On the Challenges of Charging Electric Vehicles in Domestic Environments

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ABSTRACT

This poster abstract presents a case study of charging Electric Vehicles (EVs) at home, taking into consideration the household power consumption and the vehicle driving routines of the residents. It reveals some challenges of charging EVs in the household and highlights the importance of proper charging scheduling in order to avoid potential tripping of the household circuit breaker.

CCS CONCEPTS

• **General and reference** → *Measurement*; *Experimentation*; *Estimation*;

KEYWORDS

Electric Vehicle, Household Consumption, Charging Scheduling

1 INTRODUCTION

Domestic households typically have a limit of maximum instantaneous power that can be drawn, which is determined by the contract between the household and the electricity supplier. Thus, as Electric Vehicles (EV) become more prominent, it is necessary to ensure that EV charging at the home does not cause power outages, due to excess power being drawn from the electric installation.

Still, while several studies (e.g., [1, 4, 11]) have been carried out for planning the schedule of EV charging at the micro or macro-grid level, we have not yet found such studies conducted at individual household level. In this poster abstract, we present a case study, where we simulate the charging of two EVs in a household environment, based on the analysis of the household power consumption, and the driving routines of the dwellers. Our objectives are two-fold: i) understand how the driving routines affect the charging needs, and ii) understand how the charging of EVs may affect the stability of the domestic electric circuit.
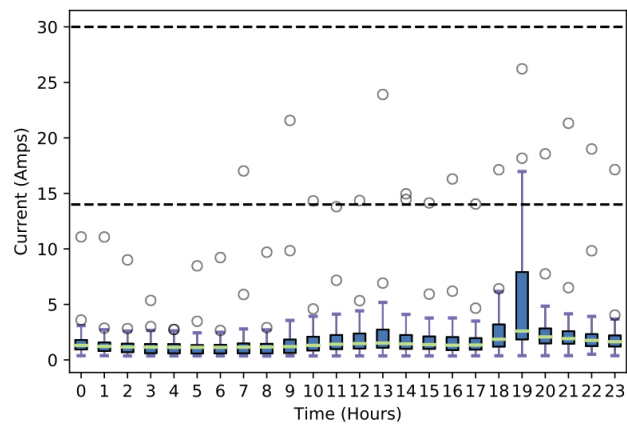
Figure 1: Hourly distribution of the current RMS. The dashed lines represent the 16A required to charge an EV.

2 DATA COLLECTION AND SIMULATION

2.1 Household Consumption Data

For this simulation, we consider a household in the city of Funchal, Portugal. The household has an electricity power contract of 6.9 kVA (30A at 230V), and it is constituted by three adults. Two members commute to work from Monday to Friday, while the third one is a house worker. The electric energy usage of the selected household was monitored between the 28th of October 2016 and the 9th of January 2017, at the frequency of 1/60Hz. Each measurement consists of a timestamp, current, voltage, active and reactive power.

Figure 1 shows the box-and-whiskers plot for each hour of the day, using the current (Amps) as the baseline metric.

2.2 Electric Vehicle Models

Currently, there are no EVs in the household. Instead, we assume that the EVs are two Renault Zoe (model R90), with a nominal energy capacity of 22 kWh since, this is the best selling EV in the region [10]. This model can be charged in the household using 10A or 16A sockets. The former takes about 13H30 to fully charge the battery, whereas the latter takes about 7H55 [7].

2.2.1 Driving Routines. Based on informal conversations with the two drivers, it was possible to compile driving routines for each EV, on a daily basis. Table 1 (appendix A) shows a summary of the expected weekly driving for each EV, with the respective probability.
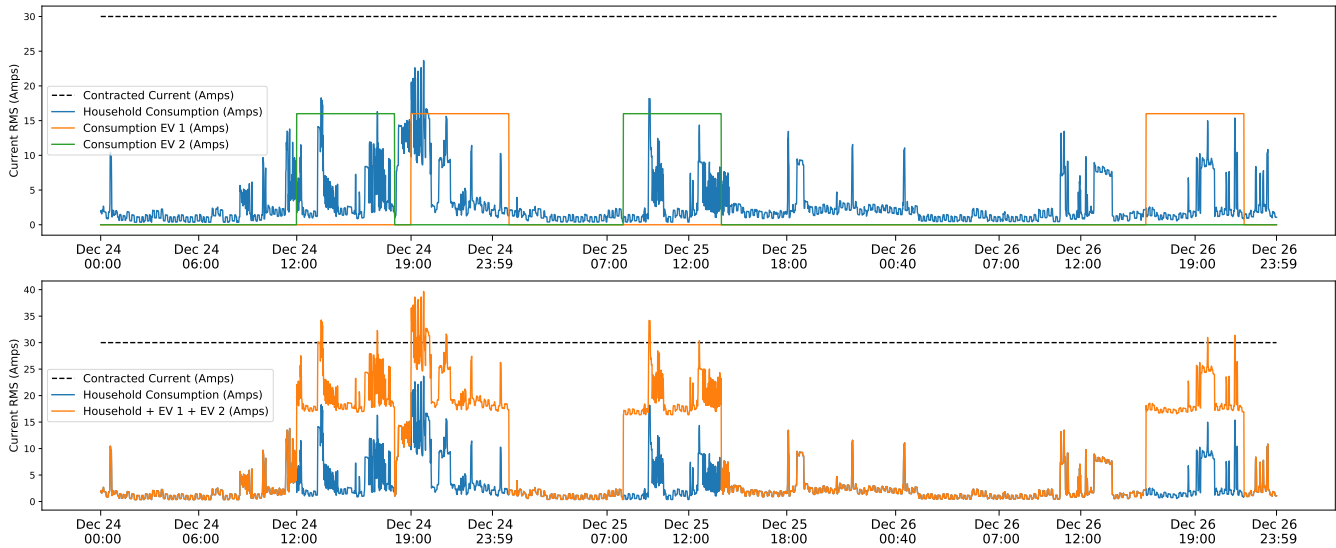
Figure 2: Electricity consumption without (top) and with (bottom) the charging of EVs during Christmas (weekend).

