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Modeling Electric Vehicle Consumption Profiles for Short-Term Forecasting and Long-Term Simulation

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Abstract—The growing number of electric vehicles (EV) is challenging the traditional distribution grid with a new set of consumption curves. We employ information from individual meters at charging stations that record the power drawn by an EV at high temporal resolution (i.e. every minute) to analyze and model charging habits. We identify 5 types of battery that determine the power an EV draws from the grid and its maximal capacity. In parallel, we identify 4 main clusters of charging habits. Charging habits models are then used for two applications: short-term forecasting and long-term simulation. We start by forecasting day-ahead consumption scenarios for a single EV. By summing scenarios for a fleet of EVs, we obtain probabilistic forecasts of the aggregated load, and observe that our bottom-up approach performs similarly to a machine-learning technique that directly forecasts the aggregated load. Secondly, we assess the expected impact of the additional EVs on the grid by 2030, assuming that future charging habits follow current behavior. Although the overall load logically increases, the shape of the load is marginally modified, showing that the current network seems fairly well-suited to this evolution.

Index Terms—electric vehicle, forecasting model, scenario generation, probabilistic evaluation.

I. INTRODUCTION

A. Context

The car stock of electric vehicles (EVs) – electric battery and plug-in hybrids – reached 2 million units worldwide in 2016, accounting for 1.1% of the global car market share [1]. This share is expected to rapidly increase over the next 15 years. Charging an EV battery requires a large amount of energy in a small amount of time. In a typical US household, EV charging requires more power than any other appliances (e.g. stoves and dryers) and is solicited just as often (daily or more). EVs are therefore important appliances to model correctly in order to manage electric household consumption. The increasing number of EVs connected to the grid, coupled with their high power requirement, is challenging the current electrical network with higher overall consumption and additional peaks.

The *Nordic EV Outlook 2018*, published by Nordic Energy Research [2], gives insight into the EV market in Nordic countries (i.e. Denmark, Finland, Iceland, Norway and Sweden). In particular, the authors provide feedback from the industry in Norway, where the market share of EVs is high (1.9%), pointing out that the electrical grid experiences periodic issues

in densely populated urban environments and recreational regions. This is attributed to the number of EVs charging on the grid. The Norwegian energy market regulator suggests that adding an average of 1 kW to the household peak load may result a 4% overloading of the transformers [3]. In Denmark, 20% EV penetration is believed to cause major grid overloading and under-voltage situations [4], while in the UK, a 20% level of penetration is likely to increase the daily peak load by 36% [5].

EVs are used in a multitude of contexts, including professional and leisure usage, meaning that the modeler is faced with a high and challenging variety of charging situations. Due to its nature, an EV can be charged at different places – at home or at work – which rules out a traditional switch-on appliance model. Researchers, such as Bae and Kwasinski, have proposed spatial models to account for different charging stations [6].

Modeling EV charging patterns is a useful tool for several types of study, such as power flow analyses of distribution grids [7], management of smartgrids [8], bottom-up simulations of demand [9], forecasting of charging stations [6], and stabilization of the power system [10]. Furthermore, EV charging involves a controllable load comparable to a washing machine or water heater. As such, EVs offer advantageous flexibility for demand response purposes, for instance, shifting charging cycles when electric demand is low. EV flexibility could be an important input for flexibility models, either at household level [11] or at the aggregated level [12]. Another promising perspective involves injecting the electricity stored in EVs' batteries back into the grid, with so-called “vehicle-to-grid” projects [13].

B. Objective

In this study, we use data measured at high-time resolution (i.e. every minute) showing the power drawn from the grid at the charging station. Each charging station is associated with a single privately owned EV. With this data, the charging habits of each EV user are modeled in a probabilistic way. This model is described in Section II. The charging habits model is then used for two applications: short-term forecasting and long-term simulation for prospective studies.

In Section III, we generate forecasting scenarios of an EV's consumption profile for the next day. Although our model forecasts a single EV, we validate the scenarios at the aggregated level, i.e. for a fleet of several EVs. We observe that scenarios result in accurate probabilistic forecasts of the fleet's aggregated consumption. In particular, we show that our bottom-up forecasting has performs similarly to an advanced machine-learning method that directly forecasts the fleet's aggregated consumption.

