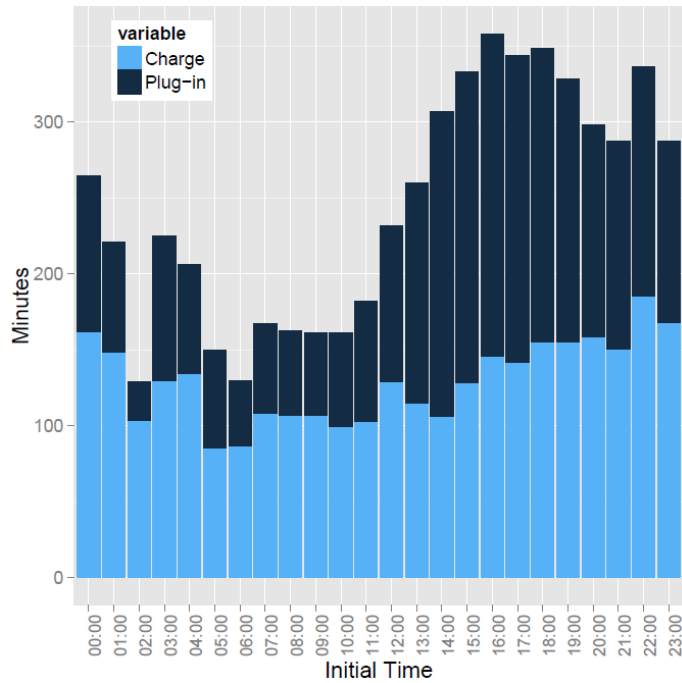


Figure 3. Barplot, average daily plug-in time versus real charging time.

B. Charging profile by charge point location

It is of great interest to analyze the different EV user behavior depending on the CP location. In the future, the most common location to charge EVs is likely to be in households; however the availability of public charging infrastructure is necessary to ensure widespread adoption of EVs (Westminster City Council (2009)).

Table 4 describes the number of CPs participating in the data collection by its location, their number of uses, the daily percentage of utilization and the daily energy consumption. Although publicly accessible CPs are the most registered (70%), only 29% of the uses, that is of the charges, are carried out in these type of CPs locations. It also shows that charging infrastructure located in public parking locations were in average the busiest, i.e. plug-in times where longer (21% of the time which corresponds to approximate 5h per day). Highest daily energy consumptions during charging processes are given in households and public parking locations with nearly 9kWh.

Table 4. Charging point usage

	N (%) Installed	N (%) Uses	% Daily utilization*	Daily energy consumption [kWh]
Household	134 (9%)	24830 (31%)	15%	8.84
Office parking	323 (21%)	32149 (40%)	17%	7.42
Public parking	63 (4%)	1132 (2%)	21%	8.89
Street	1011 (66%)	21544 (27%)	16%	6.72

*Only days with at least one charging event registered.

