Electrical Power and Energy Systems 95 (2018) 451–462

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Quantitive analysis of electric vehicle flexibility: A data-driven approach

N. Sadeghianpourhamami [a,*], N. Refa [b], M. Strobbe [a], C. Develder [a]

[a] Ghent University – imec, IDLab, Dept. of Information Technology, Technologiepark Zwijnaarde 15, 9052 Ghent, Belgium
[b] ElaadNL, Utrechtseweg 310, Building B42, 6812 AR Arnhem, The Netherlands

ARTICLE INFO

Article history:
Received 14 November 2016
Received in revised form 25 April 2017
Accepted 2 September 2017

Keywords:
Electric vehicles
Flexibility quantization
Smart grid

ABSTRACT

The electric vehicle (EV) flexibility, indicates to what extent the charging load can be coordinated (i.e., to flatten the load curve or to utilize renewable energy resources). However, such flexibility is neither well analyzed nor effectively quantified in literature. In this paper we fill this gap and offer an extensive analysis of the flexibility characteristics of 390k EV charging sessions and propose measures to quantize their flexibility exploitation. Our contributions include: (1) characterization of the EV charging behavior by clustering the arrival and departure time combinations that leads to the identification of type of EV charging behavior, (2) in-depth analysis of the characteristics of the charging sessions in each behavioral cluster and investigation of the influence of weekdays and seasonal changes on those characteristics including arrival, sojourn and idle times, and (3) proposing measures and an algorithm to quantitatively analyze how much flexibility (in terms of duration and amount) is used at various times of a day, for two representative scenarios. Understanding the characteristics of that flexibility (e.g., amount, time and duration of availability) and when it is used (in terms of both duration and amount) helps to develop more realistic price and incentive schemes in DR algorithms to efficiently exploit the offered flexibility or to estimate when to stimulate additional flexibility.

1. Introduction

Partly because of environmental constraints, electric vehicles (EVs) are increasingly being adopted as an alternative for internal combustion engine (ICE) cars. However, the load from EVs may increase the peak to average ratio of demand and hence create a need for additional generation and network capacity. That extra capacity would only be required to meet the increased peak demand and therefore is used very infrequently [1]. Integration of information technology into the power grid (in the smart grid paradigm) alleviates this challenge by enabling the exploitation of demand side flexibility to reshape the consumption to meet the supply or network constraints (i.e., by flattening demand or by balancing against renewable generation). Consequently, a substantial body of research has focused on proposing demand response (DR) algorithms to coordinate EV charging and establish their benefits (a review of various DR algorithms for charging coordination is given in [2–5]). However, one of the main limitations of such proposed DR algorithms is their potentially unrealistic assumptions about the EV owner behavior (e.g., time of availability of EV, sojourn times and the fraction of the sojourn time that is not spent for charging and is named idle time). To design an efficient and practical DR algorithm, it is necessary to accurately understand the flexibility stemming from EVs and how to influence it (through price based and incentive based schemes) to maximize DR benefits. However, despite various efforts in proposing DR algorithms, EV flexibility characteristics as DR's main asset have not been quantitatively analyzed. We believe such analysis can pave the way to more realistic demand response schemes (price-based or incentive based DR) in order to facilitate EV integration in the grid and therefore is the focus of this paper.

1.1. Objectives and contributions

Understanding the flexibility characteristics, the influencing factors, and the motivation for its exploitation is an inevitable part of designing a realistic DR algorithm. Flexibility, despite its apparent simplicity, is neither straightforward to analyze nor to quantify.

We pursue two objectives in this paper. Our first objective is to perform an in depth analysis of the flexibility characteristics of EVs based on a reasonably large real-world dataset (which to the best of our knowledge amounts to the largest dataset reported in literature, see Section 2.1 for further details). Our second objective is to

* Corresponding author.
E-mail addresses: nasrin.sadeghianpourhamami@ugent.be (N. Sadeghianpourhamami), nazir.refa@elaad.nl (N. Refa), matthias.strobbe@ugent.be (M. Strobbe), chris.develder@ugent.be (C. Develder).

http://dx.doi.org/10.1016/j.ijepes.2017.09.007
0142-0615/

quantify the flexibility exploitation and identify how the observed flexibility is utilized for various objectives (e.g., load flattening and load balancing against renewable (energy) sources) and whether there is any typical pattern in its exploitation. More precisely, we aim to answer the following research questions:

1. *Do EV owners have specific habits to charge their cars (e.g., taking their cars to a charging station at particular times of the day)?* To answer this question, we characterize the EV charging behavior by clustering the arrival and departure time combinations, as such identifying three behavioral clusters in our EV charging data (Section 2.2).
2. *Are the characteristics of the charging sessions (e.g., arrival, sojourn and idle times) sensitive to seasonal changes or weekdays?* To address this question, we systematically analyze the characteristics of the charging sessions in each behavioral cluster on weekdays and weekends and across various seasons. We also characterize the flexibility stemming from the sojourn times of EVs that are longer than the time required to (fully) charge their battery (Section 2.3).
3. *How is flexibility (in terms of amount, time and duration of the shifted energy) exploited? Which aspect of flexibility (time and duration of availability or amount of deferrable energy) is more useful at various times of the day?* We address these questions by considering two case studies (i.e., load flattening and load balancing scenarios) to investigate to what extent the observed flexibility would be exploited. To do so, we propose two measures and an algorithm to quantitatively analyze when flexibility is used in terms of the EV load volume as well as amount of time the load is deferred (Sections 3.3 and 3.4).