In Section IV, we simulate the impact of EVs on the grid in future years. The International Energy Agency (IEA) [14] anticipates a high penetration — around 30% — of EVs in 2030. Employing the four clusters of identified charging habits, we are able to extrapolate the consumption required by a large number of EVs. We show that current charging habits are sufficiently varied so as not to cause major issues on the total electrical load of a region.

C. Data Description

A set of 46 privately owned EVs located in Austin, Texas, is selected. Austinites are known to be very climate conscious and supportive of green policies [15], as exemplified by the Pecan Street project run by the University of Texas [16]. The Pecan Street platform provides us with the electric consumption of each EV recorded every minute of the year in 2015. In our dataset, electric consumption related to EVs is responsible for approximately 15% of total household consumption.

II. THE EV CHARGING MODEL

A. Processing the EV Time Series

An example of the power drawn by an EV during 36 successive hours is visible in Fig. 1. The power drawn is either null, when the EV is not charging, or close to a specific nominal power, when the EV is charging. Based on this visual inspection, which corresponds to the charging curve measured on a lithium-ion battery by Madrid et al. [17], we model a charging period with a block comprising 3 parameters:

- *Nominal power*: power demanded from the grid is constant during the whole charging period.
- *Duration* of the charging block.

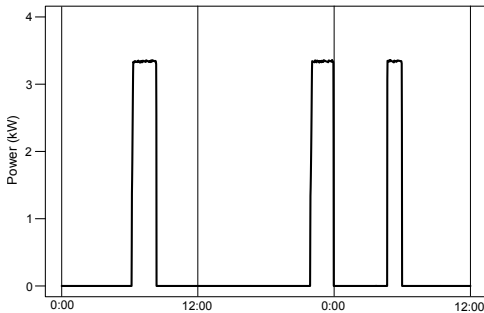


Fig. 1. Power drawn every minute by an EV during 36 successive hours. Power is null when the EV is not charging, and close to a nominal power when charging.

- *Start-up time*: moment the day when EV charging starts (between 1 and 60×24).

Real measurements do not generate perfect blocks. There is a steep ramp up to the nominal power; this ramp usually lasts less than 15 minutes. The power of the time series fluctuates slightly around a nominal value, translating a noisy phenomenon. This fluctuation is negligible compared to the nominal power, as can be seen on Fig. 1. Our hypothesis of perfect charging blocks simplifies these two facts.

Our observations indicate that nominal power is always the same for a particular EV as long as there is no technological replacement (i.e. battery and charging station). Such replacements occur for 2 of our 46 EVs in the Austin dataset (nominal power goes from 3.5 to 6.5 kW), requiring a minor adjustment in later modeling.

On the other hand, the duration and start-up time are not fixed. Charging blocks almost never start at the exact same time each day, and do not have the same duration, both of which depend on the unknown user's habits. A realistic depiction of these habits is to describe these two parameters (duration and start-up time) in a probabilistic way. Therefore, an analysis of these parameters is required, meaning that we need to detect charging blocks on the measured power time series.

B. Detection of Charging Blocks

We implemented the following procedure to automatically detect the charging blocks of an EV user from the power time series:

- *Detecting nominal power*. The density of all of the strictly positive values is estimated, and the maximum of this density function (i.e. the statistical mode) is retrieved as the nominal power.
- *Transforming time series in perfect charging blocks*. The raw time series is transformed into a simpler series of 2 values, either 0 when power is below a threshold fixed at 50% of nominal power, or 1 when it is above.
- *Pre-processing the simple time series*. The time series obtained is then refined to account for measurement errors. Missing values are filled in, and any remaining blocks that are too short (less than 20 minutes) are removed.
- *Detecting duration and start-up time*. All timestamps are processed in order to list all durations and associated start-up times in the time series. The day of the year on which the charging blocks occurred is also recorded for forecast applications.

The whole procedure runs fast on an average laptop: less than 30 seconds for the 500,000 data points of one EV yearly time series.

