A statistical analysis of EV charging behavior in the UK

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A Statistical Analysis of EV Charging Behavior in the UK

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***Abstract*—To truly quantify the impact of electric vehicles (EVs) on the electricity network and their potential interactions in the context of Smart Grids, it is crucial to understand their charging behavior. However, as EVs are yet to be widely adopted, these data are scarce. This work presents results of a thorough statistical analysis of the charging behavior of 221 real residential EV users (Nissan LEAF, i.e., 24kWh, 3.6 kW) spread across the UK and monitored over one year (68,000+ samples). Probability distribution functions (PDFs) of different charging features (e.g., start charging time) are produced for both weekdays and weekends. Crucially, these unique PDFs can be used to create stochastic, realistic and detailed EV profiles to carry out impact and/or Smart Grid-related studies. Finally, the effects of the EV demand on future UK distribution networks are discussed.**

***Index Terms*-- Electric vehicles, real data, statistical analysis.**

I. INTRODUCTION

The increasing adoption of electric vehicles (EVs) in the UK is expected to increase given their potential contribution to reduce greenhouse gases and dependency on fossil fuels [1]. This, nonetheless, may significantly stress the electricity network. If integrated efficiently, however, EVs could be used as a crucial resource in the context of Smart Grids [2]. To truly quantify the corresponding impacts or benefits it is, nonetheless, critical to understand the charging behavior of EV users. However, as EVs are yet to be widely adopted, these data are currently scarce or limited to small samples [3].

The demand from EVs is a stochastic variable difficult to model given that it depends on customer behavior. Initial works have used Travel Survey data (e.g., [4]) to understand how consumers drive traditional combustion engine vehicles to estimate how they might drive an EV. However, EV users may exhibit new behaviors given that they are capable of 'refilling' (charging) the battery at home, instead of going to petrol stations. Recent studies have used data from small-scale EV trials to model the EV demand (e.g., [3, 5, 6]). These studies have achieved their goal; however, the EV models produced may be limited to the particular set of EV users which were used to create them.

Therefore, it is clear that EV data from large-scale trials is needed to truly understand the charging behavior of a more diverse population of EV users. This in turn will benefit the corresponding analysis required to truly quantify the impact of EVs on the electricity network (e.g., [7]) and their potential interactions in the context of Smart Grids (e.g., [6]).

This work provides a set of results from a thorough statistical analysis of more than 200 Nissan LEAFs [8] used by residential UK customers (i.e., 24 kWh battery capacity, 3.6 kW demand), which have been monitored during the 'My Electric Avenue' project [9]. More than 68,000 charging events have been recorded over one year since Dec 2013. For each EV charging event, the onboard monitoring system records the start time, end time, initial state of charge (SOC), and final SOC [8]. Probability distribution functions (PDFs) are presented here from these metrics. No significant variance in the charging behavior of EVs across seasons was found; charging across all four seasons is considered. The analysis includes both weekdays and weekends. By combining the data from these unique PDFs, researchers can create stochastic, realistic and detailed profiles to adequately model the EV demand in a straightforward manner. Finally, the potential implications of EV demand on UK networks are discussed.

This paper is organized as follows. Section II creates the PDFs for the charging metrics required to model the EV demand. Section III presents the methodology to create stochastic, realistic and detailed profiles to adequately model the EV demand. Section IV analyzes the implications the EV adoption may have in the aggregated demand in UK networks, particularly in residential low voltage networks. A discussion is provided in section V and conclusions are drawn in section VI.

II. PROBABILITY DISTRIBUTION FUNCTIONS

This section details the creation of weekday and weekend PDFs for the number of connections per day, the start charging time, the initial SOC, and the final SOC.

It is known that EV users may require a period of time to familiarize themselves with the EV and establish their own charging needs. Indeed, an initial analysis found that charging behavior shows a more predictable pattern after one week, i.e., EV users understand how the battery level meets their driving requirements. Hence, the corresponding charging events (< 2%) are excluded from the analysis below.

