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.

Keywords: Agent-Based Modeling, Electric Vehicle, Electric Vehicle 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 rarity 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 highest 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, presenting results that are likely to be of interest to each of the stakeholders above.

The contributions of our work are as follows:

1) The development of an agent-based EV ecosystem model that comprises both EV adoption and EV usage.

2) Actualization of the model based on survey and environmental data from San Francisco, CA.

3) ‘What-if’ analysis of several policy and technology changes on EV adoption and usage in San Francisco.

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. 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 CO₂ emissions. This work, however, does not comprise a detailed EV usage – that is, a driving and charging – model.

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 I 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.

Table 1: Comparing Agent-Based EV Adoption Models

<table>
<thead>
<tr>
<th>Study</th>
<th>Contribution</th>
<th>Drawbacks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eppstein et al., 2011</td>
<td>This study focuses on the adoption of HEVs and PHEVs. Also uses spatial data and network externalities.</td>
<td>It assumes that the EV is charged only once a day. As a result, it does not properly consider the impacts of EVs on the grid and the availability of charging on agents. In addition, it</td>
</tr>
<tr>
<td>Study</td>
<td>Focus and Methodology</td>
<td>Limitations or Additional Considerations</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Shafiei et al., 2012</td>
<td>This is an agent-based study that focuses on BEVs and includes refueling effects.</td>
<td>It does not look at impact of the EV adoption rate on infrastructure.</td>
</tr>
<tr>
<td>Schwoon, 2006</td>
<td>This focuses on the adoption of fuel cell vehicles.</td>
<td>The modeling of refueling cannot be applied to EVs because of much longer refueling time, a very significant variable.</td>
</tr>
<tr>
<td>Sweda and Klabjan, 2011</td>
<td>Rather than focusing directly on adoption, this paper focuses on the impact of EV adoption on grid infrastructure in order to develop a charging infrastructure deployment plan.</td>
<td>It does not include spatial distribution of EV adoption; instead, it focuses on siting public charging stations.</td>
</tr>
<tr>
<td>Paevere et al., 2014</td>
<td>This study focuses on temporal and spatial changes in EV charging demand based on different adoption scenarios.</td>
<td>It only looks at the eventual impact of EV rebates on charging demand. We focus on other policy and vehicle battery impacts.</td>
</tr>
<tr>
<td>Cui et al, 2010</td>
<td>This paper models PHEV adoption and how different charging schemes can be used to manage EV charging</td>
<td>It focuses more on charging schemes rather than EV adoption under different scenarios.</td>
</tr>
</tbody>
</table>
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 example, Acha et al. (2011) use an ABM to combine EV trips and charging with optimal power flow analysis.

Cui et al. (2010) focus on how the distribution of PHEVs affects the grid via power line congestion and transformer overload, and how charging schemes can be used to manage these effects. In this study, an ABM with decisions based on a Nested MultiNomial Logit (NMNL) approach is used to determine EV adoption; this approach is similar to that used by Shafiei et al. (2012).

These studies provide the context for our work, presenting some of the electrical load impacts of EVs, including the spatial and temporal distributions of EV electricity consumption at different scales.

3. Methods

We present the details of the agent-based EV ecosystem model. The model comprises a conceptual model that guides and informs a quantitative model for simulating different EV ecosystem scenarios.

3.1. Conceptual Model

Since this work focuses on the EV ecosystem, we take a cue from the field of ecological modeling and apply ecological modeling in our work. Grant and Swannack (2008) extensively discuss the concept of ecological modeling. The parameter types used in Figure 1 and listed in Figure 2 are explained as follows:

- **State Variable**: This variable represents the collection of materials a point within the system. We are interested in monitoring the state variables of the EV ecosystem.

- **Sources and Sinks**: Sources are points of material entry in the system and sinks are points of material exit in the system.
- **Material Transfer**: This represents the transfer of materials from one state variable to another, from a state variable to outside the system (sink), or from outside the system (source) to a state variable.

- **Information Transfer**: This controls one element of the system state based on information about the state of other state variables.

- **Driving (Exogenous) Variables**: These variables affect the system but are not affected by the state of the system.

- **Constants**: These are not included in the system model unless they are conceptually important. Otherwise, they are attached to system equations.

- **Auxiliary Variables**: These are the other variables that directly or indirectly inform the state of the system, or *vice versa*. 
Figure 1: EV Ecosystem Conceptual Model
In the EV ecosystem model, the materials that ‘flow’ in and out of the EV ecosystem are EVs and energy. Simply put, EVs are bought and eventually sold or discarded, and electricity fuels these EVs. Figure 1 provides an overview of the ecosystem model and provides context for the agent, environment, and output parameters as seen in Table II. The agent and ecosystem properties in Figure 1 are expanded and explained in Table II.

