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An agent-based electric vehicle ecosystem model: San Francisco case study

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ABSTRACT

The widespread commercial availability of plug-in electric vehicles (EVs) in recent years motivates policies to encourage EV adoption and infrastructure to cope with the increasing number of EVs. We present an agent-based EV ecosystem model that incorporates EV adoption and usage with spatial and temporal considerations and that can aid different EV industry stakeholders such as policymakers, utility operators, charging station planners, and EV manufacturers. The model follows an ecological modeling approach, and is used to determine how different policies and battery technologies affect EV adoption, EV charging, and charging station activity. We choose model parameters to fit San Francisco as a test city and simulate different scenarios. The results provide insight on potential changes to the San Francisco EV ecosystem as a result of changes in rebates, availability of workplace charging, public awareness of lower EV operational costs, and denser EV batteries. We find that our results match those obtained using other approaches and that the compact geographical size of San Francisco and its relative wealth make it an ideal city for EV adoption.

1. Introduction

In recent years, there has been an increase in the market penetration of Electric Vehicles (EVs) in countries such as Norway, Estonia, and the United States (US) (EDTA, 2014; Hannisdahl et al., 2013; Merchant, 2013). Despite the well-documented barriers to EV adoption (Boulanger et al., 2011), including high initial costs, range anxiety, and the perceived scarcity of adequate charging infrastructure, EV adoption is increasing. For example, the number of Plug-in EVs (PEVs) in the US increased from zero to more than 165,000 in just 3 years (EDTA, 2014). In September 2013, the Tesla Model S, an electric car, was Norway's best-selling car, and in November 2013, more than 10% of cars registered in Norway were electric (Ingram, 2014).

This success is partly due to government policies such as EV purchase rebates, EV Supply Equipment (EVSE) rebates, high-occupancy lane access for EVs, free parking, removing import taxes, educating the general public about emissions, and encouraging businesses to have charging terminals at work. It is noteworthy that California, which has several policies that encourage EV adoption (AFDC, 2014a), also has one of the highest EV adoption rates in the US (Voelcker, 2014a; O'Connor, 2014).

Although rapid EV adoption is a generally desirable outcome, it has some potential drawbacks, including increasing grid load and the need to provision expensive charging stations. Moreover, it is not obvious which policies are most responsible for increasing EV adoption. What is needed, therefore, is a tool that carefully models the EV ecosystem to allow the exploration of 'what-if' scenarios. Using an agent-based EV ecosystem model that captures EV adoption and usage, we present a tool can be used by policymakers, electric utilities, charging station planners, and battery manufacturers for purposes such as the following:

- *Policymakers* can estimate the impact of different policies on EV adoption.
- *Electrical utilities* can estimate the spatial and temporal changes in electrical load resulting from different levels of EV adoption and different EV technologies.
- *Charging station planners* can estimate how different levels of EV adoption affect public charging station activity.
- *Battery manufacturers* can determine how battery sizes would affect EV adoption and electrical load.

We have used our tool to study EV adoption and usage in San Francisco, CA. Drawing upon the results of a comprehensive study of driving habits in this city (Caltrans, 2013), we study the impact of policy and technology changes on future EV penetration,

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presenting results that are likely to be of interest to each of the stakeholders above.

2. Related work

This section presents a number of studies on EV adoption and usage in the research literature.

2.1. EV adoption models

An EV Adoption model seeks to model the EV purchase decision. There are three major types of adoption models: Agent-Based Models (ABMs), consumer choice models, and diffusion rate models (Al-Alawi and Bradley, 2013). Al-Alawi and Bradley (2013) provide a detailed review of different EV adoption models in each of these three categories.

ABMs comprise different types of agents with specific behaviors in a certain environment. The results obtained from ABMs are a result of the interactions between agents and agent–environment interactions. ABMs are discussed in more detail in Section 3. In EV diffusion rate models, EV adoption is estimated based on the Bass diffusion model (Bass, 1969). Here, consumers are segmented based on their attitude towards an innovation: early adopters, early majority, late majority, and laggards (Rogers, 2010). Consumer choice models forecast adoption based on the vehicle preferences of a particular population. This often involves the use of logit models and discrete choice mathematical models. While diffusion rate and consumer choice models have their benefits, ABMs utilize the bottom-up system approach that enables us to understand how a system reaches a certain state, based on interactions between agents and with the environment. Since our work involves the development of an agent-based EV ecosystem model, we focus on these models next.