A. *Number of Connections per Day*

The number of connections per day presented in Table I highlights that circa 70% of the EVs are connected only once

This work has been funded by EA Technology Limited, UK, through the Ofgem's Low Carbon Networks Fund Tier 2 Project "My Electric Avenue", 2013-2015.

TABLE I. PDF OF THE NUMBER OF CONNECTIONS PER DAY (%)

No. Conns	1	2	3	4	5	6	7+
Weekday	71.26	21.15	5.41	1.51	0.44	0.14	0.09
Weekend	68.99	21.51	6.62	1.90	0.63	0.24	0.11

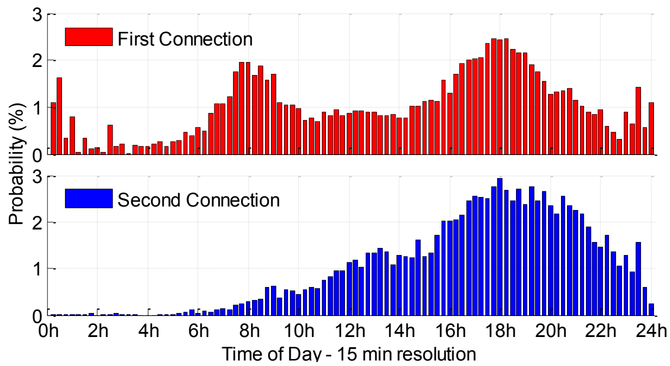

Figure 1. PDF of the start charging time per connection – Weekday.

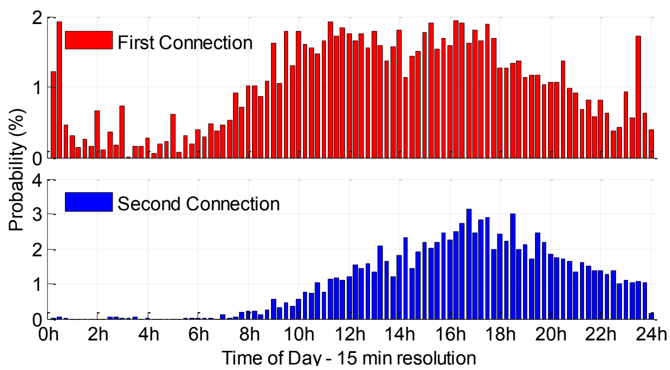

Figure 2. PDF of the start charging time per connection – Weekend.

a day, irrespective of weekday or weekend. Previous EV studies have not explored multiple charging events, and as such this finding is unique. Although this may not have a significant impact in the magnitude of the evening peak (as detailed in section III), it does affect the morning peak as well as the overall energy consumption. Since three or more connections are unlikely, and for simplicity, only two connections are studied below (the second is the aggregation of the rest).

B. Start Charging Time

Fig. 1 and Fig. 2 show the PDF per connection of the start charging time for weekday and weekend, respectively. As expected, EV users vary their start charging time. Overall, the first EV connection may occur any time during the day. Nonetheless, a second is more likely to occur after midday. During weekdays, the first connection usually starts around 8h (before work) or 18h (after work); the second connection typically starts at 18h. This highlights that a number of EVs are charged at home before and after work. During weekends, the first connection usually starts between 9h and 18h and the second later in the evening. No significant differences were found among weekdays (i.e., Monday–Friday) and among weekends, though this is not shown in Fig. 1 and Fig. 2.

C. Initial and Final SOC

The initial and final SOC depend on the number of connections and the time of the day. For instance, an EV charged overnight that is used in the morning for a short trip will have a relatively high initial SOC for the next charge. However, initial analysis highlights that time-dependency is not significant; then, this work focuses on the number of connections.

