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A methodology to generate power profiles of electric vehicle parking lots under different operational strategies

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HIGHLIGHTS

- Kernel density estimation is used to model the characteristics of the EV fleet.
- A method to derive representative electricity price series is proposed.
- Load duration curves can be closely approximated with few simulations.
- EV parking lot load profile significantly varies with the employed strategy.

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ABSTRACT

The electrification of the transportation sector through the introduction of electric vehicles (EV) has recently emerged as a remedy to environmental and economic concerns. For this reason, governments around the world have been offering subsidies and other benefits to drivers that replace their conventional vehicle with an EV in order to facilitate the commercialization of the latter. However, when compared to conventional vehicles, EVs present a key disadvantage that could hinder their widespread uptake: the time that is needed to charge an EV is in the range of hours. For this purpose, EV parking lots have been proposed in order to recharge vehicles at a higher rate. Recent studies indicate that vehicles remain parked for most of the day, implying that different operational strategies may be used in order to achieve operational or economic benefits from the perspective of the EV parking lot owner. The aim of this study is to derive representative load profiles of parking lots under different operational strategies. To perform so, the parameters of the EV fleet are modeled by estimating kernel distributions from available traffic data, while a time series transformation in combination with a clustering approach is used in order to obtain representative price patterns. The examined case studies demonstrate that by performing a reduced number of simulations regarding expected charging profiles of EV fleets, generalized results may be obtained using the proposed methodology.

1. Introduction

1.1. Motivation

Over the last few decades concerns such as the environmental degradation, the depletion and the price volatility of fossil fuels, as well as the willingness of governments to reduce their dependence on the import of foreign petroleum has stimulated the interest in the electrification of the transportation sector. More specifically, the transportation sector has been found to be responsible for more than a quarter of the total energy consumption and for one third of greenhouse gas emissions worldwide [1]. As a consequence, electric vehicles (EV) are being considered as a cleaner alternative to fossil fuel vehicles. Moreover, the large scale integration of EVs may contribute to the smoother integration of renewable energy sources (RES) generation in the power system [2], increasing the self-sufficiency of a country's electricity sector. However, RES production, which is significantly affected by meteorological and other factors, can be intermittent and volatile. The capability of EVs to act as sinks and sources of energy and therefore, their potential for increasing the RES hosting capacity of power systems has been extensively studied [3].

In order to take advantage of the projected benefits of the electrification of the transportation sector, several governments have offered a series of motives to promote the EV uptake: subsidies for the purchase of an EV, tax exemption, driving benefits such

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Nomenclature

Indices

e	index referring to electric vehicles
t	index referring to time periods (h)

Parameters

CR_e	charging rate of EV e (kW)
DR_e	discharging rate of EV e (kW)
E_e	energy EV e uses in commuting (kW h)
l	lower limit of truncation for the EV departure time (h)
m	mean of periods the EV departs after arrival (h)
N	large positive number (kW)
N^{EV}	number of EVs
SOE_e^{max}	maximum capacity of the battery of EV e (kW h)
$STATUS_{e,t}^{EV}$	binary parameter – 1 if EV e is available in period t
T	number of time periods
T_e^a	arrival time of EV e
T_e^d	departure time of EV e
$T_e^{C,E}$	exact time needed to fully charge EV e (h)
$T_e^{C,R}$	rounded number of periods EV e needs to fully charge
$Type_e$	type of EV e
u	upper limit of truncation for the EV departure time (h)
ΔT	duration of time interval (h)
λ_t	electricity price in period t (€/kW h)
σ	standard deviation of EV departure time (h)

Variables

ENS_e	energy not served to the e (kW h)
$P_{e,t}^{ch}$	charging power of EV e in period t (kW)
$P_{e,t}^{dis}$	discharge power of EV e in period t (kW)
$P_{e,t}^{dis,out}$	power from EV e that is injected back to the grid in period t (kW)
$P_{e,t}^{dis,u}$	power from EV e that is used within the parking lot in period t (kW)
P_t^{in}	power drawn from the grid in period t (kW)
P^{max}	maximum power requirement of the EV parking lot (kW)
P_t^{out}	power injected back to the grid in period t (kW)
$SOE_{e,t}$	state-of-energy of EV e in period t (kW)
$u_{e,t}^{EV}$	binary variable – 1 if EV e is charging in period t
u_t^{grid}	binary variable – 1 if the EV parking lot is drawing power from the grid in period t

as parking permits in dense urban areas (e.g., in Amsterdam) and permission to drive in bus and taxi lanes in order to save traveling time during rush hours (e.g., in Oslo). As a result, the market share of EVs has been increasing in the recent years [4].