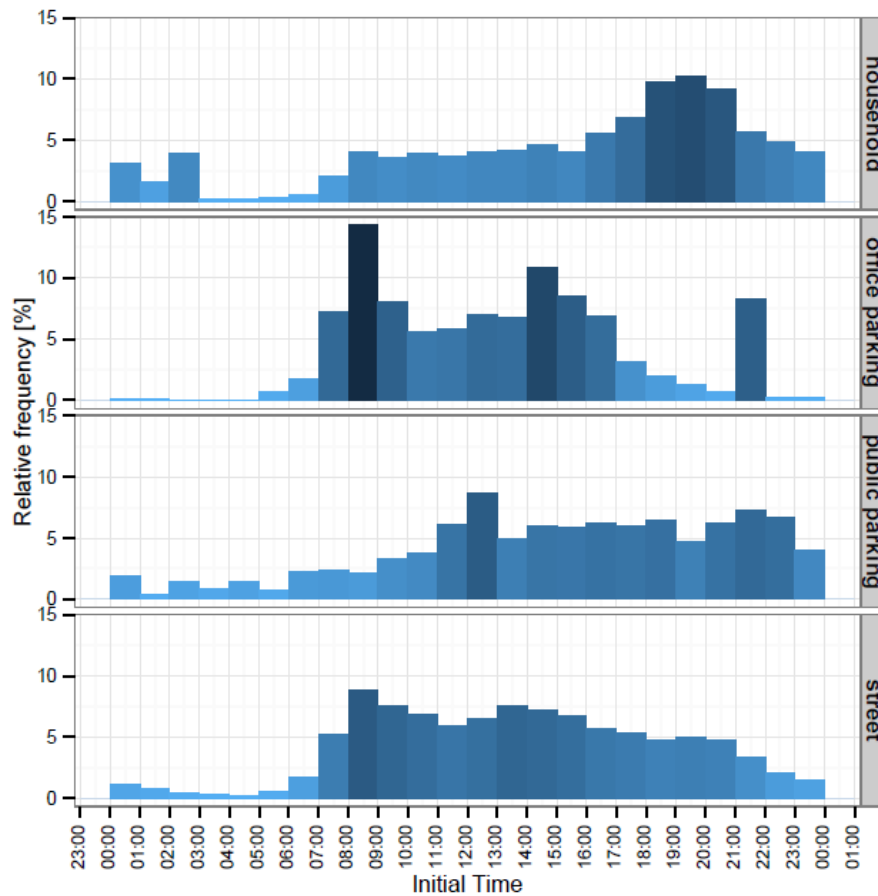


Figure 4. Histogram of relative frequency, start time by CP location.

As in Figure 2, Figure 4 represents the starting time distribution but for each type of charging infrastructure location. Private charging points located in households show higher frequency of charges during evening hours with respect to the other possible CP locations. Initial charging times for charge spots placed in office parking

follow a bimodal distribution with two prominent peaks in rush hours (8a.m and 14p.m), similar as in the case of street stations but where the distribution acquires a flatter shape.

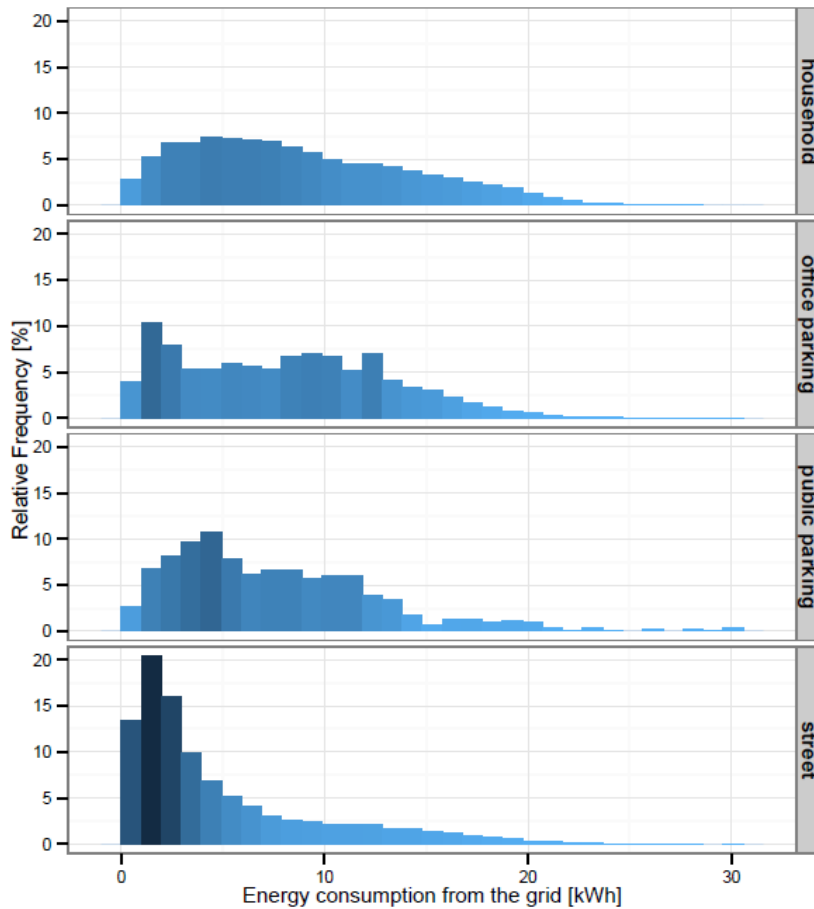


Figure 5. Histogram of relative frequency, energy consumption by CP location.

Figure 5 depicts, for a total of 56279 observations, the energy consumption distribution depending on the charging point’s location. It can be seen that charging processes in the street with small energy consumption are clearly more frequent. Actually, the average energy consumption from the grid for every charge event carried out in the street is 4.91kWh, while the average consumption in other locations is significantly higher, between 7.57kWh and 8.73kWh. Charge times duration distribution are similar among CP locations, although there is a higher frequency of shorter charges on street CPs. Longer charge time durations are given in office parking and public access parking facilities, both with an average of 4h and 19min per charge event. On the contrary, EVs charging in street locations registered the shortest charging times (nearly 3h).