Figure 1 enables us to establish the correlations between variables. For example, a policy that decreases EV rebates over time is expected to reduce the adoption of EVs, with all other things being equal. Also, the energy capacity of EV batteries and available charging opportunities affect both EV adoption and energy consumed. An agent that can charge at home and at work is more likely to purchase an EV than an agent that can only charge at home. Also, a higher battery capacity
would encourage more agents to buy EVs, as well as increase the electricity that can be taken from the grid per charge.

It should be noted that the information feedback from the Number of EVs state variable to the material transfer of EVs into the ecosystem is included because of the social influence on EV adoption, where an agent buys a vehicle because some other agents in its social network own EVs. This is discussed in more detail in Section 3.2.1.

### 3.2. Quantitative Model

The EV adoption model presented by Eppstein et al. (2011) serves as a basis for our EV adoption model. We now discuss the simulation parameters used in our model (Table II). In order to determine agent behaviour, each agent is initialized with a number of characteristics as seen in the Agent properties rows of Table II. Work days represent the days of the week during which an agent goes to work. This is necessary for activating either a workday or non-workday drive cycle each simulation day. Also, the age and fuel type of each agent’s vehicle are defined at the beginning of each simulation run.

**Table 2: Simulation Variables (DS = Dataset; E = Estimated; I = Independent)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agents</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>DS: X</td>
<td>Each resident in surveyed households is listed in an age bracket, within which we uniformly assign a particular age.</td>
</tr>
<tr>
<td>Income</td>
<td>DS: X</td>
<td>Each household is listed in an income bracket,</td>
</tr>
</tbody>
</table>
within which we uniformly assign a particular income. We divide the income among each household's working residents, if necessary.

<table>
<thead>
<tr>
<th>Work days</th>
<th>X</th>
<th>These are the days of the week that a person goes to work. In cases where it is not specified in the data, we assume work days of Monday - Friday.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home location</td>
<td>X</td>
<td>The household location of each respondent is anonymized but listed as a zip code. Even though zip codes are not areas, we uniformly assign locations close to the centers of these zip codes within a 1 km radius, by obtaining the central geographical coordinates of each zip code.</td>
</tr>
<tr>
<td>Work location</td>
<td>X</td>
<td>The work location is obtained similarly to the home location.</td>
</tr>
<tr>
<td>Vehicle fuel type and age</td>
<td>X</td>
<td>Each surveyed household has a list of vehicles already in use, with details such as the model year and fuel type assigned.</td>
</tr>
<tr>
<td>Workday and non-workday drive cycles</td>
<td>X</td>
<td>The drive cycles are based on expected trips to and from home locations, work locations, and random locations of interest. See Tables 3 and 5.</td>
</tr>
<tr>
<td>Desired vehicle range</td>
<td>X</td>
<td>This is the farthest daily driving distance, estimated based on daily drive cycles.</td>
</tr>
<tr>
<td>Desired vehicle fuel</td>
<td>X</td>
<td>This is assumed to be the highest vehicle efficiency</td>
</tr>
<tr>
<td><strong>efficiency</strong></td>
<td>available in the market today (USEPA, 2014b). See Table 4.</td>
<td></td>
</tr>
<tr>
<td>---------------</td>
<td>----------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Greenness G</td>
<td>G is correlated with some noise included. See Eq. 8.</td>
<td></td>
</tr>
<tr>
<td>Social network threshold $T$</td>
<td>$T$ is the fraction of an agent's social network that must own EVs in order for that agent to buy an EV. By default, the percentages of agents classified as early adopters, early majority, and late majority are 16%, 34%, and 50% respectively (Lin and Greene, 2010; Santini, 2005; Rogers, 1971).</td>
<td></td>
</tr>
<tr>
<td>Social network</td>
<td>Each agent's social network is selected from other agents with similar ages (±5 years), incomes (±$10,000), and residential locations (±2 km). Each agent is assigned a number of social connections, randomly chosen with minimum and maximum sizes of 1 and 14 respectively.</td>
<td></td>
</tr>
<tr>
<td>Ability to estimate TCO</td>
<td>This is a binary variable that determines if an agent can estimate the TCO of a vehicle. This is used to evaluate the impact of a policy to educate people on EVs and TCO. By default, 20% of agents are assumed to be capable of estimating TCO.</td>
<td></td>
</tr>
<tr>
<td>Option to charge at work</td>
<td>This is a binary variable that determines if an agent has a charging terminal available at the work place. By default, 20% of agents can charge at work (Lin</td>
<td></td>
</tr>
<tr>
<td><strong>EV Ecosystem</strong></td>
<td><strong>Vehicle types and specifications</strong></td>
<td><strong>Trip duration and</strong></td>
</tr>
<tr>
<td>------------------</td>
<td>-------------------------------------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>Desired vehicle longevity</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Cost of gas</strong></td>
<td>X</td>
<td>This is the equivalent cost in $/kWh obtained from the cost in $/gallon and the energy content of gasoline: 1 gallon of gasoline contains 33.7 kWh of energy (AFDC, 2014b; BLS, 2014).</td>
</tr>
<tr>
<td><strong>Cost of electricity</strong></td>
<td>X</td>
<td>This is the average cost of electricity in San Francisco (BLS, 2014).</td>
</tr>
<tr>
<td><strong>Existing rebates</strong></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Public charging stations</strong></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Trip duration and</strong></td>
<td>X</td>
<td>We use MapQuest Route Matrix to obtain driving</td>
</tr>
</tbody>
</table>
An important agent variable, $G$, is the 'greenness' or the utility-cost preference $G^1 (0 \leq G \leq 1)$ that represents an agent's tendency to purchase a vehicle with a lower carbon footprint as against its cost. We need to model the greenness of an agent since one primary advantage of EVs over ICEs is a much lower carbon footprint. However, $G$ is not the only parameter that influences an agent's decision to purchase an EV. We also model the influence of an agent's social network on the agent's decision to adopt new technology (EVs). Each agent is assigned a threshold $T$ ($T \leq 1$) (following Eppstein et al., 2011; Bohlmann et al., 2010); $T$ must be exceeded by the fraction of an agent's social network that own EVs in order for the agent to buy an EV. In other words, agents with $T=0$ are early adopters, and as $T$ increases, an agent tends towards being a late adopter. The social network of an agent is selected uniformly randomly from agents within the same age or income brackets, and from agents living within a specific spatial radius. On the other hand, agents in the same social network do not talk to one another since more modeling details would be required to adequately represent social network interactions and the resulting influences.