Despite the attractive fringe benefits targeting at motivating drivers to replace their conventional vehicles with EVs, a factor that may hinder the widespread adoption of EVs is that their charging requires several hours [5], effectively limiting the usability of EVs even for relatively short distance traveling. Specifically, a recent study supports that for an average person, the aforementioned inconvenience (also known as drivers' range anxiety) may outweigh the environmental and fuel cost benefits of the EVs [6]. Nevertheless, several studies indicate that vehicles are used only 4–7% of the time during a day [7] and therefore, remain in idle state for long periods. Based on this fact, using EV parking lots as charging points [8] while drivers are in a non-residential/commercial area [9], at work [10–12] or at municipal parking lots [13], has been proposed in order to ease this drawback.

1.2. Relevant literature

From the perspective of the power system, the increasing penetration of EVs is controversial. On the one hand, an EV fleet provides a useful flexible resource for the system that, if suitably controlled, can be used in order to provide reserve services and contribute to load shaping [14]. In addition to this, new business opportunities and market players (e.g., aggregators, EV parking lot owners, etc.) emerge. On the other hand, failing to sufficiently engage EVs is likely to increase the loading of the system, jeopardize its reliability and necessitate transmission and distribution system reinforcements [15]. A significant amount of studies is motivated by this controversy and focuses on different aspects of the EV integration.

The provision of primary, secondary and tertiary reserves together with energy services by EVs is investigated in [16]. Also, in [17] the contribution of EVs to dynamic frequency response in the system of Great Britain is studied. Another important aspect that is discussed in the relevant literature is the potential of employing coordinated EV charging in order to accommodate increased amounts of variable renewable generation [18–20]. The market integration of EVs is also the subject of various studies. For instance, in [21] a two-stage stochastic programming based model for the participation of an EV aggregation in the day-ahead market is presented, while a general framework for the charging of EVs in a market environment is presented in [22]. Another category of studies focuses on the impacts of EVs on the transmission and distribution system. In [23] a thorough review of the impacts of bi-directional EV interaction with the grid under different charging strategies is provided. The consideration of EVs in transmission expansion planning is treated in [24]. The vehicle-to-grid (V2G) service and the network constraints are taken into account in [25], while in [26] the impact of EV penetration on Volt-VAR optimization is examined. Finally, a potential implication of EV charging load, i.e. the acceleration of the thermal aging of power transformers is studied in [27].

The majority of the studies concerns EVs that are available at different locations of the distribution system. Nevertheless, an EV parking lot constitutes a distributed resource of a significant size that can be optimally placed in a distribution system in order to enhance its operation by reducing active power losses, improve voltage profiles and increase reliability. Thus, it is essential that the EV fleet parameters are suitably modeled in order to be adapted to the available real data. In order to quantify the positive and negative aspects of integrating EV parking lots in the distribution system, its load profile should be accurately derived. For this purpose, several characteristic parameters of the EV fleet such as the number of available EVs in each period, their initial state-of-energy (SOE) and the technical specifications of each car must be known. Most of the relevant studies model the EV fleet in terms of rough assumptions [7,28–30], different parametric distributions [31,32], or are based on real EV traffic behavior; yet, the number of EVs considered in the latter category of studies is limited [33]. Moreover, in [34,35] spatial–temporal models for grid impact analysis of EVs are presented. However, in the first study parametric distributions are also used in order to specify the fleet parameters, while in the second study the EVs are assumed to be charged at a constant power; therefore, the proposed techniques are not suitable for the obtainment of representative load profiles for EV fleets available at a single location under different operational strategies. A more complete overview of the mobility parameters considered