C. Charging Habits Analysis

Once the charging blocks parameters are detected, an analysis of the users' charging habits is possible. An interesting representation is to superimpose every charging block of the year on a graph with the x -axis representing the start-up time, and the y -axis representing the duration of the block. In order

TABLE I
DETECTED CHARACTERISTICS OF EVS

Nominal power (kW)	Max charging duration (min)	Battery capacity (kWh)	Number of EVs
1.5	760	19	1
3.5	120	7	2
3.3 – 3.7	210 – 240	12 – 16	35
6.6	150	17	4
6.2 – 7.4	480 – 600	53 – 71	4

to compare users’ habits, durations are normalized by the maximal duration observed — so that normalized duration is between 0 and 1. The maximal duration observed translates into the capacity of an EV’s battery. Table I lists these maximal charging durations, the nominal power of the EVs, and an estimation of the battery capacity. Estimations of capacity match the battery characteristics provided by manufacturers — such as the Nissan Leaf with a 16 kWh battery, and Tesla Model S with a 60 kWh battery. We also note that the nominal powers used to charge vehicles match the power outputs of levels 1 and 2, i.e. slow private EV chargers described in the Nordic EV Outlook 2018 [2]. We logically observe no fast chargers (> 22 kW and ≤ 150 kW) in our dataset, since these are mostly public and almost negligible compared to slow private chargers [2], although numbers are growing [18].

From the charging blocks detected, we can detail the number of charging cycles for each day and each EV. Data show that, on average for the 365 days of the year and one EV, there are 150 days with no cycle at all, 158 with only 1 cycle, and 57 with 2 or more blocks. Furthermore, considering only days with more than 2 charging blocks, the main block accounts for more than two thirds of the daily energy requirements. This shows that the main blocks are of paramount importance. Visually, the characteristics of a main block and any residuals blocks (i.e. second block, third block of the day, etc.) are almost indiscernible. We ascertain this observation with a statistical test comparing the estimated density function in the 2D plan (duration \times start-up time) for the main blocks and residual blocks separately¹. For more than half of the EVs in the dataset, p -values are below 0.01. Considering these results and the fact that we observe fewer residual charging blocks, which hinders an accurate statistical model, we consider in the following that main and residual charging blocks come from the same distribution duration \times start-up time.

Similar tests are conducted to determine whether weekdays and weekends follow different patterns. Surprisingly, for all EVs, we identify no statistical difference (p -value always below 0.01) in charging habits between weekdays and weekends. This is however in agreement with a visual inspection of the charging blocks’ characteristics, where no clear difference stands out. It is also in line with the very low intra-week variations of the electrical load in Texas. However, despite similar on weekdays and weekends — EV users charge at the same time and for the same duration — we observe notable

differences in the number of times that they charge their EVs each day of the week, e.g. some users almost never charge during the weekend.

D. Charging Habits Clustering

By making specific analysis of every user’s charging habits, we can accurately describe the associated EV’s consumption profile. However, to carry out long-term forecasting requires extending these specific habits to a larger scale. We therefore aim to cluster the charging habits to extract meaningful information that can be extended more generally.

First, we estimate the 2-dimensional density function for each EV with a kernel density estimator method: a bandwidth matrix common to all EVs was chosen and obtained with a cross-validation method [20]. Then, we compare density functions of 2 EVs by computing the integrated square differences on the density support. Such values define proximity between two charging habits. Finally, thanks to a hierarchical clustering based on the Ward linkage method [21], we retrieve 4 habit clusters from our set of 46 EVs. These clusters represent the charging habits (start-up and duration of charging blocks) regardless of the characteristics of the vehicles, i.e. regardless of the EV’s nominal power and total energy capacity. Table II

TABLE II
DETAILS ON CLUSTERS FOUND

Cluster	Charging period	Number of EVs
1	Night	24
2	Evening	9
3	Throughout the day	9
4	Late evening	4

details the 4 clusters identified. The first cluster gathers most frequent charging patterns, where EVs are charged during the night and in the morning (52% of the users). We represent the 2-dimensional density function on Fig. 2 : the green levels represent the density function estimated for all 24 users of the cluster, and the points denote the charging blocks of one of the users. This density indicates that most charging cycles occur before 12:00, and that cycles tend to last longer when started earlier in the night. The second cluster gathers users charging in the evening, presumably when people come back from work (20%). The third cluster gathers users charging throughout the day, but mostly at night-time (20%). The fourth cluster gathers users charging in the late evening so that their vehicle is charged at a precise moment — such as 03:00 (9%).

