Noname manuscript No.
(will be inserted by the editor)

The Relative Importance of Price and Driving Range on Electric Vehicle Adoption

Los Angeles Case Study

Adedamola Adepetu · Srinivasan Keshav

the date of receipt and acceptance should be inserted later

Abstract Electric Vehicles (EVs) are still a maturing technology. Barriers to their adoption include price and range anxiety. EV batteries are significant in determining both EV prices and costs. In this work, we focus on the impact of a high-capacity battery and EV rebates on an EV ecosystem. Using survey data from Los Angeles, California, we simulate different cases of battery costs and prices by means of an agent-based EV ecosystem model. We find that even in Los Angeles, a geographically spread out city, the price of EVs is a more significant barrier to adoption than EV range. In fact, even a quintupling of battery size at no additional costs improves EV adoption by only 5%. Therefore, policy makers should focus more on affordability than range in promoting EV adoption.

Keywords Electric vehicles, Agent-based modeling, Electric vehicle adoption, Range anxiety

1 Introduction

It is well known that several barriers exist to the widespread adoption of EVs. These barriers include high purchase costs, range anxiety, and lack of widespread charging infrastructure [6]. In this paper we focus on limited driving range, due to the limited capacity of electric batteries, as a barrier to EV adoption. One way to increase driving range is to increase the size of the battery. However, batteries are expensive, therefore making EVs less cost-competitive with conventional vehicles. For example, the Tesla Model S has a 85 kWh battery but costs about $80,000; the Nissan Leaf has a 24 kWh battery and costs only about $29,000. It is clear that today, increasing battery size comes at a high additional cost.

There are research efforts under way on improving battery technology for EVs, including IBM's work on a Li-500 125 kWh battery [16] that is expected to increase

Cheriton School of Computer Science
University of Waterloo
E-mail: {a2adepet, keshav}@uwaterloo.ca

the driving range of a typical EV to 500 miles at no additional cost. Such a battery is expected to make EVs range-competitive with conventional vehicles, also called Internal Combustion Engine Vehicles (ICEVs). As a result, we study how such a battery can change an existing EV ecosystem. Our expectation is that increasing driving range would greatly increase EV adoption.

To study the effect of increased driving range on EV adoption, we build on the EV ecosystem model described in our prior work [2]. This model is an Agent-Based Model (ABM) with individuals as agents, exhibiting behaviours such as purchasing vehicles, driving EVs and charging EVs. The adoption model extends the EV adoption model discussed by Eppstein et al. [15]. The outputs of this model spatially and temporally represent EV adoption by agents, public charging station usage, and charging loads on the grid. These outputs can be useful for policymakers, charging station planners, utility operators, and EV manufacturers.

In prior work, we used the EV ecosystem model to study the impact of different policies and battery sizes on the EV ecosystem in San Francisco, a city with a dense urban core [2]. These policies include varying EV rebates, improving public awareness on the low operational costs of EVs, and encouraging workplace charging stations. Several of the results obtained were found to be dependent on the length of daily driving distances. For example, we found that the number of EVs adopted did not increase significantly as the size of the EV batteries were increased because most trips were short. Here, we study EV adoption in Los Angeles, which also has a high penetration of EVs but is less spatially compact than San Francisco. Using survey and environmental data from Los Angeles, we study the impact of a 125 kWh high-end battery technology on the adoption and usage of EVs within the area.

Our expectation was that, due to the greater spatial extent of the city, an increase in EV range would boost adoption. In fact, as we discuss below, we found that even in a city as spread out as LA, cost is a greater barrier to adoption than vehicle range. Therefore, policy makers should focus more on affordability than range in promoting EV adoption.

2 Literature Review

In this section, we discuss existing literature relevant to modeling EV adoption and usage.

2.1 EV Adoption Models

In existing literature, there are three common approaches to modeling EV adoption: consumer choice models, diffusion rate models, and ABMs [3]. A review of the different EV adoption models has been carried out by Al-Alawi and Bradley [3]. Here, we discuss agent-based EV adoption models.

Pellon et al. [25] and Eppstein et al. [15] model the adoption of Internal Combustion Engine Vehicles (ICEVs), Hybrid EVs (HEVs), and Plug-in Hybrid EVs (PHEVs), using an agent-based approach. Here, agents are people who choose to buy a certain type of vehicle from the aforementioned alternatives. This model incorporates the perceived utility of a vehicle as well as social influence in the vehicle purchase decision process. Agent properties such as income, home location, trip distances, and desired vehicle longevity are included as part of the vehicle purchase decision process. In this work, it is assumed that vehicles are charged once daily. In addition, the Eppstein et al. model includes spatial orientation in the model. We add to this model by modeling BEV adoption and EV usage. The Eppstein et al. model forms the core of our EV ecosystem model and it is further discussed in Section 3.1.

Al-Alawi and Bradley identify the work Sullivan et al. [29] as one of the most comprehensive ABMs focused on EV adoption. Sullivan et al. focus on PHEV adoption, and specify the budget of an agent a critical factor in vehicle purchase. In addition, this work models vehicle owners, fuel producers, fuel producers, and the government as agents. While this study incorporates these additional agents, it does not enable the modeler to evaluate the potential impact of modeler-defined government policies. We design our model to evaluate EV-related policies by making policymakers and vehicle designers exogenous.

Wolf et al. [33] develop an ABM focused on EV adoption and influencing people's perspectives of EVs. They use an artificial neural network to model agent decisions, where each agent decides based on security, comfort, costs, image, etc. They also execute a case study on Berlin, Germany, estimating how different policies such as vehicle purchase subsidies and tax exemptions could influence EV adoption in the region. Wolf et al. focus on the factors that may affect EV adoption. Our work models EV adoption, as well as EV driving and charging by potential EV adopters.

