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Joint charging mode and location choice model for battery electric vehicle users

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ABSTRACT

This paper aims to investigate the choice for charging mode and location with the revealed preference data of battery electric vehicle (BEV) users in Japan. Three alternatives including the normal charging at home (for private BEVs)/company premise (for commercial BEVs), normal charging at public charging stations and fast charging at public charging stations are defined. A mixed logit model is developed to investigate what and how factors influence BEV users' choice of charging mode (normal or fast) and location (home/company or public stations), by identifying an appropriate instrumental variable to correct the serious endogeneity problem caused by the midnight indicator. The parameters estimation and results interpretation are conducted for private and commercial BEVs respectively. They suggest that the battery capacity, midnight indicator, initial state of charge (SOC) and number of past fast charging events are the main predictors for users' choice of charging mode and location, that the day interval between current charging and next trip positively affects the normal charging at home/company. In addition, with the increasing of vehicle-kilometres of travel (VKT)/travel duration on former/next travel day, the probability of normal charging at home/company is increased for commercial BEVs, while is decreased for private BEVs. The findings obtained herein have provided new insights into the realization of power peak-load shifting and operation strategy for public charging stations, as well as inspired the development and application of new models and methodologies to determine the density and deployment of public charging stations.

1. Introduction

Battery electric vehicles (BEVs) have been touted as one of the promising ways to achieve urban sustainable development because of their competences to fossil fuel dependency and reduce the tailpipe emissions. Over the past decades, many governments over the world have affirmed their commitments to vehicle electrification by providing considerable investments in charging infrastructure, consumer incentives as well as research and development (Trigg et al., 2013). BEVs can be replenished at charging facilities installed at homes, working places or public charging stations. Their charging magnitudes are generally classified into three levels: Levels 1, 2 and 3. In the literature, Levels 1 and 2 are collectively referred to as the "normal" or "slow" charging mode with charging time ranging from 4 to 12 h to get a depleted 24 kwh battery fully

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replenished, while Level 3 is known as the "fast" charging mode due to their great charging efficiency with charging time ranging from 0.5 to 2 hours for a full charge (Trigg et al., 2013). Although fast charging stations provide high charging efficiency, they are currently limited to public infrastructure due to high voltage requirement, and mainly for emergency usage of BEVs during their long trips. Rather, slow chargers can be installed at home and working places, thus they provide great convenience and flexibility to charge battery when BEVs are parked overnight at home or all days in working places.

Although BEVs deliver sizable social and environmental benefits, the large-scale adoption of BEVs will inevitably have a significant impact on the power grid load. To ensure that BEVs and power grid can interface with each other safely and reliably, the peak power capacity may need to be increased by upgrading the power distribution transformers. Fortunately, the desirable effect of peak-load shifting can be achieved by increasing the off-peak electricity utilization by BEVs (Hadley, 2006). The deep study on the BEV users' charging behaviour, especially their choice in charging mode and location, will enable us to understand two critical issues: (i) whether the advent of a further mass-market of BEVs is viable without largely upgrading the current power distribution transformers and (ii) whether it is possible to encourage BEV users charge at off-peak hours by fiscal incentives.

Apart from the added load on the power grid, how to deploy charging infrastructures intelligently in prospect of large-scale BEVs' uptake, especially in public locations, is also one of the most pressing challenges for any local governments. Even excluding the expense for additional electrical or construction works, the simple procurement and installation of one public charging station can easily cost up to USD 5000 to 15,000 (Trigg et al., 2013). However, without any information regarding charging demand and behavior, early attempts to merely maximize the coverage of charging stations result in the low or almost no utilisation of some charging points (Hagerty and Ramsey, 2011; Russo, 2015). When the demand for BEVs is uncertain, especially for the countries in the initial stage to demonstrate vehicle electrification, how to determine the appropriate number of public BEV charging stations and deploy them intelligently remains the most prominent issue going forward along the way to achieve widespread jumpstart of BEVs. Given the limited knowledge and experiences, one of the best practices to address the aforementioned problem is to analyse the available historical data about BEV users' travel pattern, charging behavior and infrastructure utilization.