The ecosystem input variables (Table 2) are used to represent different simulation scenarios, and these variables affect EV adoption and usage, as described next.

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1 The 'greenness' of an agent is also deemed appropriate since the primary advantage of EVs over ICEs is fuel economy.
3.2.1. EV Adoption

In our model, vehicle purchases are executed quarterly. We define the vehicle purchase process for each agent as follows:

(i) Determine which vehicles on the market the agent can afford.

(ii) Determine which BEVs can meet the agent's daily trip requirements, such that the agent would not get stranded in transit with a fully-discharged EV (required for BEVs only).

(iii) Rank the affordable vehicles according to desirability (explained in Equation 5 below).

(iv) If the most desirable vehicle is an ICE, buy that vehicle. Otherwise, if the most desirable vehicle is bought.

(v) If, for any reason, no suitable vehicle is found, keep using existing vehicle.

For each agent, the relative desirability $D$ of each pair of vehicles is obtained based on their utility and cost (Eppstein et al., 2011). Utility, in turn, is dependent on two attributes: range and fuel economy. For estimating the fuel economy of PHEVs, the fuel efficiency of the electrical and combustion engines in a PHEV are scaled with respect to the ratio of the charge-sustaining and charge-depleting distances traveled during an agent's typical drive cycle. The utility of a vehicle, then, is given by (Schwoon, 2006):

$$U = 1 - \frac{1}{n} \sum_{i=1}^{n} (pref_i - v_i)/pref_i$$

(1)

where $n$ is the number of attributes, $pref_i$ is the agent's preference for attribute $i$, and $v_i$ is the value of the vehicle's attribute $i$. The scaled comparison of agent preferences and vehicle attributes is bounded by 0 and 1. For example, if an agent's range preference is 100 km and a vehicle's range is 110 km, the
vehicle surpassed the agent's range requirement. Therefore, the comparison would result in range utility of 1, rather than 1.1.

$D$ is estimated from the relative benefit $RB$ and relative cost $RC$ of each pair of vehicle choices, scaled by the agent's greenness $G$. More specifically, the desirability of car $j$ over $i$, $D_{ij}$, is a function of the relative cost $RC_{ij}$ and relative benefit $RB_{ij}$ (Eppstein et al., 2011). The relative cost is given by:

$$RC_{ij} = (C_j - C_i)/C_j \quad (2)$$

where $C_i$ is the cost of car $i$, and the relative benefit $RB_{ij}$ is given by:

$$RB_{ij} = (U_j - U_i)/U_j \quad (3)$$

where $U_i$ is the utility of car $i$.