TABLE II. PDF OF THE INITIAL AND FINAL SOC PER CONNECTION (%)

Units	Weekday				Weekend			
	Initial SOC		Final SOC		Initial SOC		Final SOC	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd
0	0.57	0.91	0.00	0.05	0.67	1.21	0.03	0.02
1	3.52	4.23	0.15	0.28	3.74	5.28	0.10	0.44
2	8.38	7.55	0.39	0.96	7.45	8.68	0.53	0.81
3	11.75	9.59	0.74	0.89	9.45	9.91	0.62	0.79
4	11.86	9.51	0.78	1.21	10.09	9.66	0.84	1.01
5	10.87	9.34	1.27	1.42	10.31	8.93	1.47	1.63
6	11.62	11.17	2.07	2.48	10.99	9.54	1.93	2.56
7	12.21	10.51	2.58	3.18	11.80	9.76	2.65	2.81
8	9.46	8.54	3.55	3.63	9.59	9.59	3.80	3.80
9	6.56	6.79	7.05	6.31	7.63	7.22	7.28	6.53
10	6.08	7.91	7.34	9.48	7.83	7.52	8.75	12.50
11	4.03	6.94	5.16	6.46	5.99	6.51	6.20	8.53
12	3.09	7.01	68.92	63.65	4.46	6.19	65.80	58.57

Table II shows the PDF per connection of the initial and final SOC during weekdays and weekends. The Nissan LEAF (24kWh) represents the SOC in 12 units/segments (2kWh per segment, i.e., 1 segment equals 8.3% of battery capacity). Irrespective of weekday or weekend, Table II highlights that the first connection starts in more than 70% of the EVs when their initial SOC is between 3 and 9 segments (i.e., 25 to 75%). It can also be seen that second connections occur with higher SOC. In terms of final SOC, Table II highlights that approximately 65% of the EVs finish their first connection with full battery. Table II finally shows that during weekends, disconnections are more frequent before EVs are fully charged.

III. CREATION OF EV PROFILES

A. EV Demand and Power Factor

To create daily time-series EV profiles (see section III-B), it is important to understand the typical EV demand (in kW) as well as its power factor. To determine these features, the active, reactive, and apparent power monitored on a specific EV over a period of four months are used. Fig. 3 shows the monitored apparent and active demand of this EV for three different days (represented by different line styles). It should be noted that the EV demand is similar to a square waveform.

A total of 78 days were fully monitored (1-min average samples, i.e., a total of 112,320). Fig. 4 shows the PDF of the EV demand. When the EV battery is being charged, it is clear that it typically demands 3.6kW. Although lower demand values exist, these occur when the battery is reaching full charge (see in Fig. 3 the charging event represented by the dotted line). This effect is ignored in this work. In terms of the power factor, Fig. 5 highlights that the typical EV power factor is 0.98 (inductive, i.e., absorbing reactive from the grid).

B. Methodology to Create EV Profiles

Daily time-series EV profiles can be produced using the PDFs presented in section II. The initial and final SOC define how long the EV needs to be connected to the charging point. Typically an EV draws 3.6 kW (0.98 inductive power factor) of continuous demand. One segment (2 kWh) of charge in a

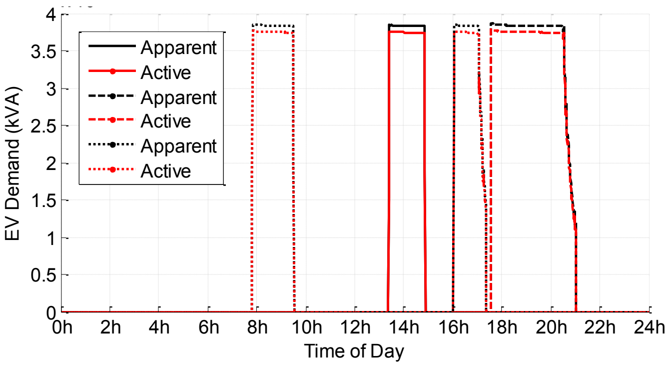

Figure 3. Three examples of monitored active and apparent EV demand.