¹using package *ks* available on **R** software [19].

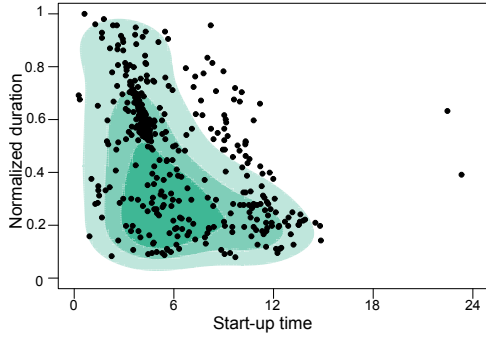


Fig. 2. Representation of the charging patterns for cluster 1: the two dimensional density function estimated for the 24 EVs in cluster 1 (filled contour) and points representing the charging block a specific EV in the cluster. On the x -axis is the normalized duration, i.e. the charging duration normalized by maximal duration observed for this EV. On the y -axis is the hour of the day.

No statistical link is observed linking the characteristics of the battery and the charging patterns. Although this is in part due to the fact that most batteries are similar, we assume that the two aspects (Tables I and II) are independent.

III. DAY-AHEAD FORECASTING SCENARIOS OF DAILY CONSUMPTION PROFILES

A. Scenarios of a Single EV

For a specific EV, charging habits detected from the time series data allow us to forecast daily profile scenarios. This forecasting process is done in 3 steps:

- 1) Forecast number of charging blocks for next day;
- 2) Forecast possible patterns (normalized duration \times start-up time) for each block;
- 3) Use characteristics of the EV (maximal duration and nominal power) to obtain a consumption profile.

For step 1), the forecasting model used is a probabilistic random forest, which provides a convenient way to draw random numbers of charging blocks according to forecast probabilities². The following inputs are used : weekday, number of blocks 1 day ago, number of blocks 7 days ago, median number of blocks during the 7 previous days, mean temperature of the previous day. These inputs have been selected based on standard inputs for household demand forecasting and empirical tests. Parameters of the forest — number of splits for each tree and minimal size of the branches — are carefully tuned on a grid with a cross-validation approach. For step 2), we draw patterns (normalized duration \times start-up time) according to the 2D distribution observed. Forecast charging blocks are drawn from previous ones weighted by a decreasing exponential parameter λ , so that former blocks are forgotten. A 2D Gaussian noise, with observed covariance, is added to the block drawn. Checks are operated to rule out impossible situations: overlapping blocks, negative durations and so on.

²using package *ranger* available on **R** software [22].

It is difficult to assess the quality of forecast scenarios for an individual EV. Standard statistical indices (such as Mean Absolute Error) are not adapted to such 2-level time series, where the start-up times of charging blocks are highly uncertain. Forecasting methods relying on such indices lead to flat forecasts with no charging block: indeed, a correctly forecast but wrongly timed charging block — e.g. starting at 08:00 instead of 10:00 — would be subject to a “double penalty” [23].

B. Bottom-Up Forecast of the Aggregated Fleet

Instead of evaluating forecasting performance at the individual level, the aggregated fleet consumption is forecast for the next day with a bottom-up approach. Each EV consumption profile is forecast with the 3-step method described in Section III-A, and the sum of all of the individual scenarios generates a forecast scenario for the aggregated profile. Such a day-ahead forecast is represented in Fig. 3 where the aggregated profile can be clearly seen as a sum of the 46 individual EVs profiles.

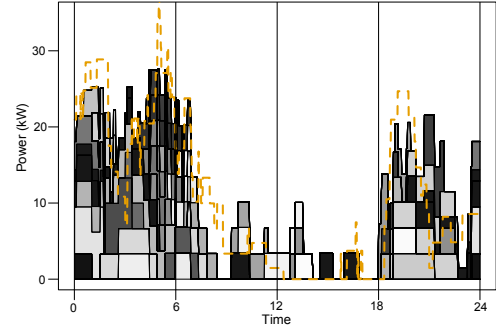


Fig. 3. Day-ahead scenario forecast of a fleet of 46 EVs on Saturday 12th December 2015. The orange dashed line shows the actual consumption to be forecast. Each individual scenario is represented by a filled area.