$C$ is either the sticker price or TCO of a vehicle, because, according to Boulanger et al. (2011) and EPRI (2013), not all vehicle purchasers fully consider the expected lower operational costs of EVs. We represent this distinction in our model, following Eppstein et al. (2011). For estimating the TCO, we use the Net Present Value (NPV), which is given by:

$$NPV = \sum_{t=0}^{N} C_t/(d + 1)^t \quad (4)$$

where $N$ is the number of years, $C_t$ is the net cost in year $t$, and $d$ is the discount rate. In the current version of our model, the recurring costs consist, solely, of fuel costs. Note that the sticker price of a vehicle is the only initial cost. However, the model provides room for a more detailed cost estimation process if desired.

We apply a general rule that an agent cannot spend more than 20% of its income on the vehicle purchase (Eppstein et al., 2011). This is used to determine the vehicles each agent can afford. Our model does not consider financing options as part of the vehicle purchase process.
Finally, the relative desirability of two vehicles is given by:

\[ D_{ij} = G \times RB_{ij} + (1 - G) \times RC_{ij} \]  \( (5) \)

The most desirable vehicle is purchased by the agent.

### 3.2.2. EV Usage

The aspects of EV usage included in our model include EV charging – at home, at work, and at public charging stations – and driving (discharging). Each agent is assigned a workday drive cycle and a non-workday drive cycle. The current version of our model does not include long-distance trips. These drive cycles are used to represent the typical trips a person takes each week. These include trips to work, public charging stations, and other Locations of Interest (LoI) used to represent places such as a shopping mall. Each agent is uniformly assigned two LoIs, out of a set of possible LoIs within the city. Also, all daily drive cycles start and end at home. An example of a drive cycle is shown in Table 3.

**Table 3: Example of a Workday Drive Cycle**

<table>
<thead>
<tr>
<th>Trip Number</th>
<th>Start Time</th>
<th>Trip Destination</th>
<th>Stay (hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8:00 AM</td>
<td>Work</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>--</td>
<td>Lol</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>--</td>
<td>Home</td>
<td>--</td>
</tr>
</tbody>
</table>

Each trip is associated with spatial coordinates of the origin and destination. We use the Route Matrix request option to obtain this information, which from OpenStreetMap® and the MapQuest Directions API (MapQuest, 2014) to estimate driving distance and time between these locations. The start time
for each trip after the first trip of the day is updated based on the arrival time and duration of stay at the
destination of the prior trip. The energy consumed for each trip is obtained by

\[ E_{\text{trip}} = EV \text{ Efficiency} \times \text{Distance traveled} \quad (6) \]

Similarly, the charging time for an EV is a function of the energy required to fill the battery and the
charging level.

\[ \text{Charging time} = \text{Energy required} \times \text{Charging level} \quad (7) \]

For agents with BEVs, it is crucial not to get stranded in transit due to inadequate charge. As a result,
before a BEV-driving agent executes its drive cycle for a particular day, it checks that the EV State-of-
Charge (SoC) is sufficient. If not, it chooses to visit a public charging station close to its route or doesn’t
drive the EV that day if the EV cannot reach any charging station.

One benefit of using a spatially-oriented model is the ability to accurately model public charging
stations. Each public charging station is defined by its location, charging capacity, and number of
charging terminals. In our model, only BEV owners visit public charging stations since PHEV owners do
not need to visit public charging stations. EVs drive to the closest charging station to get charged,
regardless of its load. A future refinement would be to include the option of going to a more distant but
less busy charging station. Typically, agents do not visit public charging stations except in two cases:
when the agent cannot make the next trip due to insufficient battery SoC for the remainder of its drive
cycle or the trip to the public charging station has been added at the beginning of the day (also due to
insufficient battery SoC). Also, a public charging station trip can only be added once a day, except in
cases where an agent searches for alternative public charging stations as discussed above. At a public
charging station, an agent is modeled to charge its EV just enough to complete its drive cycle for that
day. That is, it does not charge to the full battery level.
4. Results and Discussion

In this section, we discuss the results from different simulated scenarios. First, we explain the process of tuning agent behaviour.

4.1. Experiment

We focus on San Francisco as a case study for evaluating the impacts of EV-related policies on EV adoption. The city of San Francisco was studied since it is one of the cities with the highest penetration of EVs (O’Connor, 2014).