The recovery of BEVs has brought in the extensive studies during the last few decades. For example, Brownstone et al. (2000), Dagsvik et al. (2002), Hackbarth & Madlener (2013) and Glerum et al. (2013) analysed household's or individual's preferences for BEVs by applying different discrete choice models. Jensen et al.(2013) investigated the effect of experiencing an electric vehicle on individual's preferences for electric vehicle. Fetene et al. (2016) recently proposed a microeconomic model of charging at working place and gave a rationale for the public initiatives to boost the provision of charging at working place. Moreover, on the one hand, some studies sought for strategic or operational decision-makings to accelerate the adoption of BEVs, including (i) how to distribute the budget to charging infrastructure, incentives, etc. to better facilitate the uptake of BEVs (Nie et al., 2016) and (ii) how to optimally deploy charging infrastructure to sustain the mass-adoption of BEVs (He et al., 2013; Nie and Ghamami, 2013; Sathaye and Kelley, 2013; Mak et al., 2013; He et al., 2015; Arslan and Karaşan, 2016; Ghamami et al., 2016; Li et al., 2016a; He et al., 2016; Hof et al., 2017; Liu and Wang, 2017) as well as (iii) how to address the routing, touring, fleet deployment or relocation problem of BEVs to facilitate their integration in urban logistics and shared mobility (Li et al., 2016b; Liao et al., 2016; Boyacı et al., 2017). Understanding how the incentives affect the adoption of BEVs and how to deploy the charging infrastructure calls for a tangible behavioral model that can capture the charging pattern of BEV users. On the other hand, others investigated the impact of jumpstart of BEVs on the power grid, environment and climate, traffic assignment, etc. (Clement-Nyns et al., 2010; Waraich et al., 2013; Jiang et al., 2012; He et al., 2014; Xu et al., 2017). These impact analyses are closely related to the deployment of charging infrastructure and resultant charging behavior of BEV users. In the other words, the existing studies generally assume that the deployment of charging infrastructure and charging pattern/behavior are exogenously given.

Although the charging behavior modeling is of great importance, it has been examined by a few studies due to the lack of real revealed preference data. Smart et al. (2013) studied various driving and charging behavior across electric vehicles enrolled in a project conduced in 21 metropolitan areas in the USA. Sun et al. (2015a) applied a mixed logit model with unobserved heterogeneity in an effort to investigate the timing choice for the normal charging of private and commercial BEV users in Japan after their last trip of a day. They found that the normal charging behavior was driven by electricity demand and BEV users preferred to charge at night for the sake of low electricity tariff. Jabeen et al. (2013), explored the BEV users' charging preference to home, work and public places with the stated choice experiments conducted in Australian. They showed that BEV users preferred to charge their vehicles at night and they were sensitive to charging cost and duration generally. However, their models did not differentiate the charging level of public charging stations, and the interaction of driving and charging behaviors was not revealed due to the lack of explanatory variables concerning the driving behavior. With data collected from a real-world fleet of instrumented plug-in hybrid electric vehicles (PHEVs) deployed in the USA, Zoepf et al. (2013) adopted a mixed logit model to study whether PHEV users charge at the end of each trip. They found that PHEV users generally preferred to charge their PHEVs after a day's last trip ending at home with the next trip occurring in more than 3 hours later. Daina (2013) used the multinomial logit model to investigate the choice of charging timing and trip adaptation with data from the stated preference survey conducted in UK for the non-electric vehicle drivers.

To the best of our knowledge, no research has been conducted so far to investigate the joint choice of charging mode (normal or fast) and location (home/company or public) with revealed preference data. By considering the charging modes and locations jointly and allowing the correlation between alternatives, the specified choice situation is more realistic, resulting in more credible estimation results. More importantly, the distinct behavior of BEV users towards normal charging