1.2. Related work

Estimating the EV charging load to assess its impact on the power grid has been the primary focus of research in facilitating EVs integration to the grid. In initial studies, before the widespread use of EVs, probabilistic models of driving behavior (with conventional ICE cars) were used to characterize a charging session. This was done by estimating arrival and departure patterns, energy requirements and the covered distance in between trips. For example Lampropoulos et al. [6] derive an EV charging data profile from statistical characteristics of the driving behavior of conventional ICE cars. Clement-Nyns et al. [7] base their analysis on extrapolation of non-EV car usage in Belgium. Paevere et al. [8] model the spatio-temporal impact of EV load based on a linked suite of models of future EV uptake, their travel and charging/discharging models. Grahn et al. [9] derive EV charging behavior from non-EV driving behavior in Sweden. Pashajavid et al. [10] derive the demand profile of EVs from traveling and refueling information of non-EV in Tehran, and a more recent study [11] estimates possible states of EVs, regarding their demand, location and connection period, based on synthetic data which mimics reality.

Later studies, when EV penetration had increased, relied on the availability of EV charging datasets to use data-driven approaches to model the charging behavior of EVs and assess their impact on the grid. For instance, Xydas et al. [12] characterize the charging demand of EVs by statistically analyzing and clustering a dataset of 22k sessions in UK. Khoo et al. [13] derive the impact of EV charging on peak load based on around 5k sessions from an Australian field trial and establish the expected impact on the total power demand in 2032–33 for the state of Victoria. Brady et al. [14] use a probabilistic charging module to translate the travel patterns of EVs into the respective power demand of the vehicles. Quiròs-Tortòs et al. [15] and Navarro-Espinosa et al. [16] use the probability distribution of start charging time and energy demanded during a connection of charging sessions in a one-year EV trial in Ireland to obtain the EV load demand and assess their impact in the low voltage distribution grid. The aforementioned works focus mainly on analyzing the impact of EVs on the load curve and do not provide any quantitative analysis of the flexibility characteristic of EV charging sessions. The objective of our analysis presented here rather is to quantify the flexibility of the EV load, and quantitatively study user behavior.

User modeling (not focusing on flexibility) has been the subject of earlier works to assess the influence of charging behavior of different user categories on the load curve. For example, Franke et al. [17] examine the psychological dynamics underlying charging behavior of EV users. Spoelstra [18] aims at understanding the charging behavior of EV users and the factors constituting such behavior. Khoo et al. [13] have modeled the charging sessions for households and EV fleets during weekends and on weekdays in terms of arrival times and energy demands. Quiròs-Tortòs et al. [19] produce probability distribution functions (PDF) of different charging features (e.g., start charging time) for both weekdays and week-ends based on 68k samples from 221 residential EV users. They further discuss the effects of the EV demand on future UK distribution networks. Similarly, Richardson et al. [20] produce PDF of connection times and daily energy requirements of EV based on the charging behavior of 78 users for a duration of 1 year. Helmus et al. [21] distinguish a priori defined different user types (residents, commuters, taxis, etc.) and characterize them in terms of EV charging session start and end times and the associated energy needs. Similarly, Aunedi et al. [22] characterize the charging behavior and the demand diversity of two predefined user categories: residential users and commercial users. Instead of defining the user categories a priori, Xydas et al. [12] cluster the observed charging sessions into distinct types of behavior. They derive aggregate models for three specific geographical areas, characterized by different clusters of "typical EV charging demand profiles". Similar characterization of charging session timing is presented by Kara et al. [23]. Similar to [12,23] (but using different clustering technique), we cluster the EV charging sessions into behavioral clusters. However, our work differs from the aforementioned papers: instead of focusing on the impact of EVs on the load curve, we characterize the flexibility stemming from the EVs as well as how such flexibility is used (in terms of both amount and duration) to flatten the load or balance against renewable energy.

Quantification of demand side flexibility and assessing its impact on alleviating the EV charging burden on the grid has been tackled before. Aunedi et al. [22] characterized the flexibility of EV charging demand in terms of the amount of load shifted in time from the peak consumption without compromising the ability of EV users to make their intended journeys. Their analysis suggested that it is possible to shift 70–100% of EV demand from peak hours towards the night. Kara et al. [23] defined the flexibility matrix as the fraction of total connection time that is not spent on charging. They presented the variation of this measure over different months. Teng et al. [1] defined the potential flexibility of EV demand as the amount of the shifted energy in the coordinated vs. the uncoordinated charging. They further establish the benefits of this flexibility in reducing carbon emissions and cost of integration of renewable energy sources (RES) through appropriate measures. Pavić et al. [24] estimated the EV flexibility benefits for providing spinning reserve services through matrices expressed as operational costs, environmental benefits and reduced wind curtailment. Salah et al. [25] used the parking data from a car park in southern Germany, which is mainly used for shopping and working. They modeled parking duration distribution for two types of parking behavior: shopping and workplace. They inferred the flexibility thereof by assuming an average EV charging time of 45 min at 11 kW per car. Kheserzadeh [26] inferred the probability of availability of EVs in the parking lots for different EV owners