4.1.1. Data Description

The data used to populate the ABM model in this study was obtained from a survey conducted by the National Renewable Energy Laboratory’s (NREL’s) secure transportation data project (Caltrans, 2013). The survey comprises anonymized household data: home and work zip codes, work days, vehicle specifications of the residents in each surveyed household, as well as total household income. The survey was carefully chosen to be representative of California’s population. This is crucial for our study since our estimations for EV adoption are extrapolated from this survey sample. It should be noted that San Francisco is a spatially compact city, resulting in shorter driving distances compared to more spatially distributed cities. The effect of the short distances traveled in some of the results is discussed in Section 4.

The ratio of the actual population of San Francisco population in reality to the number of participants in the survey is about 366. In order to have adequately detailed EV ecosystem dynamics, but without having to simulate the entire population of the city, we duplicated each agent 10 times with the same income, vehicle type, and home and work zip code values, but with different values for G and T (Explained in Section 4.2). This enables us to achieve finer and more detailed simulation results. Therefore, the magnitudes of EV adoption and load values obtained in this study are at a scale of about...
1:37 to reality. This scaling is also reflected in the number of public charging stations and their locations (i.e., we scaled down the true number of charging stations and the number of charging points at these stations by a factor of 37).

Figure 3: Income Distribution
4.1.2. Simulation Description\textsuperscript{2}

The characteristics which define the behaviour of an agent in the EV ecosystem model are listed in Section 3.2.1, and these characteristics are obtained from the data survey and resulting correlations. All members of a family household were considered to be a single agent in the simulation since families typically purchase vehicles together, and the corresponding household income was used as the agent's income. On the other hand, the income of non-family households were divided equally by the number of workers in each of such households, and each worker is represented by an agent. In each family household, the effective agent age is set to be the age of the household’s survey respondent. Also,

\textsuperscript{2} The simulator described here is publicly available at bitbucket.org/adeda/agent-based-ev-ecosystem.
persons or households without vehicles were not included in the simulation, since the reason for not owning a vehicle could not be modeled and these agents could skew the results.

Each agent is also initialized to have a range preference equal to its maximum daily driving distance and a fuel economy preference equal to the best possible fuel economy in the modeled vehicle market (5.55 km/kWh). Each vehicle type in the model is shown in Table 4. The rebates are based on the US and California EV rebate programs while the sticker price, engine efficiency, and battery capacity of each vehicle closely tracks real-world values (USEPA, 2014). The combustion engine efficiency of the ICE and PHEV in Table 4 is based on fuel energy content conversions (AFDC, 2104).

Table 4: Vehicle Models

<table>
<thead>
<tr>
<th>Vehicle Type</th>
<th>Combustion Engine Efficiency (km/kWh eq.)</th>
<th>Electrical Efficiency (km/kWh)</th>
<th>Battery Capacity (kWh)</th>
<th>Existing Rebate ($)</th>
<th>Sticker Price ($)</th>
<th>Vehicle Make (2013)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICE</td>
<td>1.4</td>
<td>--</td>
<td>--</td>
<td>0</td>
<td>16,230</td>
<td>Toyota Corolla</td>
</tr>
<tr>
<td>PHEV</td>
<td>2.34</td>
<td>5.55</td>
<td>6.7</td>
<td>4,500</td>
<td>32,000</td>
<td>Toyota Prius</td>
</tr>
<tr>
<td>BEV</td>
<td>-</td>
<td>5.55</td>
<td>24</td>
<td>7,500</td>
<td>28,800</td>
<td>Nissan Leaf</td>
</tr>
<tr>
<td>BEV</td>
<td>-</td>
<td>4.6</td>
<td>60</td>
<td>10,000</td>
<td>69,900</td>
<td>Tesla Model S</td>
</tr>
</tbody>
</table>
The workday drive cycles are similar to Table 3 and non-workday drive cycles are shown in Table 5. However, all agents do not start their daily trips at the same time as one another. The workday drive cycles are randomized to start between 5 AM and 10 AM while non-workday drive cycles are randomized to start between 6 AM and 12 Noon, with start times chosen uniformly randomly in this range. In order not to skew results such as the daily load profiles, each agent has a fixed start time for each daily drive cycle in all simulated scenarios.

### Table 5: Non-Workday Drive Cycle

<table>
<thead>
<tr>
<th>Trip Number</th>
<th>Start Time</th>
<th>Trip Destination</th>
<th>Stay (hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10:00 AM</td>
<td>Lol</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>--</td>
<td>Lol 2</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>--</td>
<td>Home</td>
<td>--</td>
</tr>
</tbody>
</table>

In addition, eight level-2 public charging stations and one level-3 public charging station are also spatially distributed according to the public charging stations already present in the San Francisco area (Plugshare, 2014; Figure 5). All agents can charge at home, with a capacity of 3.3 kW (Level 1) while chargers at workplaces are set at 10 kW (Level 2). Also, the preferred vehicle longevity, i.e., the number of years which agents own a car before selling, was obtained from a normal distribution with an average of 11 years (Voelcker, 2014) and a standard deviation of 1 year. Other ecosystem variables are initialized as follows: cost of gas = 0.107 $/kWh (eq.)\(^3\); cost of electricity = 0.221 $/kWh; and discount rate = 8%.

