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An empirically-validated methodology to simulate electricity demand for electric vehicle charging

Chioke B. Harris *, Michael E. Webber [1]

Department of Mechanical Engineering, The University of Texas at Austin, 204 E. Dean Keeton, Stop C2200, Austin, TX 78712, United States

HIGHLIGHTS

- Monte Carlo simulation is used to estimate plug-in electric vehicle (PEV) charging.
- The effect of PEV fleet growth on peak electric load is considered for three regions.
- By 2025, PEV charging is estimated to increase peak load by less than 2%.
- Changes in PEV owner demographics have a limited effect on charging patterns.

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ABSTRACT

With recent changes in the availability and diversity of plug-in electric vehicles (PEVs) in the United States, there is increasing research interest in the interaction between PEVs and the electric grid. Extensive work in the literature examines these interactions with the assumption that the timing of PEV charging will be scheduled, and that charging loads can be adjusted dynamically at the behest of the utility and the system operator. While it might be technically feasible to aggregate the data on driver schedules and historical PEV use and charging decisions, it is unclear whether PEV owners will readily share these data and accept partial third-party control of their vehicle's charging. Given the uncertainty in the future relationships between electric utilities and PEV owners, this study examines the region-level effects of PEV charging in the absence of the additional data utilities would need to realize these idealized charging scenarios. In particular, this study focuses on temporally-resolved prediction of electricity demand needed to serve PEV charging loads if charge scheduling or control is not widespread.

Vehicle trip data from the National Household Travel Survey (NHTS) were converted into individual vehicle charging profiles. Monte Carlo methods were then used with these profiles to simulate electricity demand for PEV charging. These simulations include accounting for the potential demographic characteristics of PEV drivers and the estimated charging behavior of those drivers. The simulation results were validated using empirical vehicle charging data collected by the Pecan Street Research Consortium from households in Austin, Texas. The simulation results compared favorably with the empirical data, estimating charging behavior to within 7% throughout most of the day. Two different simulation approaches were considered to show that a reduced-order simulation approach yields similar results. Finally, having demonstrated the stability of the simulation to assumptions about PEV owner demographics and PEV type-dependent charging patterns, the simulation results were used to determine the effect of unscheduled PEV charging on peak load in three different regions, Texas, New York, and New England, with three PEV fleet growth projections. These results indicate that for the moderate growth scenario considered, unscheduled charging will increase peak load by less than 1% by 2025 in each of the three regions.

1. Introduction

Plug-in electric vehicles (PEVs) facilitate the decoupling of light-duty vehicles (LDVs) from petroleum-dependent propulsion. Since PEVs are designed to rely primarily or exclusively on an electric drivetrain for motive power, the fuel use and emissions of the vehicle are associated with those characteristics of the regional electric

* Corresponding author. Tel.: +1 206 226 7884.
E-mail addresses: chioke@utexas.edu (C.B. Harris), webber@mail.utexas.edu (M.E. Webber).
[1] Tel.: +1 512 471 7838.

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grid. A thorough understanding of the relationship between PEVs and the electric grid is important, as a wide array of PEVs are now commercially available nationwide and offered by several major automakers. Zero-emission vehicle mandates, tax incentives, and decreasing battery and power electronics costs all foreshadow future growth in PEV sales [1,2].

The widespread availability of PEVs has led to questions about the impacts associated with light-duty vehicle (LDV) fleet electrification on the electric grid [3]. The need to continuously balance supply and demand on the electric grid motivates extensive planning and forecasting efforts to predict and mitigate any uncertainties in the system, thus an ability to anticipate PEV charging loads could be valuable. It has been claimed that the electric load associated with PEV battery charging could increase peak electricity demand and lead to distribution network disruptions [3]. Much has been made of the available generating capacity to support overnight charging [2,4–6], but most PEV owners do not currently receive incentives to schedule their charging for the middle of the night. Because charge scheduling is not currently widespread, it is as yet unclear whether system operators, as PEVs increase in popularity, will need to accommodate unscheduled charging in their long-term planning efforts and operations strategies. Moreover, the impact of pervasive unscheduled charging on future grid operations is not well-understood.

To address the relationship between PEVs and the electric grid, this work details a methodology developed to simulate unscheduled PEV charging load as a function of the size of the PEV fleet in a single region. The future impact of unscheduled PEV charging on peak load is estimated from the simulation results for three regions in the United States. These simulations rely on national vehicle travel data, which is modified to better reflect PEV charging based on observations from empirical charging data and demographic characteristics of PEV owners detailed in the literature. The methodology is validated using empirical charging data collected from residential PEV charging equipment.