V. CHARGING, DRIVING AND PARKING DAY PATTERNS

Finally, an analysis which classifies data as sequences of daily charging, trip and parking events is here presented. Prior to that and in order to enrich and improve the operativeness of the analysis, first a typology to characterize charge and then trips registers is defined. An agglomerative hierarchical clustering analysis which gathers data into groups with similar patterns has been computed and the resulted dendrogram suggested the classification of the charge events into three groups.

Figure 6 depicts the initial state of charge of 12371 registers and its increment clustered into low, medium and high charging levels. A noticeable diagonal is observed since most of the charging processes end with a fully charged battery. The low charge group tends to have an elevated initial SOC (an average of 82.9%) with the lowest SOC increment (15%) which means that small quantity of energy is being recharged. On the opposite, the high charge cluster has the lowest initial SOC (34.9%) but with the highest SOC increase (51.3%) which implies that charging events belonging to this group require high energy demands. The medium charge level

has an average initial SOC of 55% and a SOC increment of 26%.

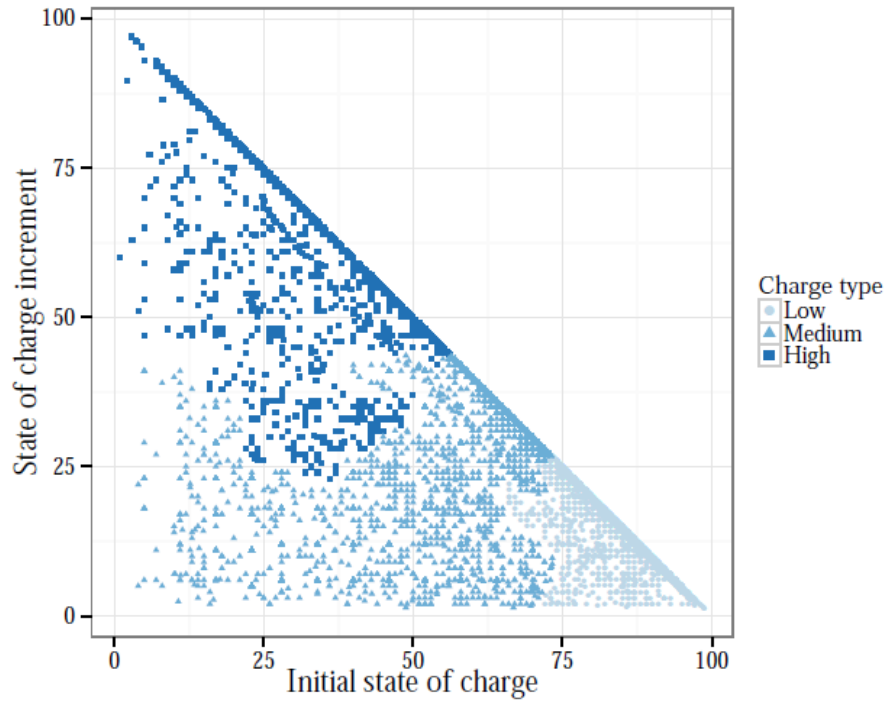


Figure 6. Scatter plot of initial SOC vs SOC increment by charge type.

In the case of the registered trip events, its diversity can be mainly described by the run distance and the average speed during the trip, as plotted in Figure 7. Analogously, a similar cluster technique has been applied to define the trip typology and the result also suggests the classification into three groups. The Figure shows the classification of 57604 trips events. Short-slow labeled trips are the shortest (with a mean distance of 3.9km) and the slowest (3.7km/h on average), while long-fast trips are significantly longer and faster (22.7km and 52.1km/h, on average respectively). An additional average trip category has values in between the previous mentioned levels.