\(^3\) The equivalent kWh obtained from gasoline. This price is the same as \(~\$3.6\) per gallon.
Figure 5: Public Charging Station Locations Scaled from Real-World Locations (Plugshare, 2014)

Figure 6: EV Adoption Parameter Tuning
4.2. Parameter Tuning

In our adoption model, an agent's decision to purchase a vehicle is dependent on the agent's income, its greenness $G$, social network threshold $T$, and typical driving behaviour, as well as the prices and attributes of the vehicles on the market. We realize that $G$ and $T$ are essentially unknowable quantities. However, in order to achieve realistic results, we tune the $G$ and $T$ of the agent population such that the predicted EV adoption matches what was observed in practice in San Francisco. Specifically, the distribution of $G$ determines the fraction of the agent population that buy EVs, and $T$ determines the rate at which these agents purchase EVs. Tuning these two parameters in the agent population enables an approximate estimation of system dynamics.
Figure 4 shows the distribution of initial values for San Francisco, where \( G \) has been estimated from agent annual income. Specifically, \( G \) can be positively correlated with each agent’s income; each agent’s \( G_i \) is obtained via

\[
G_i = (m + \omega) \times (\text{income}_i + K)
\]

(8)

where \( \text{income}_i \) is the agent’s income, \( K \) is a scaling constant, \( m \) is the slope of the \( G \) and income axes as seen in Eppstein et al. (2011), and \( \omega \) is a random variable drawn from a uniform distribution. Eq. 8 is defined such that agents with high incomes are more variable in their greenness while agents with lower income are more focused on the cost of a vehicle rather than its greenness or utility. Figure 3 shows the income distribution of agents.

We classify agents based on their inclination towards EV adoption (Table 2) as follows: early adopters (16%), early majority (34%), and late majority (50%) (Lin and Greene, 2010; Santini, 2005; Rogers, 1971). Based on the survey data, 260 out of 6,100 agents own EVs. Since we do not have access to San Francisco EV sales data, we assume a plug-in EV adoption growth in San Francisco that is similar to the US (EDTA, 2014) between 2011 and 2014. With a target EV number of 260, we define \( T \) for early adopters, early majority, and late adopters as 0, 0, and 0.04 respectively. These low \( T \) values were necessary to match the penetration of EVs that we obtained from the data. Figure 6 shows the EV adoption, averaged over 20 simulation runs with these \( T \) values and similar \( G \) distributions (Figure 4). To summarize, we obtain the \( G \) values from Equation 7 and the income data from the survey, and we then find a value of \( T \) such that the forecast adoption of EVs matches reality.

We evaluated the usefulness of our approach by studying outcomes that may be of interest to each potential user of the model: policy makers, utilities, and battery manufacturers. The impacts of different policies are evaluated in different simulation scenarios. The policies considered are as follows:
1. Reducing the effective costs of EVs via rebates, therefore making EVs affordable for more people and making EVs more competitive with ICEs.

2. Encouraging the availability of charging stations at the work place. The EVSE rebate provided by the Los Angeles Department of Water and Power (AFDC, 2014) is an example of a policy that provides incentives for charging station installation.

3. Educating the population on TCO estimation.

Also, the impacts of different battery sizes on EV adoption are estimated by multiplying the existing EV batteries by factors of 1.25, 1.5, and 2. Each scenario is simulated over a periods of 5 years (2014 - 2018). It is noteworthy that all the results have been averaged over 20 simulation runs and each data point shows the 95% confidence interval.

4.3. Policies

The results from different policy scenarios are compared and discussed here. In the base case, the rebates are defined as seen in Table 4. Also, we assume that 20% of agents can charge at work, and that 20% of agents are able to estimate vehicle TCO.

4.3.1. EV Rebates

In addition to the base case, two scenarios are considered:

- No rebates for EVs.
- An additional rebate of $2,000 for all EVs.

These scenarios determine the possible impact of removing EV rebates as well as increasing the existing rebates by a fixed value. Figure 8 shows the sensitivity of EV adoption to rebates. As expected, more EVs are bought when rebates are increased by $2,000 and the growth of EV penetration is reduced when rebates are removed. Figure 9 shows the spatial distribution of home locations of EV owners in each
scenario. This also informs public charging station planners on where stations should be sited. Figure 10 shows the spatial income distribution, and this provides an overview of the relationship between agent income and EV adoption. The electrical load impacts are discussed in Section 4.6.

