Transport Policy 54 (2017) 30–42

Contents lists available at ScienceDirect

Transport Policy

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

A comprehensive model of regional electric vehicle adoption and penetration

Roxana J. Javid[a,*], Ali Nejat[b]

[a] Department of Engineering Technology, Savannah State University, Savannah, GA 31404, USA
[b] Department of Civil, Environmental and Construction Engineering, Texas Tech University, Lubbock, TX 79409, USA

ARTICLE INFO

Keywords:
Plug-in electric vehicles
Adoption behavior modeling
Regional penetration level
Sustainable transportation
Charging stations
Socioeconomic factors

ABSTRACT

This study focused on the adoption of Plug-in Electric Vehicles (PEVs) as a policy towards having a more sustainable transportation with lower Greenhouse Gas (GHG) emissions. The current paper aimed to explore potential factors that can be attributed to purchasing PEVs in order to estimate their penetration in 58 California counties. A Multiple Logistic Regression Analysis was applied to the 2012 California Household Travel Survey dataset, which includes both PEV and conventional car buyers' information, as well as some other secondary data sources. The model developed a broad set of factors including demographic and travel-related characteristics, socioeconomic variables, and infrastructural and regional specifications. The results identified that a household's income, maximum level of education in the household, the buyer's car sharing status, charging stations density, and gas price in the region can significantly impact PEV adoption. The model was validated using data from the 2012 Household Travel Survey conducted in the Delaware Valley region. With sufficient data availability, the methodology can be applied to evaluate changes in vehicle fleet composition and the levels of emissions in response to transportation policies. The model is believed to have a wide range of applications in electricity utilizing, gasoline/diesel retailing, and battery and automotive manufacturing. Additionally, the model can assist policy makers and transportation planners to optimize their infrastructural investments by identifying counties where the response of drivers to added charging station would be maximized, implying that larger benefits can be achieved.

1. Introduction

In the United States (U.S.), Greenhouse Gas (GHG) emission levels from the transportation sector have risen more than any other sectors over the last two decades (EPA, 2013). Transportation is responsible for nearly one-third of total emissions in the U.S. (Salari and Javid, 2016) among which, over one-third can be attributed to passenger cars and another one-third to light and heavy trucks. Due to a rapid increase in motor vehicle ownership, vehicle demand has to be controlled in order to reduce the adverse impacts of transportation (Liu and Cirillo, 2014). This highlights the potential impact of on-road transportation policies in reducing GHG emissions. GHG emission mitigation not only reduces the human-induced climate change (Arce et al., 2014; Ghommem et al., 2012; Khatiwala et al., 2013), but it can also potentially reduce air pollution, which in turn benefits human health and natural ecosystems as well as conserving finite resources of oil and other fossil fuels (Javid et al., 2014).

Policies to reduce GHG emissions from road transportation encompass a wide range of strategies, which are used in European countries (Andersson et al., 2010; Daly and Ó Gallachóir, 2012; Rogan et al., 2011; Smith, 2010), Asia (Chandran and Tang, 2013; Ong et al., 2012; Yedla and Shrestha, 2003), Africa (Jones et al., 2013), Australia (Stanley et al., 2011), and the U.S. (Leighty et al., 2012; McCollum and Yang, 2009; Yang et al., 2009). In the U.S., under the Clean, Low-Emission, Affordable New Transportation Efficiency Act (CLEAN-TEA) introduced in March 2009, local governments with a population of over 200,000 are required to determine a plan to mitigate GHGs from the transportation sector (Houk, 2010). This GHG mitigation will need a large-scale investigation and implementation of sustainable transportation policies.

Common examples of the policies include high efficiency vehicles (Yang et al., 2009), travel demand management (flexible hours, teleworking) (McCollum and Yang, 2009), shifting from personal car to public transport (McCollum and Yang, 2009; Stanley et al., 2011), alternative fuels (hydrogen, electricity, biofuel) (Bubeck et al., 2016; Leighty et al., 2012), various types of taxation (road toll, parking charges) (Chapman, 2007), reducing engine weight (Skippon et al., 2012), zero-carbon alternatives (cycling and walking) (Chapman, 2007;

* Corresponding author.
E-mail address: javidr@savannahstate.edu (R.J. Javid).

http://dx.doi.org/10.1016/j.tranpol.2016.11.003
Received 1 July 2016; Received in revised form 6 October 2016; Accepted 14 November 2016
Available online 24 November 2016
0967-070X/

Stanley et al., 2011), and high occupancy vehicle (HOV) lanes (Javid, 2016; Javid et al., 2016). All of the strategies for reducing emissions can be classified into three groups: *Reduce* (Reducing GHG emissions per passenger kilometer), *Avoid* (Avoiding unnecessary energy consumption and promote other modes of transportation), and *Replace* (replacing fossil fuels with low-emission alternative fuels) as described in (Javid et al., 2014; Javid et al., 2017).

Towards a sustainable transportation, one or a combination of these strategies can be employed. *Replacing* strategy and adoption of cleaner fuels and vehicles is the focus of the current study. Plug-in Electric Vehicles (PEVs), including Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) (Tal and Nicholas, 2013), are one of the means to improve the sustainability of the road transportation by replacing fossil fuels. The main advantages of PEVs are reducing vehicle operating cost, reducing the dependency on fossil fuel, and especially decreasing GHG emissions (Bradley and Quinn, 2010). To assess the environmental and economic impacts of PEVs, two main steps need to be explored. First, their level of penetration- percentage of PEV buyers to the total car buyers- and second, their usage patterns (Tamor et al., 2013). Estimation of PEVs' level of penetration and their adoption is the motivation of this study, as it is the first and the main step to study this developing technology. This section is followed by motivation, which is then succeeded by the related works and then data description. Research methodology, results, and model validation are presented in subsequent sections. Finally the last section provides the conclusion of the study.