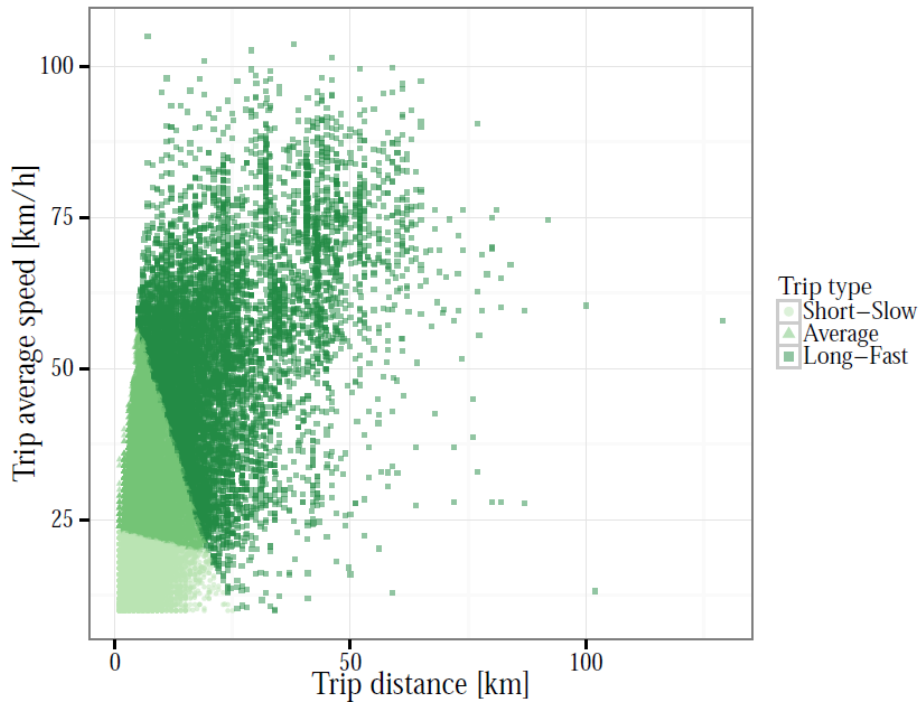


Figure 7. Scatter plot of trip speed vs trip distance by trip type.

To complete the typology analysis, a daily sequence for each of the main patterns found has been computed. First, the distance between day sequences (charge, trip or parking) has been calculated and then an agglomerative hierarchical clustering using the dissimilarities has been used to gather these sequences. Although day sequences form several sub- groups due to high variability among sequences, the daily typology can be classified into four main patterns.

Figure 8 describes the day state distribution of the sequences of these four patterns detected. Day pattern 1 is characterized by homogeneous significant low activity both in terms of trip and charge events where parking state clearly predominates along the day. It is, in fact, similar to day pattern 2 but this one presents higher charging events during daylight time. Pattern 3 is characterized by high energy charges during afternoon and evening hours and approximately equal distributed short-slow, average and long-fast trips, with lower occurrences during nighttime. Nonetheless, in day pattern 4 night high energy charges are clearly preferred. The correlation of these patterns with its descriptive analysis allows an identification of clusters of early users of electric vehicle.