Figure 8: EV Adoption; Sensitivity to Rebates
Figure 9: Spatial Distribution of EV Adoption; Sensitivity to Rebates (a) Base Case (b) No rebates (c) Additional Rebate of $2,000
4.3.2. Charging at Work

The two scenarios to study the impact of different percentage of agents that can charge at work are:

- An additional 10% of agents with a charge-at-work option (base case has 20%).
- An additional 20% of agents with a charge-at-work option.

To our surprise, increasing the number of agents that can charge at work does not appear to have a significant impact on EV adoption. This is due to the combined effect of San Francisco being a spatially compact city - shorter distances traveled - and the possibility of charging at work not being a significant aspect of the EV purchase decision (Figure 7). However, there are impacts on the grid and these are discussed in Section 4.6.

4.3.3. Estimating TCO

Figure 11 shows the sensitivity of EV adoption to the percentage of the population that can estimate the TCO. One additional scenario is executed where 40% of agents can estimate the TCO of a vehicle (base case has 20%). There is a slight but insignificant increase in EV adoption when more people know the TCO of a vehicle. This slight increase results from short distances traveled within the city; making the gain in TCO smaller than in a city with longer driving distances.
4.4. Charging Station Planning

Figures 12 and 13 show the average daily EV arrivals summed over all public charging stations for rebate and battery size scenarios. Figure 11 shows an expected increase in public charging station activity over time that is proportional to EV growth (Figure 8). Figure 13 shows an interesting behaviour in public charging station activity as battery sizes are changed. This reduction in public charging station visits results from larger batteries, which indicates that as battery sizes increase, the need for public charging stations may disappear over time.
Figure 12: EV Arrivals at Public Charging Stations; Sensitivity to Rebates

Figure 13: EV Arrivals at Public Charging Stations; Sensitivity to Battery Size
Figures 14 to 16 show the average hourly arrival profile at the public charging stations over the simulated period in different scenarios. It should be noted that these profiles are dependent on the drive cycles of the agents. These figures show that public charging station activity increases with the number of EVs and decreases when more 40% of the agents can charge at work. As seen in Figure 13, the battery size increase has a significant impact on charging station activity.

Figure 14: EV Arrivals at Public Charging Stations; Sensitivity to Rebates
Figure 15: EV Arrivals at Public Charging Stations; Sensitivity to Charging at Work

Figure 16: EV Arrivals at Public Charging Stations; Sensitivity to Battery Size
4.5. Battery Sizing

To study the effect of battery size on EV adoption and usage, we have simulated scenarios where batteries can hold 1.25, 1.5, and 2 times more energy than in the base scenario. However, we have not increased EV prices accordingly and we do not model the increased usage of an EV if it has a bigger battery (i.e., we are assuming that the drive cycle is independent of battery size, which is admittedly a naive assumption). Figure 17 shows that increasing battery sizes, thereby increasing the electrical range of the EVs, does not significantly change EV adoption in the San Francisco area mostly likely due to the short distances traveled daily. As a result, we have EV adoption curves similar to the base case. It should be noted that agent range preferences are set at the maximum distance covered daily. The load impact of EVs with larger batteries is discussed in Section 4.6.

![Graph showing EV adoption sensitivity to battery size](image)
4.6. Impact on Utilities

Figures 18 to 21 show the EV load growth over time for different scenarios. In Figure 18 and 20, we see a load growth proportional to the growth of EVs. Also, Figure 21 shows that there is only a slight change in load when the battery sizes are increased by a factor of 1.25 up to a factor of 2. We attribute this, again, to the compact size of the city. Also, higher loads are also due to PHEVs using less gasoline.

Figure 18: Load Growth; Sensitivity to Rebates
Figure 19: Load Growth; Sensitivity to Charging at Work

Figure 20: Load Growth; Sensitivity to TCO Estimation
Figures 22 to 24 show the hourly EV load profile in the last simulated month in different scenarios. In Figure 22, we see higher loads as the number of EVs increases with additional rebates, and Figure 23 shows that charging at work may not be an adequate scheme for leveling the charging load. Also, increasing battery sizes slightly increases the duration of the peak charging period at the end of the day (Figure 24).
Figure 22: Average Hourly Load Profile in Last Simulated Month; Sensitivity to Rebates

Figure 23: Average Hourly Load Profile in Last Simulated Month; Sensitivity to Charging at Work
Figure 24: Average Hourly Load Profile in Last Simulated Month; Sensitivity to Battery Size