Eppstein et al. (2011) and Pellon et al. (2010) study the adoption of EVs by modeling agents (people) that choose between Internal Combustion Engine Vehicles (ICEs), Hybrid EVs (HEVs), and PHEVs. For each agent, factors such as age, income, house location, expected years of vehicle use, mileage, etc. are considered. Network externalities are modeled based on an agent's susceptibility to media campaigns and social influence. This work also spreads out agents over a geographical area. This spatial orientation is used in conjunction with social networks to estimate agent network externalities. This work serves as a basis for our model and is discussed in more detail in Section 3.2.1.

Shafiei et al. (2012) also present an agent-based EV adoption model. In order to estimate the probability of a person buying a particular vehicle out of a pool of vehicles, an agent's willingness to pay for the vehicle is combined with customer preferences and vehicle attributes. This work also uses a refueling effect variable to incorporate the availability and acceptability of public charging stations that is linearly proportional to the market share of EVs. The results show the potential impacts of changing EV and gas prices on EV adoption. However, since this work focuses on EV adoption, it does not incorporate a detailed EV usage model.

The approach by Schwoon (2006) estimates the availability of hydrogen refueling stations for fuel cell vehicles, based on the penetration of these vehicles and the maximum possible increase in hydrogen refueling stations over a period of time. This work does not focus on EVs but serves as a basis for agent-based EV adoption models.

Sweda and Klabjan (2011) present an ABM focused on the deployment of charging infrastructure, and the ABM includes an EV adoption model. Agent properties include income, vehicle class preference, range anxiety, and preferred vehicle longevity. An agent buys a vehicle based on price, fuel cost, greenness, social influence, long distance penalty, and infrastructure penalty. The study, however, does not detail how these variables are quantified. The model also includes three drive cycles for each agent: local, work, distant. We use a similar approach in our work.

Sullivan et al. (2009) model PHEV penetration using an ABM. In addition to EV owners, the model represents the government, fuel producers, and vehicle producers as agents. This paper stresses that the budget of an agent is the most important factor considered when buying a car. It also adds that agents are likely to buy vehicles ‘proportional’ to their income and area of residence. Each agent has specific home and work addresses, income, budget for transportation, driving cycles, and preferred vehicle longevity. The study further mentions that the vehicle choice is dependent on an agent's willingness-to-pay and peculiar preferences. According to Al-Alawi and Bradley (2013), this is one of the most detailed agent-based EV adoption models. However, including governments and fuel producers as agents gives the modeler less control on estimating the sensitivity of EV adoption towards government policies or fuel producer decisions. As a result, we structure our model to provide insight on the impacts of different policies and EV technologies that are exogenous to the model.

Shepherd et al. (2012) study the factors affecting EV adoption using a systems dynamics approach. Using the UK as a case study, they focus on the impact of factors such as rebates, EV range, and charging availability on EV sales and reduction of CO_2 emissions. This work, however, does not comprise a detailed EV usage – that is, a driving and charging – model.

Lin and Greene (2010) use a Nested Multinomial Logit (NMNL) model with variables such as customer driving needs and availability of refueling to forecast PHEV adoption. The potential customers are segmented based on factors including location of residence, ability to charge at work, and affinity for new technology. The results show that PHEV adoption is influenced the most by availability of charging stations. This study, however, models only PHEVs and does not detail EV usage.

Brown (2013) studies the influence of factors such as financial incentives and vehicle range on the market penetration of PHEVs and BEVs, using an ABM with a mixed logit approach for agent vehicle choices. Our study takes a step further by estimating the energy impacts of EV penetration based on agent driving and charging decisions.

Table 1 shows a summary of these vehicle adoption studies and how we improve on each study. Our EV ecosystem model attempts to improve on existing EV adoption and usage models by combining EV adoption and use. Specifically, our model integrates daily drive cycles with real-world trip characteristics (duration and distance), public charging stations, policies, and EV loads. Using an ABM provides granularity; each agent makes purchase, driving, and charging decisions, and this results in additional electrical load on the grid.

2.2. Impact of EV usage on the grid

Paevere et al. (2014) focus on the temporal and spatial distributions of the impact of EV charging demand. Focusing on Victoria, Australia they study scenarios with different rebates and EV penetrations, as well as different charging schemes, and how the resulting load adds to the existing residential load. This is similar to our approach since one of the cases it focuses on is the impact of EV purchase rebates on EV adoption, and the resulting electrical load. We go further by considering the impacts of other policies: encouraging workplace charging stations and educating the population on estimating the Total Cost of Ownership (TCO) of vehicles. There are other studies (Arellano et al., 2013; Pellon et al., 2010) that also focus on the impact of different fixed EV penetration scenarios and charging rates on the daily load profile. For