To assess forecasting performance, we generate S scenarios, and turn these scenarios into probabilistic forecasts at each instant by computing quantiles at levels $\tau \in \{0.05, 0.10, \dots, 0.95\}$.

We compare our method with two benchmarking forecasting models that do not model individual EVs but consider only the aggregated consumption. First, a persistence model using the value of the aggregated consumption at the same minute on the previous day as a forecast point³. Second, an advanced benchmark is a gradient tree boosting model (GTB)⁴ using 5 standard inputs: minute of the day, weekday, temperature forecast, consumption 1 day ago, median consumption during the 7 previous days [25]. Parameters are carefully tuned (number of trees, shrinkage parameter, and tree width) and probabilistic forecasts are made using a pinball loss with quantile levels $\tau \in \{0.05, 0.10, \dots, 0.95\}$.

We evaluate the forecasting quality of the 3 models with two standard indices: MAE (Mean Absolute Error) for deterministic forecasts and CRPS (Continuous Ranked Probability

³no probabilistic framework is proposed with this model.

⁴using package *gbm* available on **R** software [24].

Score) for probabilistic forecasts. Indices are estimated over a training set of 6 months and reported on Table III. Thanks to this score, we select two meta-parameters of our bottom-up forecasts: forgetting parameter $\lambda = 50$ days and number of scenarios $S = 400$. Results show that our bottom-up deterministic forecasts, in addition to the decomposition of the aggregated consumption profile, greatly outperform the persistence model, and perform similarly to the advanced GTB benchmark. Concerning the probabilistic framework, our bottom-up model is more efficient (i.e. lower CRPS) than GTB. In particular, it is especially efficient to forecast the lower tail of the distribution.

TABLE III
INDICES OF TWO BENCHMARKING METHODS AND OUR BOTTOM-UP APPROACH

Index	Persistence	GTB	Bottom-up
MAE (kW)	6.24	4.86	4.87
CRPS (kW)	—	3.63	3.59

IV. LONG-TERM IMPACT OF HIGH PENETRATION OF EVs

A. Hypotheses

Our dataset describes EV charging habits in Austin, Texas. We want to extend the study area to a larger region. Therefore, we focus on the South Central region of Texas. The main Texan Distribution System Operator, ERCOT (Electric Reliability Council Of Texas), defines this region as a weather zone covering 25 contiguous counties, comprising two major cities, Austin and most of San Antonio. According to the Texas Demographic Center, the total population of the 25 counties was 4.8 million in 2017, meaning that there are about 3.4 million vehicles. According to the 2017 National Household Travel Survey, the current market share for EVs in Texas is around 1.9%, meaning that the current number of EVs — or hybrid EVs — is around 65 thousand in the South Central zone of Texas.

Considering a 1% immigration scenario in the future, the Texas Demographic Center forecasts that there should be around 6.5 million people by 2030, and thus around 4.6 vehicles⁵. In addition, the IEA's EV30@30 Campaign has set an ambitious goal of a 30% EV penetration rate by 2030. This would result in around 1.4 million EVs by 2030, which means there would be around 1.3 million additional EVs compared to the natural increase of EVs due to population growth over the period. A 30% market share is higher than that predicted in the detailed study by Musti and Kockelman in 2011 focusing on the city of Austin [26]. These authors estimate the market share to be 19% in 2034 under a favorable feebate scenario.

B. Simulation

ERCOT manages electricity representing 90% of the Texan load. The company openly publishes its hourly load curve by

⁵considering that the average number of vehicles per person remains the same.

weather zone⁶. Without any major technological changes, the load curve should have approximately the same shape in 2030, but at a higher level due to population growth. For a Tuesday in March, Fig. 4 shows the actual load curve in gray, and the expected future load in black.