2. Motivation

Although there is an extensive newly emerged literature on exploring the most influential factors on PEV demand, given an early market in PEVs, the near future of PEV market is not clear (Carley et al., 2013). Most studies on PEV adoption are based on travel surveys, in which vehicles are *assumed* to be PEVs, or surveys from small samples of *hypothetical* PEV buyers, which evaluate consumers' attitudes towards buying a PEV. Since statements about intent to purchase a product are rarely validated with data on actual purchasing decisions (Carley et al., 2013), previous studies lack the *real* PEV buyer data to support their findings. This paper uses the 2012 California Statewide Travel Survey that includes both conventional car (total of 15,942) and PEV buyers' (total of 406) detailed information. California is responsible for about 42% of the total U.S. PEV market (Tal and Nicholas, 2013), making it a suitable region for the purpose of this research.

The contribution of this study to the related literature is threefold. First, it employs real micro-level dataset to provide more realistic estimates for the electrification (potential for transportation to switch to electricity based) and the actual demand of PEVs in California. Second, the study assesses PEV demand by exploring a more comprehensive set of factors including demographic and travel-related characteristics, socioeconomic variables, infrastructural, and regional specifications. Last, its customizable methodology allows for extending the model to any other regions with a homological dataset.

The proposed model has a two-fold objective. The first is to use a descriptive approach to investigate potential factors affecting PEV purchasing behavior. The second is to use a predictive approach to investigate regional PEV penetration rates. The model is believed to have a wide range of applications in electricity utilizing, gasoline/diesel retailing, and battery and automotive manufacturing. Additionally, the model can assist city authorities, policy makers and transportation planners to optimize their marketing and infrastructural investments by identifying and targeting communities that are more prone to buy PEVs.

3. Related works

Based on the U.S. Energy Information Administration (EIA, 2012), there were about 70,000 BEVs and 104,000 PHEVs out of 226 million registered vehicles in the U.S. by 2013 (United States Energy Information Administration). PEV sales continue to grow rapidly (He et al., 2013) from 0.4% in 2012, to 0.6% in 2013 and 0.7% in 2014 (United States Energy Information Administration). Purchasing patterns can differ substantially based on the situation. PEV purchasing behavior is even more challenging since vehicle buyers are mostly unfamiliar with them. Existing literature on the subject matter differ from one another based on studied region, dataset, methodology, vehicle(s) type, and influencing parameters.

The study area could be a country (Krupa et al., 2014; Lieven et al., 2011; Schuitema et al., 2013), a state (Tamor et al., 2013), or a city (Carley et al., 2013; Khan and Kockelman, 2012; Musti and Kockelman, 2011). In terms of dataset, either small (Egbue and Long, 2012; Khan and Kockelman, 2012; Türnau, 2015) or large (Higgins et al., 2012; Tamor et al., 2013) surveys or questionnaires from conventional car buyers are used. Assigned methodologies consist of a wide range of statistical models. Among them, the most widely adopted approaches use Ordinary Least Square (OLS) regression. There is a critical distinction among these studies based on vehicle types and influencing parameters integrated into the models. There are different types of electric vehicles; from conventional hybrid electric cars to more recently developed PHEVs. Conventional hybrid electric vehicles have a diesel engine and an electric motor powered by a battery that gets charged when the car is in motion. This kind of vehicles does not need a power outlet for charging. On the other hand, PEVs get charged using a power outlet. PEVs include BEVs, which are powered only by electricity, and PHEVs, which run on both electric power and diesel engine (Schuitema et al., 2013; Tal and Nicholas, 2013). In preliminary studies to assess cleaner vehicles such as conventional hybrid electric vehicles, the acceptance of these vehicles was investigated (Diamond, 2009; Gallagher and Muehlegger, 2011; Li et al., 2013) however this study focuses on BEVs and PHEVs adoption and the related literature. In this study PEVs are used collectively for both unless stated otherwise.

The most important factors that influence PEV adoption are investigated in the previous studies, including buyers' socio-demographic characteristics such as age, gender, and level of education, travel patterns, household attributes such as income, location-related and infrastructure variables, or even vehicle-related factors. Table 1 summarizes some of the most recent studies on this topic.

There are many different variables that have been discovered to influence the PEV market; however, none of the previous studies have developed a comprehensive model using all the assessed factors. The current study addresses these challenges using real-world data of both PEVs and conventional car buyers and develops a new comprehensive model to assess PEV penetration. The next section provides a thorough description of all datasets, which were incorporated into this study.

4. Data and variables

Potential factors that explain PEV purchasing behavior can be classified into three main categories (Sierzchula et al., 2014): vehicle-related factors, consumer-related factors, and context factors that are external to both first and second categories. This paper explores 17 variables in these three categories that might affect PEV adoption and employs several datasets to encompass these variables. Fig. 1 shows the variables and the related categories. A detailed description of each variable and its corresponding dataset is provided in the next subsections. To the authors' best knowledge, these variables are the most common factors that can have significant impacts on the model. The final model includes a selection of these factors.