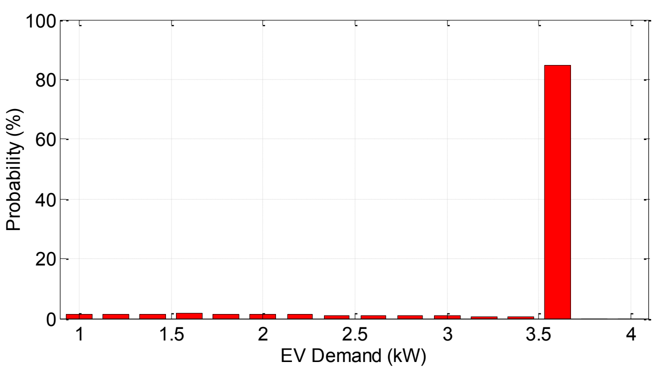

Figure 4. PDF of the real EV demand monitored in the project.

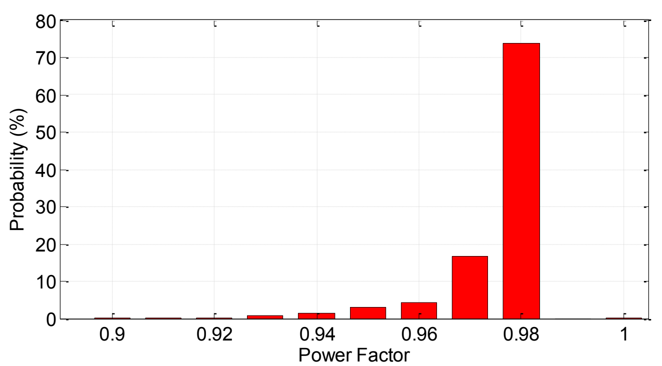

Figure 5. PDF of the real EV power factor monitored in the project.

Nissan LEAF needs approximately 40 minutes (3.6 kW).

With the above considerations, it is possible to create stochastic, realistic and detailed EV profiles to be used in EV-related studies. The next steps are required for each profile:

1. Random selection of the number of connections using Table I. Then, for each connection follow steps 2 to 5.
2. Random selection of the start charging time using Fig. 1 and Fig. 2.
3. Random selection of the initial SOC using Table II.
4. Random selection of the final SOC using Table II (larger than that of step 3).
5. Calculation of the time needed from the initial SOC to the final SOC based on the required number of segments to be charged (final SOC minus initial SOC).

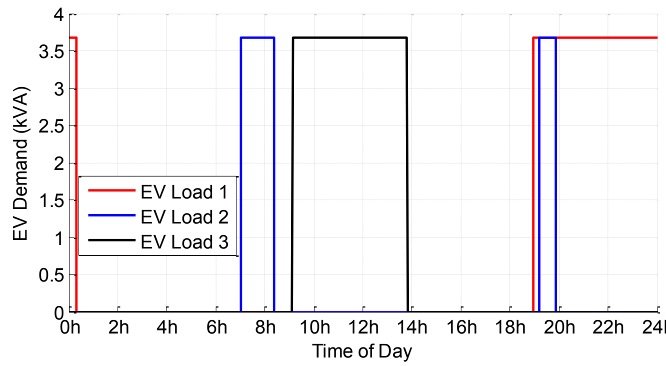

Figure 6. Example of individual EV profiles – Weekday.

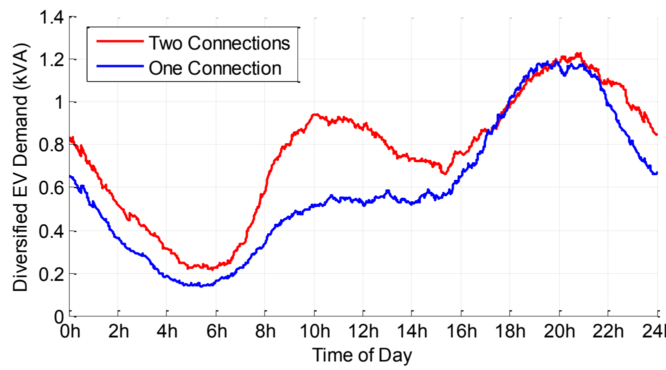

Figure 7. Example of diversified EV demand – Weekday.