Using a mixed logit model in an ABM, Brown [7] focuses on the adoption of HEVs, PHEVs, and BEVs, and studies the impact of vehicle range and financial incentives on EV adoption. Shafiei et al. [28] use a willingness-to-pay method to model agent EV adoption decisions in their ABM. The authors study scenarios with different EV and gas prices, forecasting the changes in EV adoption. Also, this work uses a refuelling effect variable [27] to incorporate the effect of charging infrastructure availability. Similar to Brown, Shiafei et al. focus only on EV adoption. Our work goes further to model EV usage.

Sweda and Klabjan [30] focus on using an ABM to solve the problem of charging station deployment. This is based on forecasting EV adoption and estimating where charging stations are required the most. Factors that determine an agent's vehicle purchase decision include vehicle price, fuel cost, the agent's greenness, social influence, an infrastructure penalty, and a distance penalty. However, the quantification of these parameters was not clearly stated in the paper. We present a detailed EV adoption and usage model that can be used not only EV charging station planners, but by utility operators and policymakers.

In summary, our model extends these models, adopting an EV ecosystem approach – EV adoption, driving, and charging – to better understand the immediate and cascading impact of EVs in different scenarios.

2.2 EV Usage Models

Using Victoria, Australia, as a case study, Paevere et al. [24] study the spatial and temporal impact of EV charging on the electric grid. They study different EV adoption and rebate scenarios and discuss the changes in EV charging load. Similarly, Arellano et. al [5] and Pellon et al. [25] investigate how differnet adoption and EV charging scenarios change the temporal load distribution.

Acha et al. [1] integrate EV driving and charging with power flow analysis, which is a level of detail greater than used in our work. However, they do not model EV adoption since their work is focused on the impact of EVs on the grid. Cui et al. [11] use a Nested Multinomial Logit model to estimate PHEV adoption, and investigate the resulting changes in the grid such as power line congestion and transformer overload. They study how charging schemes could be used to avoid these problems. However, this study focuses only on PHEVs. We include BEVs in our study and study load impacts and charging infrastructure requirements.

Neubauer and Wood [22] study the utility of a BEV over it's lifetime by simulating BEV trips using real-world data, while considering the impact of range anxiety and availability of charging infrastructure on the said trips. They outline that range anxiety can be reduced by increased availability of charging infrastructure – home, workplace, and public charging stations. Here, range anxiety is assumed to be synonymous to the minimum range margin desired by the driver. Our work differs from this study by incorporating EV adoption and different EV types.

Kim and Rahimi [20] estimate the impact of EV adoption on the electric grid in Los Angeles. Using the Bass diffusion model, they focus on three adoption scenarios, and highlight the increased EV charging loads and the resulting changes in greenhouse gas (GHG) emissions. The results of this study are useful for peak demand management and electricity generation planning in Los Angeles. This study does not forecast EV adoption but only details the impact of EVs on the grid in possible scenarios.

3 EV Ecosystem

In this section, we describe our EV ecosystem model[1]. Our model is an EV ecosystem model because it goes beyond EV adoption and incorporates EV usage, that is, both driving and charging. This provides a more complete model for estimating the impacts of EVs within a socio-technical system. For example, our model can forecast the number of EVs bought each year to allow electric grid operators to gauge the increases in electrical load at different parts of the grid corresponding to home and work locations. In addition, our model takes an agent-based approach, where the agents are people who decide whether to buy EVs or not, and use the EVs according to their driving needs.

Agents have three behaviours in our model: vehicle purchase, EV driving, and EV charging. Generally speaking, we have tried to make the agent behaviour as realistic

[1] The EV ecosystem model is also described in greater detail in our prior work [2]. Here, we sketch the model for the sake of making this paper self-contained.

Table 1: Agent Variables (DS = Dataset; E = Estimated; I = Independent)

Variable	Source			
	DS	**E**	**I**	**Description**
Age	X	X		Each resident in surveyed households is listed in an age bracket, within which we uniformly assign a particular age.
Income	X	X		Each household is listed in an income bracket, within which we uniformly assign a particular income. We divide the income among each household's working residents, if necessary.
Work days	X			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.
Home location		X		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.
Work location		X		The work location is obtained similarly to the home location.
Vehicle fuel type and age	X			Each surveyed household has a list of vehicles already in use, with details such as the model year and fuel type assigned.
Workday and non-workday drive cycles	X			The drive cycles are based on expected trips to and from home locations, work locations, and random locations of interest. See Table 4.
Desired vehicle fuel efficiency	X			This is assumed to be the highest vehicle efficiency available in the market today [32]. See Table 3.
Cost sensitivity G		X		G is correlated with income with some noise included.
Social threshold T			X	T is the fraction of an agent's social network that must own EVs in order for that agent to buy an EV.
Social network		X		Each agent's social network is selected from other agents with similar ages($\pm$5 years), incomes($\pm$\$10,000), and residential locations ($\pm$2 km). Each agent has a social network that is randomly selected, with a minimum and maximum sizes of 1 and 15 respectively.
Ability to estimate TCO			X	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.
Option to charge at work			X	This is a binary variable that determines if an agent has a charging terminal available at the work place.
Desired vehicle longevity	X	X		This is the number of years an agent decides to use a vehicle before selling it off. For each agent, this variable is obtained from a normal distribution with an average of 11 years [19] and a standard deviation of 1 year.