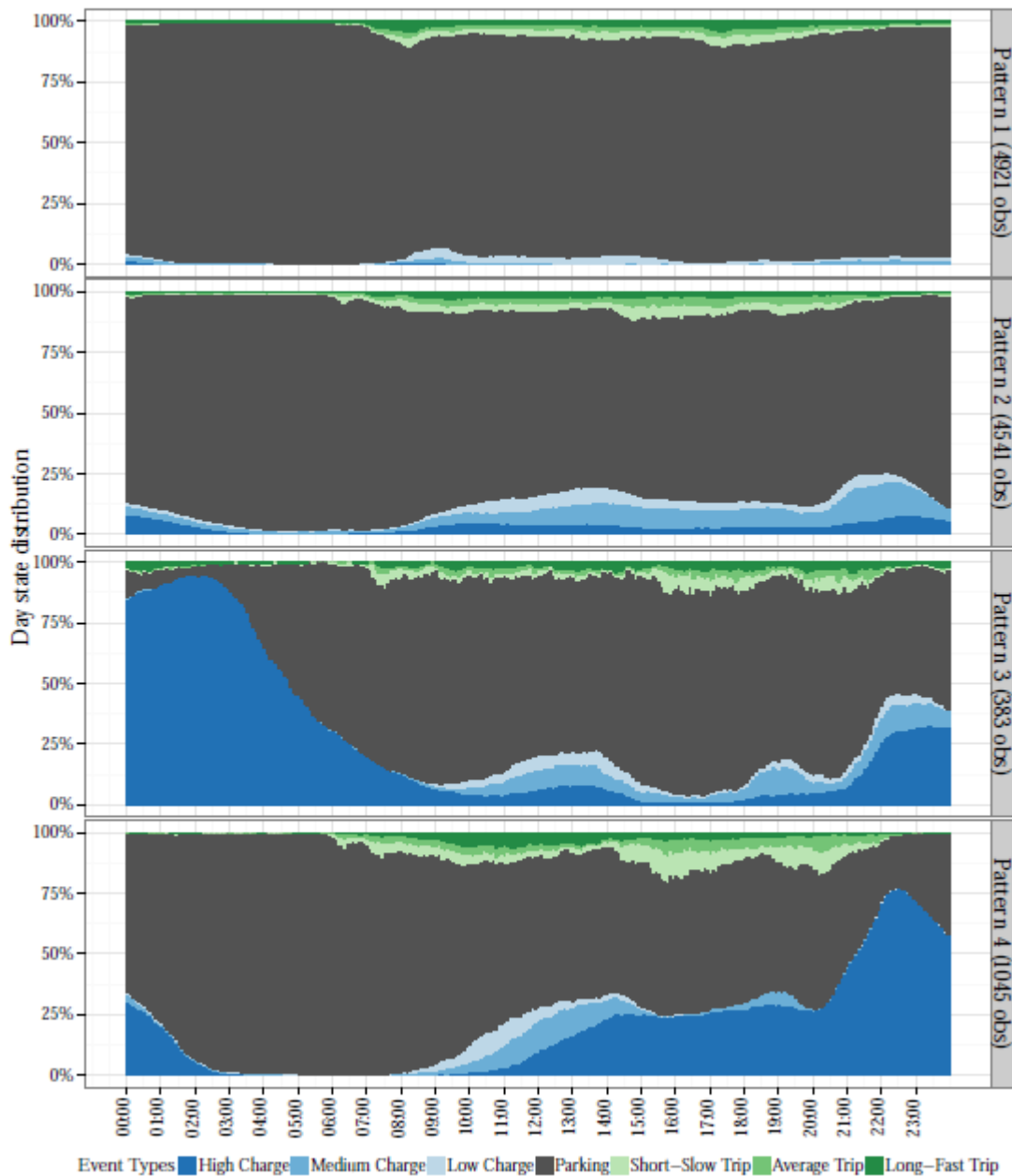


Figure 8. Day patterns, state distribution plot.

VI. CONCLUSIONS

During three years, a set of charging points and electric vehicles around ten European demonstration regions have collected data on a monthly basis. During this work, these registers have been analyzed and results have been evaluated. Since there are many studies that try to foresee the charging and trip patterns of EV users, the work presented here is very valuable given that analyzed data come from real charging and trip events of current existing EVs. Data on electric vehicles (for both trip and charge events) and later on charging points have been considered. In general, charging start times tend to be uniform with some peaks in rush hours, they depend on CP locations and EV ownership and use. Actually, EV ownership and usage purposes are key variables to detect differences among the monitored elements behavior. In terms of mileage, it has been observed that the average daily driving distance is 40km and the expected distance since last charging process is approximately 30km. This indicates that range anxiety should be limited to punctual long trips and not to everyday journeys. It has been also proved that CP location has a great influence on consumed energy and charge duration. Parking times have a significant influence on charging behavior and those depend on the points of interest located in the nearby of the charging stations (Wagner et al (2013)).

During this work, the difference in the impact on CO₂ emissions between EVs and conventional fuel powered cars has been also evaluated. The quantity of CO₂ saved is calculated as the difference between the amount of CO₂ emitted in order to produce the electricity needed to charge the EV (given the official electricity production mix of every participating country) and the CO₂ emitted by the average EU fleet of combustion vehicles, given the travelled distance. More than 380,000km¹ was driven during these three years, which represents nearly 26 tons of greenhouse gas emissions saved. Overall, the CO₂ emitted to produce the necessary electricity to run EVs is approximately 50% lower than the emissions produced in the case of conventional fuel powered cars, for the same travelled distance.

The results of this study have already been used in some studies. Del Rosario et al (2014) used the charging profiles resulting on the analysis to evaluate smart-charging applications and its impact in the distribution network congestion management. Benveniste et al (2014) used data from charging events and trip consumption to calculate the potential externalities savings due to electric vehicle smart charge.

As stated before, this comprehensive study and its results can help planning authorities, investors, infrastructure and energy suppliers, policy makers... to evaluate the future viability of the EV deployment. Results on charging and trip behavior can be regarded as a benchmark to develop a method to derive the future charging infrastructure as well as to evaluate the EV integration into electrical grids, for a higher EV penetration.

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¹ Note that not every EV recorded travelled distances. This means that the real greenhouse gas emissions saved are higher than the estimated.

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