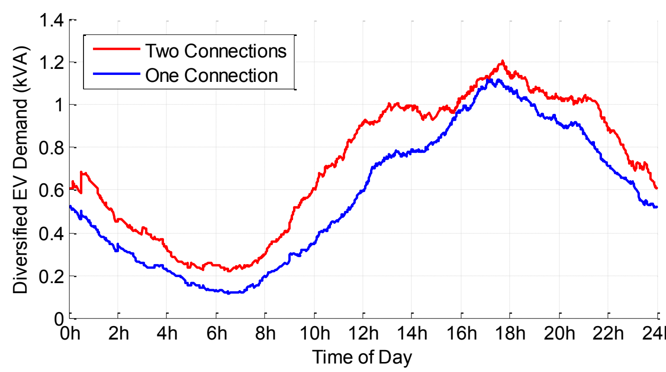

Figure 8. Example of diversified EV demand – Weekend.

From the above steps, the charging process (i.e., a constant 3.6 kW demand with a 0.98 power factor) for each connection occurs between the connection time (step 2) and finishing time (step 2 + step 5). If there are two connections, each charging process must not overlap with the other.

C. *Example of EV Profiles*

For weekdays, Fig. 6 shows examples of individual EV profiles. As observed, these EV profiles represent the connection of EVs at different times of the day. Moreover, they have different charging needs (duration). Finally, they consider one car connecting twice in the same day (EV Load 2).

Fig. 7 and Fig. 8 further present the diversified demand for 1000 profiles for both weekday and weekend, respectively. The diversified demand corresponds to the aggregated demand divided by the number of profiles. As expected, the diversified demand shows a similar behavior as that of the start time

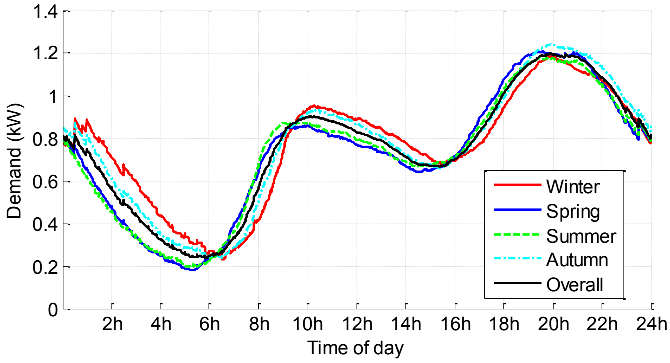

Figure 9. Monitored diversified EV demand per season – Weekday.

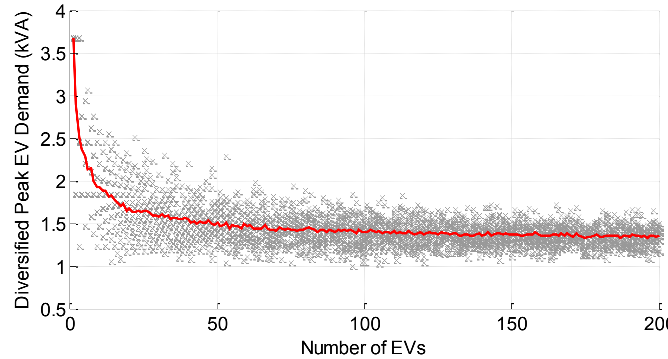

Figure 10. Diversified peak EV demand for various EV numbers – Weekday.

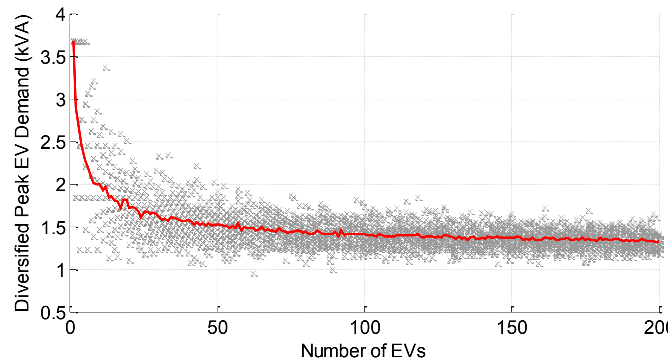

Figure 11. Diversified peak EV demand for various EV numbers – Weekend.