as possible by relying on comprehensive surveys, large datasets, and published values for environmental variables such as gasoline prices and EV battery sizes. Table 1 highlights the agent variables such as age, income, home and work locations, drive cycles, preferred vehicle preferences, etc. These variables are used to define specific agent behaviours. For example, each agent has a social network that comprises other agents with similar income, age, and home location. Similarly, the start time of an agent's trip and the trip duration is dependent on home and work locations. In ad-

Table 2: EV Ecosystem Variables (DS = Dataset; E = Estimated; I = Independent)

Variable	**Source**			
	DS	**E**	**I**	**Description**
Cost of gas	X			This is the equivalent cost in \$/kWh obtained from the cost in \$/gallon [8] and the energy content of gasoline: 1 gallon of gasoline contains 33.7 kWh of energy [4].
Cost of electricity	X			This is the average cost of electricity in Los Angeles [8].
Existing rebates	X		X	This is a reduction in the effective cost of an EV, based on federal and state policies [9, 31].
Charging stations	X	X		Real-world map and specifications of charging stations [26]. This includes level 2 and 3 charging stations, scaled according to the number of agents in the simulation.
Vehicle types and specifications	X			See Table 3 [32].
Trip duration and distance		X		We use MapQuest Route Matrix to obtain driving distance and duration [21].
Discount rate	X			This is useful for TCO estimation. Typical discount rates fall between 2% and 10% [14]. We set this variable at 8%.

dition, Table 1 shows the variables obtained from data, estimation, and independent distribution.

Table 2 highlights the environment variables such as cost of electricity, cost of gas, existing EV rebates, etc. These variables also play significant roles in agent behaviours. We next describe how we model the purchase and usage of EVs by an agent.

3.1 EV Adoption

Our EV adoption model is based on the work done by Eppstein et. al [15], which is focused on Plug-in Hybrid EV (PHEV) and Hybrid EV (HEV) adoption. The two specific additions we make are to model the adoption of BEVs, and to incorporate vehicle range and fuel economy as attributes that affect agent purchase choices.

For each agent, the vehicle purchase process is summarized as follows:

1. Determine which vehicles on the market the agent can afford: we assume that an agent cannot spend more than 20% of its annual income on purchasing a vehicle [15].
2. 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 (this check is required for BEVs only).
3. Rank the affordable vehicles according to desirability. Desirability is a function of benefits and costs of different alternatives (discussed in more detail below).
4. Buy the most desirable vehicle.
5. If, for any reason, no suitable vehicle to purchase is found, keep using the existing vehicle.

6. Overall, if the EV-owning fraction of an agent's social network is less than the agent's social threshold T, then the agent does not buy an EV.

In our model, vehicle purchases are executed quarterly, and an agent chooses from three different vehicle types: ICEV, Plug-in Hybrid EV (PHEV), and Battery EV (BEV). For each agent, the relative desirability D of each *pair* of vehicles is obtained based on their utility (i.e., the benefit expected from the purchase) and cost [15], where these depend on the agent's cost sensitivity G ($0 \leq G \leq 1$) and social threshold T ($0 \leq T \leq 1$), described next (also see Figure 1).

G is used to model the degree to which an agent values a vehicle's benefits such as a long driving range and high fuel efficiency, over its costs. For example, if an agent has $G = 0$, then that agent would rank a vehicle's desirability based only on its costs, but if $G = 1$, the agent would rank a vehicle's desirability based only in its benefits regardless of its costs. The relative desirability D is computed as the weighted difference between the relative benefit RB and relative cost RC of each pair of vehicle choices, scaled by the agent's cost sensitivity G. The computation of RC and RB is discussed below.

T determines the degree to which an agent is an early adopter and is used to model social influence on vehicle purchase decisions. For example, if an agent has $T = 0.1$, the agent will buy an EV only if at least 10% of its social network already owns EVs. An agent with $T = 0$ is considered to be an early adopter, since it can buy an EV regardless of the EV-owning proportion of its social network. The distribution of G among agents determines how many agents buy EVs, and T determines when EVs are bought based on EV penetration in the agent population. The social threshold is included in the model in order to determine the impact of social networks on agent decisions. This is similar to the work by He et al. [17] that incorporates social network influence in a discrete choice model with a case study on HEV adoption in California.

The desirability of a vehicle j over i, D_{ij}, is a function of the relative cost RC_{ij} and relative benefit RB_{ij} [15]. Specifically, the relative desirability of two vehicles is given by:

$$D_{ij} = G \times RB_{ij} - (1 - G)RC_{ij} \tag{1}$$

The most desirable vehicle is purchased by the agent.

The relative cost is given by:

$$RC_{ij} = \frac{C_j - C_i}{C_j} \tag{2}$$

where C_i is the cost of car i. C is either the sticker price or TCO of a vehicle, because, according to Boulanger et al. [6] and EPRI [14], not all vehicle purchasers fully consider the expected lower operational costs of EVs. For estimating the TCO, we use the Net Present Value (NPV), which is given by:

$$NPV = \sum_{t=0}^{N} \frac{C_t}{(d+1)^t} \tag{3}$$

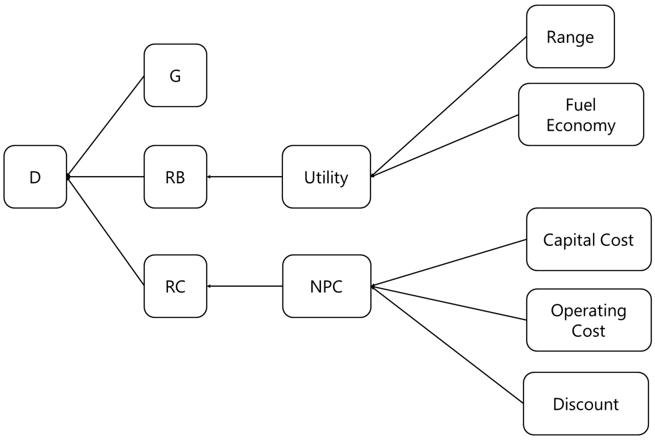


Fig. 1: Derivation of Desirability

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. Also, 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. Our model does not consider financing options as part of the vehicle purchase process.