2.3 EV Commuting and Charging Simulation

Using the driving routines and household consumption data, we ran a simulation to get the necessary data for this case study.

2.3.1 Assumptions. The following assumptions were made: i) A fully charged battery is enough for 202 km (both drivers' speed limit is 50 km/h [6]), ii) Charging is done at 16A and its duration is linear with the required charge, ii) EVs start simulations with the batteries fully charged and cannot charge simultaneously, iv) From Monday to Thursday, charging can only happen between 7 PM and 7 AM, v) From Friday to Sunday, EVs can be charged anytime between Friday 7 PM to Monday 7 AM, and vi) If both EVs have to charge on the same day, we estimate the time available for charging and divided it equally among the EVs.

2.3.2 Simulation. Three simulations were conducted by generating the daily commutes for each EV in km and changing the percentage of energy that must be in the battery at the beginning of the next day. Regarding the energy consumed from the battery, 25%, 50%, and 75% were selected to simulate when EVs need battery recharge. For each of these values, five simulations were in the monitoring period. Concerning the charging process, we tested every possible combination in the allowed time interval and recorded the number of times that the drawn current was above the 30A threshold. Whenever there was not enough time to fully charge an EV this event was flagged. As a practical example, if an EV needs 4 hours of charge (240 minutes), and this can be done any time between 7PM and 7AM (12 hours - 720 minutes), we tested the $720 - 240 + 1 = 481$ possible time slots.

3 RESULTS AND DISCUSSION

For each simulation we analyzed: i) the number of days that EVs needed a recharge, ii) number of days where issues occur while charging, and ii) number of weekend days that EV charging was requested. The results are summarizes in Table 2 (appendix B).

As expected, most problems happened when it was necessary to charge after only 25% of the battery capacity was used. These issues occurred mostly on weekends since no restrictions were made on the allowed time-slots. Further analysis revealed that the periods with higher chances of going over the contracted power happened on weekdays between 7 PM and 8 PM. To illustrate the jeopardizing effect, figure 2 shows a comparison of the household electricity demand with and without charging EVs, for the period of December 24-26 of 2016 (Saturday, Sunday, and Monday).

Ultimately, our study indicates that it is necessary to plan and schedule the use of electrical appliances once the EV charging is introduced into the households in order to prevent any potential tripping of the electrical circuit.

4 LIMITATIONS AND FUTURE WORK

There are a few limitations that should be addressed in future iterations of this work.

First, linear loading times are assumed to simplify the simulation. Since this is not the case in real-world, in future iterations submetering should be employed to gather more realistic charging times. Second, although the average speed of 50 km/h is a fair assumption in this study, it may not be the case in other scenarios. As such, one possible improvement would be to monitor the actual driving routines using smartphone applications (e.g.,[3, 5, 8]).

Regarding the actual simulation, future work should also consider producing different combinations of charging thresholds as this is highly dependent on driver preferences. Furthermore, individual appliance consumption information can be used to improve the scheduling as many of the peaks in consumption happen only when some appliances are switched ON. Thus, by inferring when such appliances will be used (e.g., [2, 9], it should be possible to briefly disable EV charging.

A DRIVING ROUTINES

Table 1: Distance covered by each EV with the respective probability shown in parenthesis.

	EV 1		EV 2	
Distance Mon.-Fri. [km/d]	12 (.40)	18 (.60)	20 (.95)	60 (.05)
Distance Sat.-Sun. [km/d]	25 (.50)	12 (.50)	6 (.75)	20 (.25)

B SUMMARY OF RESULTS

Table 2: Average results of the five simulations per threshold (25%, 50%, and 75 %). The data represents the number of days that each EV (or both) requested charge, the number of days when problems can occur if the charging is not correctly scheduled, and the number of days that corresponds to weekends (from 7 PM on Friday to 7 AM on Monday). Comparing the three different thresholds, it can be observed that when only a short percentage of the stored energy can be used (25 % simulation), more charges are required. In contrast, when an EV is allowed to almost fully discharge the battery (75 % simulation), the number of charges required decreases considerably.

25% Threshold			
	Requested Charges	Total Problems	Problems on Weekend
Car 1	14 ± 3	8 ± 1	7 ± 1
Car 2	15 ± 2	5 ± 1	2 ± 1
Both	4 ± 2	1 ± 2	1 ± 2

50% Threshold			
	Requested Charges	Total Problems	Problems on Weekend
Car 1	8 ± 1	4 ± 1	4 ± 1
Car 2	9 ± 0	2 ± 0	1 ± 0
Both	0 ± 0	0 ± 0	0 ± 0

75% Threshold			
	Requested Charges	Total Problems	Problems on Weekend
Car 1	6 ± 1	3 ± 0	2 ± 0
Car 2	6 ± 1	2 ± 0	1 ± 0
Both*	0 ± 0 *	0 ± 0*	0 ± 0*

* Simultaneous charging was only required 4 times. In 2 out of the 4 occasions, it was not possible to fully charge both EVs.

C RESOURCES

The consumption data, simulation source code, and simulation results can be found at the following web page: https://www.alspereira.info/pubs/e-energy-2018/.

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