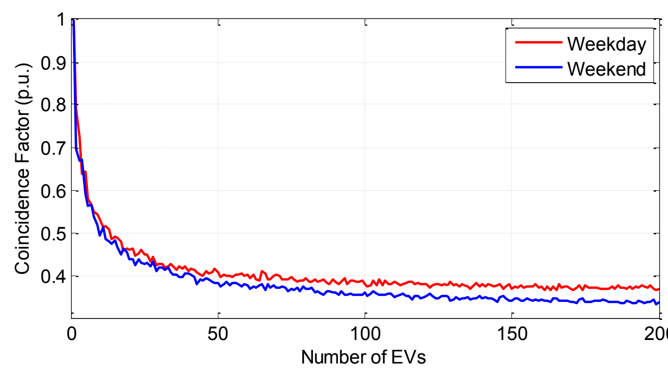

Figure 12. Coincidence Factor for various EV numbers.

(Fig. 1 and Fig. 2). Fig. 7 and Fig. 8 also compare the diversified demand when considering one and two connections. For weekdays, it is clear that the latter does not affect the evening peak (~1.2 kW in both cases) but it does affect the weekday morning peak (from 0.58 to 0.91 kW).

Crucially, it is clear that two connections have a significant effect on the overall daily energy consumption. While the daily energy consumption considering a single connection during weekdays and weekends is 13.9 and 13.7 kWh, this value increases to 17.8 and 16.9 kWh when two connections are considered for the same type of days. As previously highlighted, this analysis is unique given that previous EV studies have not explored multiple charging events.

D. *PDFs For Different Seasons*

No significant variance in the charging behavior of EVs across seasons was found; the above analysis considered the whole year. The analysis included both weekdays and weekends. To demonstrate the limited impact of seasonality, the diversified EV demand for different seasons during weekdays is shown here. Similar analysis for weekends is provided in [10, 11] as part of the ‘My Electric Avenue’ project.

Fig. 9 shows the average diversified EV demand for 100 sets of 1000 EV profiles for each season, as well as the yearly (overall) charging behavior (PDF created in section II). Fig. 9 clearly shows no significant change in the EV demand across seasons. If the overall diversified peak-demand (1.20 kW) is considered as a reference, then the peak difference for each season is: -0.68, 0.89, -1.80 and 3.69% for winter, spring, summer and autumn, respectively. In terms of energy consumed, seasonal differences were found; 2.11, -2.67, -2.90 and 2.20%, considering again as a reference the diversified energy consumed for the whole year (17.92 kWh).

IV. Analysis of EV Profiles and Implications on UK Distribution Networks

A. *Diversified Peak Demand and Coincidence Factor*

The diversified peak demand (i.e., also known as the after diversity maximum demand) is typically used in the design of the electricity networks [12]. This section quantifies the diversified peak demand for different numbers of EVs (from 0 to 200 EVs) in a Monte Carlo approach. For each one, 100 random selections (from the pool of 1000 EVs) are carried out and the corresponding diversified peak demand is calculated. Fig. 10 and Fig. 11 highlights that the lower the number of EVs, the higher the diversified peak demand. Crucially, it can be seen here that the diversified peak EV demand for more than 50 EVs decreases slowly. As expected this approaches a value of circa 1.2kW for large number of EVs.

Given the diversified peak demand of EVs, it is possible to determine the coincidence factor among EVs, i.e., the diversified peak demand per individual EV. For both weekdays and weekends, Fig. 12 highlights that the higher the number of EVs, the lower the coincidence factor of EVs. Although not shown in Fig. 12, the coincidence factor for a large number of EVs (e.g., 1000) is 0.33 (i.e., 1.2 kW / 3.6 kW = 0.33).