The relative benefit RB_{ij} is given by:

$$RB_{ij} = \frac{U_j - U_i}{U_j} \tag{4}$$

where U_i is the utility of car i. 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 [27]:

$$U = 1 - \frac{1}{2}\sum_{i=1}^{2}(\frac{pref_i - v_i}{pref_i}) \tag{5}$$

where $pref_i$ is the agent's preference for attribute i, and v_i is the value of the vehicle's attribute i. Figure 1 shows the relationship between all the variables used to define desirability D.

We model only two attributes: vehicle range and fuel economy – details can be found in [2]. This is a deviation from the EV adoption model in [15] where a vehicle's electric range is used as the only vehicle attribute.

While comparing driving range of vehicles, we incorporate the non-linearity of the relationship between driving range and customer vehicle valuation [12]; this study is based on a survey focused on vehicle purchase decisions, with respondents from California. As a result, each agent's range preference is represented by the agent's Willingness To Pay (WTP) for a vehicle with a particular range. According to Daziano [12], the WTP per unit distance has a non-linear relationship with vehicle range. Therefore, an agent's valuation of a vehicle's range is given by:

$$WTP = WTP_{per\ unit\ distance}(range) \times range \tag{6}$$

We use the average values in the fixed parameter logit analysis from the work by Daziano [12] to model the agents in our simulations.

3.2 EV Driving and Charging

To model EV usage, each agent carries out workday and non-workday drive cycles that model daily trips. Table 4 shows an example of a workday drivecycle. The drive cycles were created to realistically represent a person's daily trips. The workday drive cycle includes a home-to-work trip and a trip back home at the end of the day, and on non-workdays, an agent makes trips to places of interests not far from its home location. In addition, our model incorporates a spatial orientation for home, work, and charging station locations. We split the modeled geographical area into cells and use the MapQuest API [21] to estimate the real-world length and duration of each trip between these cells.

As for EV charging, an agent can charge its EV at home, workplace, or public charging stations. An agent charges its EV in the following cases:

- At the end of each trip, an agent charges its EV if a charging terminal is available at the trip destination. This could be at home or at work.
- If an agent cannot meet a trip due to insufficient charge, it makes a trip to a public charging station, before continuing with its drive cycle for that simulation day. It should be noted that in our model, only agents with BEVs visit public charging stations because PHEVs are unlikely to wish to spend time charging at a public location when they can use their gasoline engine.

4 Experiment

We carry out a case study to forecast the impact of EV rebates and EV battery technology improvements on patterns of EV adoption and EV usage. Agents are initialized based on a transportation survey of residents in Los Angeles with a focus on transportation. Next, we describe the Los Angeles Li-500 case study in more detail.

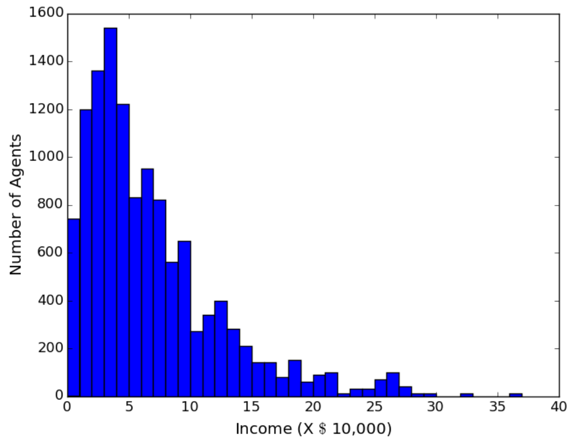


Fig. 2: Agent Income Distribution

4.1 Data

We focus on Los Angeles in this study due to its overall spatial sparseness (though it is known to have a dense urban core) and high-penetration of EVs [23]. 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 [10]. For each household surveyed, the data provides home and work zip codes (i.e. coarse-grained geographical locations), work days, and vehicle specifications of the residents, as well as total household incomes.

The ratio of the actual population of Los Angeles population in reality, to the number of participants in the survey is about 1:789. 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. 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 1:80 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 80).

4.2 Parameter Tuning

The agents are initialized with different properties that determine agent behaviour, as highlighted in Table 1. However, we could not obtain data to determine the appropriate values for G and T. Instead, we study a range of plausible values for (G,T) pairs and choose the one that creates an EV adoption curve that best matches the historical record. Specifically, we tuned G and T in order to match the simulated EV adoption to

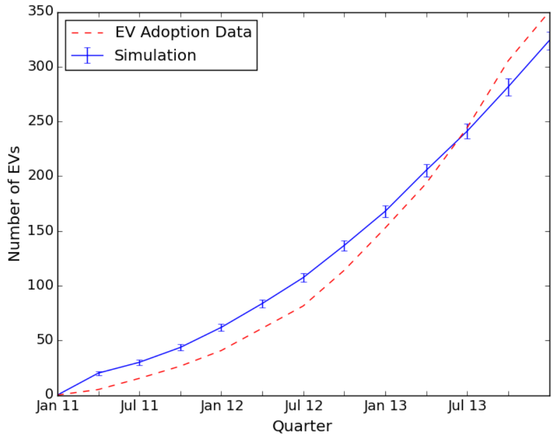


Fig. 3: Parameter Tuning Results

historical EV adoption. Specifically, following Eppstein et. al [15], we first correlate G with each agent's income. We obtain this by:

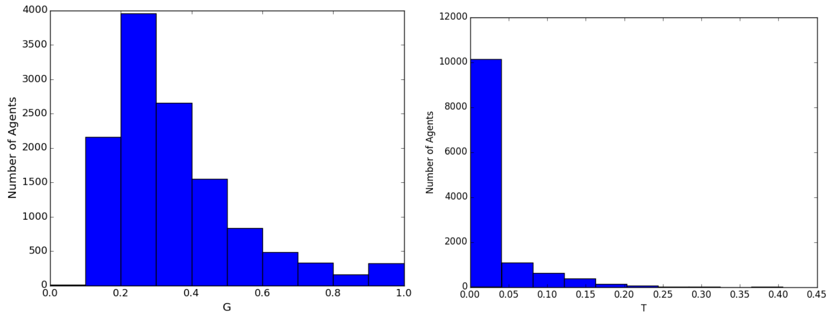
$$G_i = (m + \omega) \times (income_i - min.\ income) \tag{7}$$

where $income_i$ is the agent's income, $min.\ income$ is the lowest recorded agent income, m is the slope of the G and income axes [15], and ω is a random variable drawn from a uniform distribution. Eq. 7 is defined such that agents with low incomes are more focused on costs than utility. However, some variability is included so that even agents with high income can still be more concerned about costs while choosing a vehicle.

Next, we assumed that EV adoption in Los Angeles follows the same trend as EV adoption in the US [13]. Then, to find the distributions of G and T that result in the simulated adoption trend for EVs to match historical EV adoption, we conducted several hundred simulations, each varying the means of both distributions and found the combination that resulted in the least squared errors between the actual and predicted adoption trend. Specifically, each possible combination of G and T distribution means was simulated nine times and the squared errors of EV adoption were averaged. Figure 5 shows a heatmap of the errors associated with different G and T distributions; the cell with the lowest errors corresponds to the distributions used in the scenario simulations, and is shown in Figures 4a and 4b. In addition, the tuned EV adoption result is shown in Figure 3: 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 Experimental Design

Here we discuss the initialization of other agent and environment variables. Table 3 shows a list of the vehicles used in the simulations. The vehicles are chosen to



(a) Cost Sensitivity G (b) Social Threshold T

Fig. 4: The best-fit G and T Distributions used in our simulations

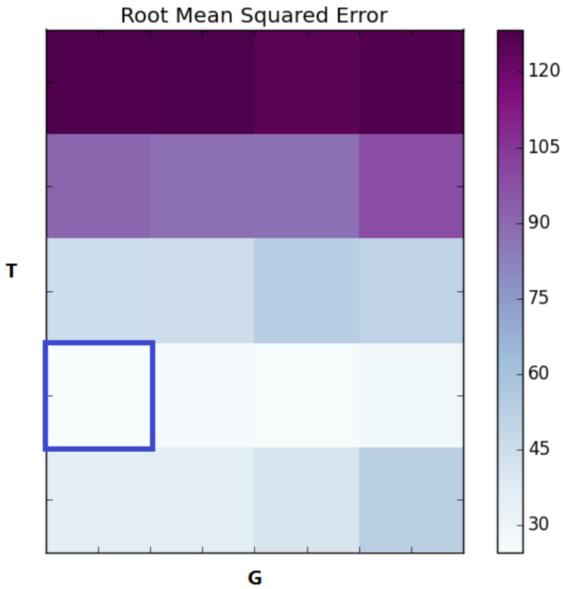


Fig. 5: Tuning Errors from Varying the Means of the G and T Distributions

be representative of the different available vehicle fuel types, as of 2014. Figure 6 shows the typical daily driving distances of the agents, based on the trip database described in Table 4. Also, the full set of charging stations within the Los Angeles area were obtained from [26], and the number of stations was scaled down eight-fold as discussed earlier. Furthermore, we assume that 20% of agents can charge EVs at work and 20% of agents can estimate the Total Cost of Ownership (TCO) of EVs. These assumptions were not changed in the different scenarios, since the focus in this study is on the impact of price and driving range.

We studied four scenarios in addition to the base case:

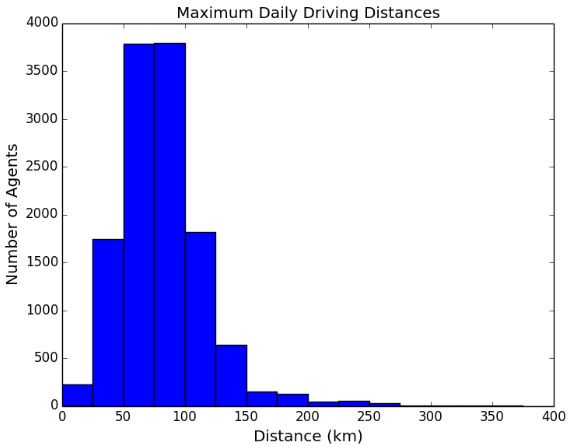


Fig. 6: The Distribution of Driving Distances in the NREL Secure Transportation Dataset. Note that most distances are under 100km.