However, as we estimated, there should be 1.3 million new EVs charging on the grid in 2030, which will impact the load curve. We simulate all of this additional load by generating scenarios for each EV. We consider 2 possible evolution paths for EVs:

- 1) Habits and characteristics of EVs remain the same (sample from complete Table I and Table II)
- 2) Habits remain the same but characteristics evolve (sample from last 2 lines of Table I and complete Table II)

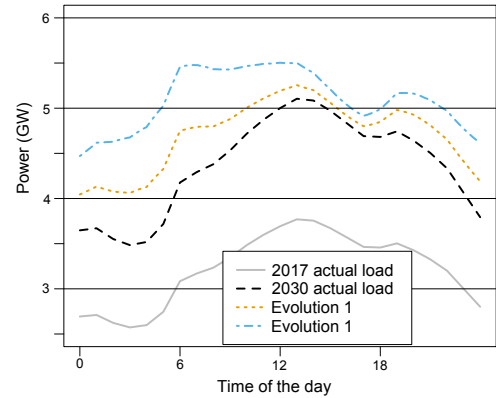


Fig. 4. Load curves in South Central zone of Texas in a typical Tuesday in March. The grey solid line represents the load measured in 2017; the black dashed line represents the expected load in 2030 with the same EV market share (1.9%); the orange dotted line represents the expected load with a 30% EV market share and same EV characteristics as today; the blue mixed line represents this expected load with larger batteries in EVs.

The first evolution path assumes that the habits of future users will fall into the 4 clusters found in Section II-D, and that the EVs' characteristics will remain the same. The second path considers the future evolution of EV chargers and batteries. Although fast or ultra-fast chargers are planned to be deployed (nominal power above 22 kW), these are expected to remain public, and public chargers are rarely used compared to private chargers due to consumer preferences. Currently, in the Nordic region, fast chargers represent less than 1% of the total charging load [27], and the growth rate of private chargers is far greater than that of public chargers [2]. However, private chargers may all reach a nominal power of 6.6 kW. We therefore retain only the last two characteristics of Table I with half of the future batteries of 17 kWh capacity and half in the 53–71 kWh range capacity. Evolution 1 is represented by the orange line, and evolution 2 by blue line in Fig. 4.

Simulation shows that even when a high number of EVs are added to the grid by 2030, their charging only moderately

⁶This curve can be found on their website http://www.ercot.com/gridinfo/load/load_hist/

impacts the shape of the load curve at the regional scale of South Central Texas. The overall load is naturally higher with the additional EVs, especially in scenario 2 with larger batteries, but the current charging habits do not cause unmanageable peaks or unstable variability for the load. Both simulations even show that, with the additional EVs, the load curve would be smoothed out during the night, diminishing the intra-day variation. With adequate planning, there should be no major problem with such market share growth. However, since there could be issues at a local scale, some kind of coordination is required to *smart-charge* the EVs [5], for instance by optimally scheduling the charging of EV fleets [28], or through targeted price incentives [29].

V. CONCLUSION

In this paper, we model the consumption profile of EVs from raw power measurements. Based on minute-by-minute power measurements, an algorithm is developed to retrieve each charging block during which an individual charges his or her vehicle. Thanks to this detection, a probabilistic model is proposed to describe the charging habits of the user. From the measurements, we detect 5 kind of plugs and EV batteries determining the power drawn from the grid and the battery capacity. Furthermore, we identify 4 major types of charging habits depending on the duration and start-up time of charging.

Probabilistic models of charging habits can be used to forecast the consumption profiles of single EVs for the next day through scenarios. By adding the scenarios of multiple EVs, models produce bottom-up probabilistic forecasts of the aggregated consumption of a fleet of EVs. A performance evaluation assesses that this method is as efficient as the advanced machine-learning method, but decomposes the aggregated load into single EV consumption profiles.

Since the market share of EVs is expected to greatly increase in the next 15 years, we evaluate the impact of the additional load on the total electrical load in a region in Texas with a population of around 5 million. Based on the 4 types of charging habits identified on our reduced dataset, we simulate the future load expected in 2030 with and without the EV market share increase, and show that it seems to only moderately impact the shape of the load curve. However, the future of EVs is uncertain, especially concerning the battery capacity and deployment of fast chargers, which may lead to complications for the grid, requiring carefully coordinated charging planning for a large number of vehicles.

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