B. *Net Demand Analysis*

The adoption of EVs is expected to increase the net demand in electricity networks. Fig. 13 and Fig. 14 show the diversified demand of 1000 households (domestic unrestricted) in the UK for a typical weekday and weekend in winter -

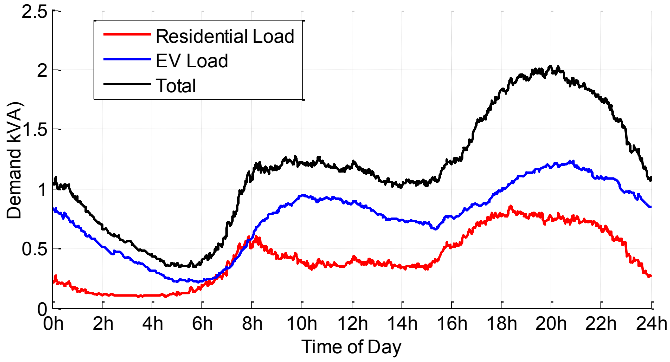

Figure 13. Diversified winter weekday profile: Residential + EV Demand.

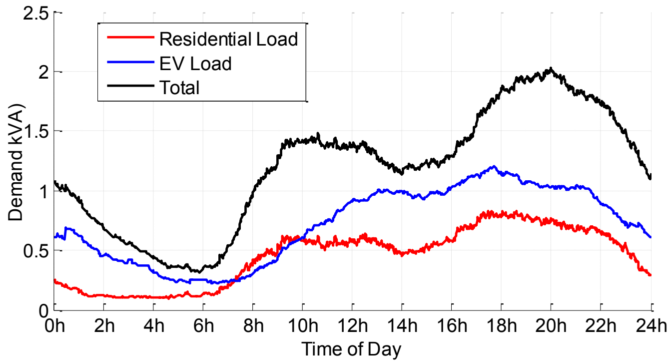

Figure 14. Diversified winter weekend profile: Residential + EV Demand.

(e.g., January, maximum demand in the UK). These residential profiles were created using [13]. Fig. 13 and Fig. 14 also present the weekday and weekend diversified demand of 1000 EVs and the net (residential + EV) demand. Irrespective of the type of day, the diversified peak demand increases from 0.8 (without EVs) to about 2 kW when all houses have one EV. This means an increase of more than 100%.

V. Discussion

The PDFs presented above represent the charging behavior of residential EV users. The behavior of a small set of commercial EV users has also been analyzed in the project (see [11]). The residential and commercial charging behavior can be potentially combined to create demand scenarios to be used in planning of future UK electricity networks.

To create the PDFs presented in section II, this work has investigated charging days only, thus resulting in the highest EV demand. However, it is expected that some EV users will not charge their vehicle every day (indeed, some days no EV may be charged). This information (i.e., the percentage of EVs charging during the same day) can be used to create different scenarios to be used in different EV studies (e.g., provision of reserves to the national or regional system operator).

This work has quantified the changes in the net demand for large number of loads (1000 residential and 1000 EV loads). However, care should be taken when studying low voltage networks as the number of customers can be much lower.

VI. Conclusions

This paper has presented results of a thorough statistical analysis of the charging behavior of 221 real residential EV users (Nissan LEAF, i.e., 24kWh, 3.6 kW demand and 0.98 inductive power factor) spread across the UK and monitored over one year (68,000+ samples). PDFs of the number of connections per day (overlooked in most studies), start charging time, initial SOC, and final SOC (per connection) for both weekdays and weekends have been created.

It has been shown that approximately 70% of the EVs are connected once a day, irrespective of weekday and weekend. In terms of the start charging time, EV users do change the start charging time from weekdays to weekends and the start charging time follows the UK residential load curve. The first connection typically happens (for more than 70% of the EVs) when the SOC is between 25 and 75%. Approximately 65% of the EVs finish their first connection with a full battery. Second connections normally occur with higher SOC, but disconnections before EVs are fully charged are more frequent.

A methodology that uses these unique PDFs to create stochastic, realistic and detailed EV profiles for impact and/or Smart Grid-related studies has also been proposed. It has been shown that multiple daily connections do not impact the evening peak, but this behavior does affect the morning peak as well as the overall energy consumption, compared to most of the studies that only consider single daily connections.

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