Table 3: Vehicle Models

Vehicle Type	Combustion Engine Efficiency (km/kWh eq.)	Electrical Efficiency (km/kWh)	Battery Capacity (kWh)	Electric Range (km)	Existing Rebate ($)	Sticker Price ($)	Vehicle Make (2013)
ICE	1.4	–	–	0	0	16,230	Toyota Corolla
PHEV	2.34	5.55	6.7	107	4,500	32,000	Toyota Prius
BEV	–	5.55	24	30	7,500	28,800	Nissan Leaf
BEV	–	4.60	60	221	10,000	69,900	Tesla Model S

– **Case 1:** Li-500 battery technology is supposed to improve the energy density of the batteries, approximately, by a factor of 5 [18]. Therefore, we increase the battery sizes of all EVs in Table 3 by a factor of 5 but without increasing the EV price.
– **Case 2:** The existing EV rebates are increased by $2,000. We execute this scenario in order to compare the impacts of reductions in price and improved batteries.
– **Case 3:** The existing EV rebates are increased by $4,000.
– **Case 4:** The EV batteries are increased by a factor of 5 and the existing rebates are increased by $2,000.

Table 4: Example of a Drive Cycle

Trip Number	Start Time	Trip Destination	Stay (hours)
1	8:00 AM	Work	8
2	–	Mall	1
3	–	Home	–

5 Simulation Results

Here, we look at the temporal and spatial changes in EV adoption, electrical load, and charging station activity in the different simulated scenarios.

5.1 EV Adoption: Range *vs.* Price

The adoption of EVs is influenced by the costs and utility associated with each EV. Figure 7 shows EV adoption over the simulated period of 5 years across the four simulation scenarios. We see that the additional rebate of $4,000 results in the highest EV adoption. Surprisingly, increasing the battery size alone does not result in a significant improvement in EV adoption. Factors that lead to this insignificant change in EV adoption include the large proportion of agents that cannot afford EVs, and the parameter tuning process that found that, historically, most agents have focused more on vehicle costs than benefits (Figure 4a).

However, reducing the EV price by means of a $2,000 rebate and increasing battery size shows a significant increase in EV adoption; in the base case about 7% of the population own EVs at the end of the simulation, whereas, about 9% of the population own EVs when batteries are better and the rebate is higher. This suggests that for increasing EV adoption in Los Angeles, improved batteries should not be at the expense of increased EV costs.

To get more insight into our results, compare the electric range of each EV in Table 3 with the driving distances seen in Figure 6. We can see that, surprisingly, even for a spatially spread-out city like Los Angeles, current EV technology can already meet existing daily driving distances. This is because most of the wealthy people in LA, who can afford EVs, live and work in the downtown core. A relatively inexpensive EV such as the Nissan Leaf can meet the driving requirements of about 70% of the agents. Considering that Los Angeles already has a high penetration of EVs compared to the rest of the US, we can draw the conclusion that improved range alone cannot bring about significant improvements in EV adoption: improvements in battery technology are better used to reduce costs rather than increase range.

Figure 9 shows the spatial adoption of EVs based on the home locations of agents in three different cases. The difference in EV adoption between scenarios can be seen spatially as the battery size and EV rebates are increased. Also, more EVs are adopted in the central area, where wealth is concentrated (see Figure 8); this informs charging station planners of the locations that may require public charging stations and the number of charging stations required.

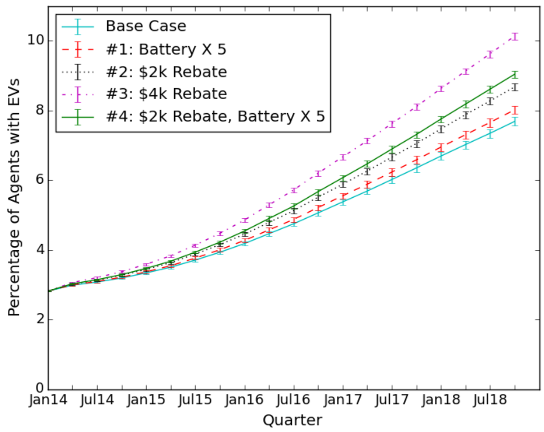


Fig. 7: EV Adoption

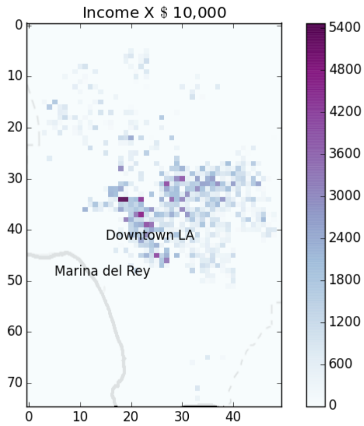
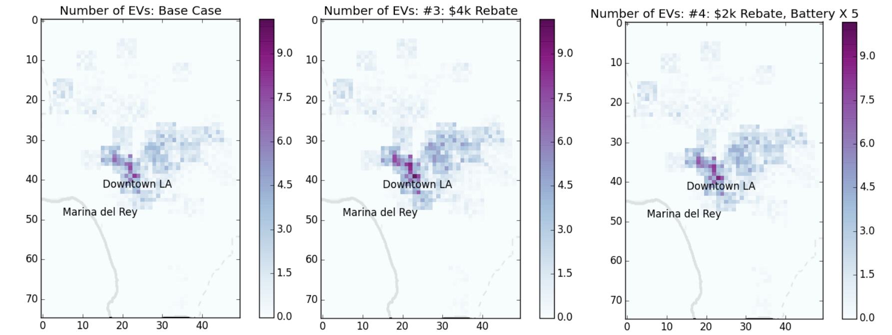


Fig. 8: Spatial Distribution of Income

5.2 Electrical Load

EV adoption will add to the overall electrical load. We now study the areas in LA that could be affected due to EV adoption. Figure 10 shows the electrical load growth from EV charging over the simulated years. Increased batteries result in more electrical load over time, especially due to PHEVs using more electricity and less gasoline. Comparing Figures 7 and 10, larger batteries would have more significant impacts on EV charging than on EV adoption, as expected.