2. Background

PEVs can be divided into two categories: battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). PHEVs have both an electric drivetrain and an internal combustion engine (ICE), allowing them to drive a limited distance relying exclusively on the onboard battery, typically between 10 and 40 miles, before requiring the use of the ICE to continue driving. BEVs have a larger battery than PHEVs but do not have an ICE to extend their range once the battery is exhausted. The range of BEVs is typically less than 100 miles. While hybrid electric vehicles (HEVs) also have a large onboard battery pack, it is typically much smaller than those found in PEVs. The motive power for an HEV is primarily provided by the ICE, and the battery facilitates more efficient operation of the ICE.

Extensive prior work examining the interaction between PEVs and the grid ignored temporal variations in vehicle use. Dallinger et al. [7] compared this assumption of constant vehicle availability with the results of a Monte Carlo simulation of vehicle use and demonstrated that such an assumption is entirely inconsistent with empirical vehicle use data. Newer studies have begun to account for time-of-day variations in vehicle availability, though authors have not generally undertaken a close examination of underlying vehicle use trends. As a result, many models use a single daily profile to represent all days of the year [8–11]. Pearre et al. [12] did perform a close study of longitudinal Global Positioning System (GPS) derived travel data, but focused primarily on daily driving distances. Harris and Webber [13] used the same longitudinal GPS-derived travel data to determine whether meaningful trends existed in vehicle use. Their study revealed that vehicle use patterns might not vary significantly from month-to-month, but differ significantly between weekdays and weekends. Based on these conclusions, the analyses herein were performed on only weekday vehicle travel data; weekend data were not subject to detailed study.

Several authors have attempted to account for uncertainty in PEV charging on the electric system, but many of these efforts focus on identifying charge control strategies. Fettinger et al. [14] proposed that centralized coordination of vehicle charging reduces communication bandwidth requirements as compared to a decentralized system. Aabrandt et al. [15] developed optimal charging control strategies using a centralized approach based on prior work from Sundstrom and Binding [16]. Kristoffersen et al. [17] and Acha et al. [18], among others, also used a centralized control conceptual framework for their vehicle charge management simulations. Su and Chow [19] and Mets et al. [20] developed approaches for decentralized control to reduce system-wide peak electricity demand through an EVSE or home energy management infrastructure.

To mitigate the potential variability presented by PEV charging some researchers have proposed that vehicle owners simply notify aggregators of their schedules in advance, thus ensuring vehicle use can be considered as a deterministic, exogenous component of their model [8,9,11,21]. For example, Han et al. [22] assumed that vehicle use behavior cannot be readily quantified and that vehicle-to-grid (V2G) program participants would need to notify the aggregator before using their vehicles. Stein et al. [23] developed a model for PEV charging that requires user input so that charging loads can be scheduled optimally. Sioshansi and Denholm [21] and Saber and Venayagamoorthy [24] both assume that vehicles can be optimally scheduled for charging or V2G services. The approach in this work builds upon these previous efforts by avoiding the use of deterministic methods to describe PEV use or electricity demand for vehicle charging and avoiding the assumption that vehicle charging loads can be made deterministic [8,11,21].

Many studies have used national travel survey data to characterize PEV charging or simulate charge scheduling or optimization strategies, including much of the work previously cited. Additionally, Kelly et al. [25] employed the US National Household Travel Survey (NHTS) to examine the effect of owner demographics on PHEV charging patterns, while Zhang et al. [26] used the same data to evaluate the sensitivity of PEV charging infrastructure needs to various charging control strategies. Rautiainen et al. [27] used data from the Finland National Travel Survey to simulate PHEV charging effects at the distribution level. Huang and Infield [28] also examined conditions associated with PHEV charging at the distribution level, in their case using UK travel data, and employed a Monte Carlo simulation approach similar to the methodology developed in this work.

There are also a few studies that focus specifically on the impact of unscheduled vehicle charging on electric system operating conditions. Weiller [29] converted NHTS data into PHEV charging load and used the full data set to characterize unscheduled charging patterns. The MERGE project in the EU considered, as part of their work, the effect of unscheduled vehicle charging on electric load as a function of PEV fleet size for several EU nations [30]. Similarly, Coldwell et al. [31] and Papadopoulos et al. [32] both considered the impact of charging patterns on loads in regions of Europe, either focusing exclusively on Great Britain or comparing Spain and Great Britain, respectively. Wu et al. [33] propose two methodologies to simulate unscheduled PEV charging using NHTS data but use highly simplified assumptions regarding the times when PEV drivers will charge their vehicles. Some of the work focusing on charging control strategies or optimal charging strategies also discusses unscheduled charging patterns, but generally for the