Figure 25 shows the spatial distribution of EV loads in the scenarios focused on sensitivity to rebates. This could also inform the utility on the magnitudes and locations of EV loads. We also see the changes in load in each location as a result of rebate removal, as well as increasing the rebate by $2,000. The spatial load patterns in Figure 25 are similar to the EV adoption patterns in Figure 9.
5. Limitations and Future Work

We have designed a simple yet effective EV ecosystem model that uses realistic data (see Table 2) to assess the impact of changes in policies and technology on EV adoption and use. Any model abstracts certain aspects of reality; ours does too. Specifically, our model suffers from the following limitations:

- A simple TCO estimation process.
- Lack of a financing option for EV purchase.
- Only two vehicle preferences (range and fuel economy) are used in the agent EV purchase decision.
• Linear estimation of battery charging and discharging, without considering acceleration or auxiliary energy consumption in EVs, e.g., cooling or heating.

We now discuss some avenues for future work.

One area of future work is the forecast of EV adoption by fleet services. The criteria for individuals and fleet services to purchase EVs differ, therefore, posing an interesting research question. Also, we realize that many of our conclusions are a direct consequence of the compact geographic size of San Francisco. In future work, we intend to study more spread-out cities, such as Los Angeles. Another area of future work is to study the impact of demand response policies and distributed generation resources on EV adoption.

6. Policy Implications

Here, we discuss the effects of the EV-related policies on the EV ecosystem.

6.1. Rebates
Canceling EV rebates at a point in time when EVs are not cost competitive with ICEVs would result in a steep reduction in EV adoption. On the other hand, increasing current rebates in San Francisco by $2,000 would not result in a significant increase in EV presence. The current subsidy level is nearly optimal. EV technologies should be allowed to mature until they can effectively compete with ICEVs in terms of range and costs before rebates are removed. Furthermore, while policies are put in place to provide rebates, public charging stations need not be subsidized in order to support the expected increase in EV adoption.

6.2. TCO
The primary advantage of EVs over ICEVs is fuel efficiency, and the degree of this advantage is dependent on the mean distances traveled: the longer this distance, the more energy saved per km,
resulting in lower fuel costs. In the case of San Francisco, educating people on the importance of TCO will not increase EV adoption, considering the spatial compactness of the city. Educating people on TCO would be more apt in locations where longer distances are traveled.

6.3. Charging at work
We find that in the case of San Francisco, although subsidizing workplace charging stations may reduce public charging station activity, it is not likely to reduce peak charging loads. The presence of workplace charging stations would encourage more EV adoption, albeit slightly, resulting in slightly higher loads especially at peak periods. The hourly EV charging profiles show that there is no EV charging during the early hours of the day. EV peak load reduction approaches such as Time-of-Use (ToU) pricing, or incentivizing EV owners to charge their EVs during off-peak periods, may be more effective in moving peak loads to these early hours. Moreover, the effectiveness of increased workplace charging in reducing peak loads is dependent on the percentage of residents that work within the city.

6.4. Battery Size
In San Francisco Bay Area, 81% of EV charging is done at home (Baker, 2013). Increasing battery sizes would result in fewer public charging station visits per car since EV owners can charge more at home. In this study, we have focused on short-distance trips, but larger batteries may result in more EVs being used in long distance trips due to increased range. As a result, installing Level 3 public charging stations may become more useful than installing Level 1 and Level 2 public charging stations. Policymakers need to make decisions on subsidizing charging station installations based on the dynamics between battery size and typical distances traveled: the larger the battery size, the greater the mean distance traveled and the greater the need for Level 3 charging stations (in contrast to Level 1 or Level 2 stations).
7. Conclusions
The nascent state of the EV industry brings about a need to implement effective energy policies, build the required infrastructure, and produce battery technologies sufficient for typical driving behaviour. We have presented and discussed the details of an agent-based EV ecosystem model, motivated by the emergence of plug-in electric cars in the transportation industry, and the resulting challenges such as increased electrical load and meeting driving range requirements within a population. This makes our model suitable for policymakers, utility operators, charging station planners, and EV manufacturers. Our model provides spatial and temporal estimates of EV adoption and charging activity.

Using San Francisco as a simulation city with corresponding survey data, we have exemplified the functionality and scope of the agent-based EV ecosystem model. The results show a significant increase in adoption and charging load with an additional rebate value of $2,000. Also, the ability of more people to estimate the TCO of a vehicle does not make a significant change in EV adoption, especially when short driving distances are involved. In addition, increasing the battery sizes results in increased charging load due to less gasoline use in PHEVs, and also less charging station activity. Thus, as battery sizes increase, the need for public charging stations may disappear over time.

References