(a) Base Case (b) Case 3 (c) Case 4

Fig. 9: Spatial EV Adoption in Last Simulation Year

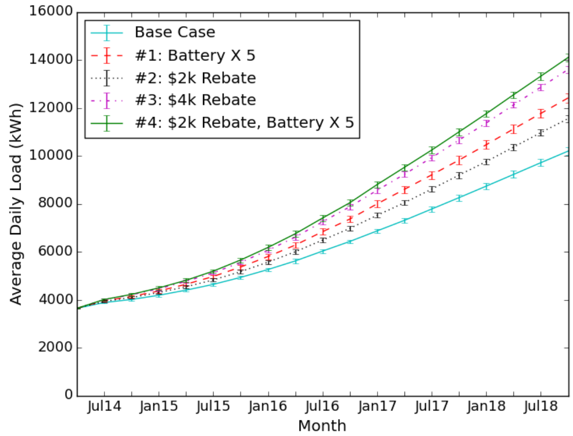


Fig. 10: Charging Loads

Figure 11 shows the total EV charging load profile from charging at home, work, and public charging stations. For all cases, the peak charging loads are proportional to the number of EVs. The larger batteries in Case 1 also result in higher electrical loads. The evening charging load peak would help utilities to know how much additional load to plan for, and the locations of these loads. If the time of the existing daily load peak in a particular location coincides with the time of the charging load peak, utility operators might have to improve the existing distribution infrastructure. It should be noted that the daily charging profile shown in Figure 11 is dependent on the trip structure (Table 4).

Figure 12 shows the spatial distribution of EV charging load in three different cases. The variations in load between the different scenarios are more evident at the central areas of the map. This indicates that changes in EV adoption from rebates and batteries could result in a need for grid infrastructure upgrades. Also, the load

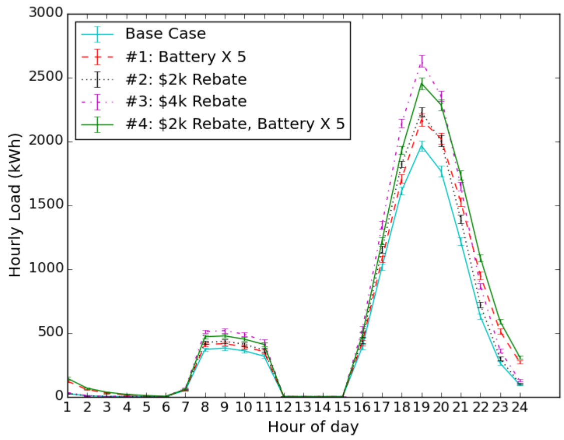
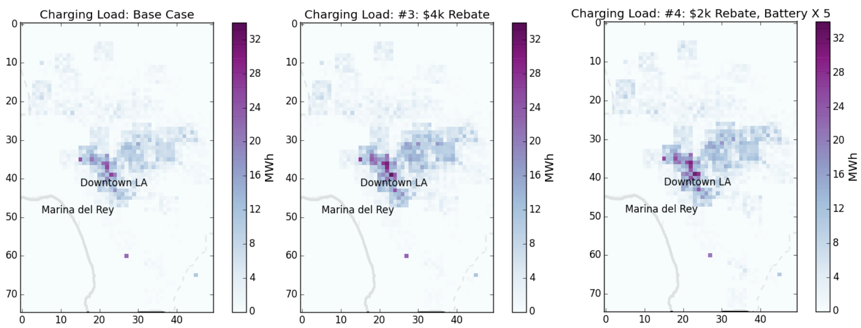


Fig. 11: Hourly Charging Loads in the Last Simulation Month



(a) Base Case (b) Case 3 (c) Case 4

Fig. 12: Spatial Loads in Last Simulation Year

increase in the simulated cases see here is consistent with the annual load increase (Figure 10) and the spatial distribution of EV adoption (Figure 9).

Figure 13 shows the number of EV arrivals at public charging stations in the last simulated month. There is no significant change in public charging station activity in the different scenarios. Figure 14 shows the change in public charging station activity over the years, and a slight decrease in charging station arrivals can be seen. It should be noted that in the EV ecosystem model, only BEVs visit public charging stations, therefore, Figure 14 represents the expected minimum charging station activity for each scenario.

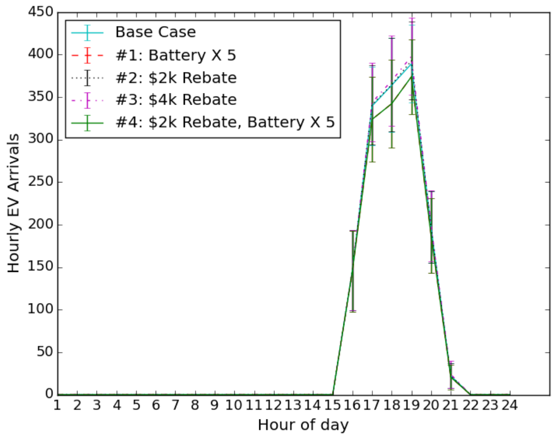


Fig. 13: EV Arrivals at Public Charging Stations in Last Simulation Month

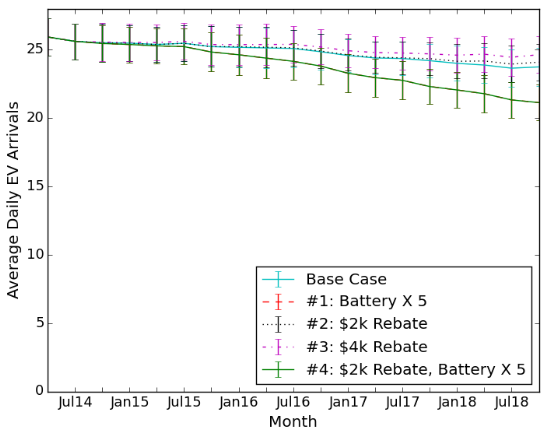


Fig. 14: EV Arrivals at Public Charging Stations

6 Conclusion

In this work, we have studied the impact of a high capacity battery on EV adoption and usage, using Los Angeles as a case study. This has been done using the agent-based EV ecosystem model: EV adoption is based on vehicle costs and utility, and EV usage – driving and charging – is dependent on an agent's daily drive cycle. The results show that a high capacity battery would increase EV adoption slightly, but EVs are still too expensive for a significant increase in adoption. Increasing EV rebates shows significant improvements in EV adoption. In order to encourage EV adoption, EV costs should be reduced in addition to battery improvements. We show that existing EV battery technology is sufficient to meet range requirements of a large number of Los Angeles residents. With an increase in battery size, there is a proportional increase in electrical load on the grid over time: this is due to PHEVs using more electricity because of larger batteries and the adoption of more EVs.

We find that the cost-competitiveness of EVs is a more significant barrier to EV adoption than range anxiety. Since there is already a high penetration of EVs in Los Angeles, the need for joint EV cost and battery improvements can be generalized. In the future, we plan to study the impact of distributed generation on EV adoption and usage.

In summary, the contributions of our work are:

1. the use of an ABM to study the impact of vehicle range and affordability on EV adoption in Los Angeles;
2. studying the impact of EV penetration on the electricity grid in Los Angeles; and
3. the surprising conclusion that vehicle affordability is a greater determinant of EV adoption than range, even in a geographically dispersed city such as Los Angeles.

References

1. Salvador Acha, Koen H van Dam, James Keirstead, and Nilay Shah. Integrated modelling of agent-based electric vehicles into optimal power flow studies. In *21st International Conference on Electricity Distribution, Frankfurt*, pages 6–9, 2011.
2. Adedamola Adepetu, Vijay Arya, and Srinivasan Keshav. An agent-based electric vehicle ecosystem model: A san francisco case study. Technical report, University of Waterloo, 2014.
3. Baha M Al-Alawi and Thomas H Bradley. Review of hybrid, plug-in hybrid, and electric vehicle market modeling studies. *Renewable and Sustainable Energy Reviews*, 21:190–203, 2013.
4. Alternative Fuels Data Center. Fuel Properties Comparison. Accessed on 18 March 2014, at `http://www.afdc.energy.gov/fuels/fuel_comparison_chart.pdf`.
5. B. Arellano, S. Sena, S. Abdollahy, O. Lavrova, S. Stratton, and J. Hawkins. Analysis of electric vehicle impacts in new mexico urban utility distribution infrastructure. In *Transportation Electrification Conference and Expo (ITEC), 2013 IEEE*, pages 1–6, June 2013.
6. Albert G Boulanger, Andrew C Chu, Suzanne Maxx, and David L Waltz. Vehicle electrification: Status and issues. *Proceedings of the IEEE*, 99(6):1116–1138, 2011.
7. Maxwell Brown. Catching the phever: Simulating electric vehicle diffusion with an agent-based mixed logit model of vehicle choice. *Journal of Artificial Societies & Social Simulation*, 16(2), 2013.
8. Bureau of Labor Statistics. Average Energy Prices, San Francisco-Oakland-San Jose January 2014. Accessed on 17 March 2014, at `http://www.bls.gov/ro9/cpisanf_energy.htm`.
9. California Center for Sustainable Energy. Clean Vehicle Rebate Project. Accessed on 17 March 2014, at `http://energycenter.org/clean-vehicle-rebate-project`.
10. California Department of Transportation. 2010-2012 california household travel survey final report. 2013.
11. Xiaohui Cui, Cheng Liu, Hoe Kyoung Kim, Shih-Chieh Kao, Mark A Tuttle, and Budhendra L Bhaduri. A multi agent-based framework for simulating household phev distribution and electric distribution network impact. *TRB Committee on Transportation Energy (ADC70)*, 2010.
12. Ricardo A Daziano. Conditional-logit bayes estimators for consumer valuation of electric vehicle driving range. *Resource and Energy Economics*, 35(3):429–450, 2013.
13. Electric Drive Transportation Association. Electric Drive Sales. Accessed on 02 March 2014, at `http://www.electricdrive.org/index.php?ht=d/sp/i/20952/pid/20952`.
14. Electric Power Research Institute (EPRI). Total cost of ownership model for current plug-in electric vehicles. Technical report, June 2013.
15. Margaret J Eppstein, David K Grover, Jeffrey S Marshall, and Donna M Rizzo. An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy Policy*, 39(6):3789–3802, 2011.

16. G Girishkumar, B McCloskey, AC Luntz, S Swanson, and W Wilcke. Lithium – air battery: Promise and challenges. *The Journal of Physical Chemistry Letters*, 1(14):2193–2203, 2010.
17. Lin He, Mingxian Wang, Wei Chen, and Guenter Conzelmann. Incorporating social impact on new product adoption in choice modeling: A case study in green vehicles. *Transportation Research Part D: Transport and Environment*, 32(0):421 – 434, 2014.
18. IBM. Battery 500 Project: 800 km range for electrovehicles. Accessed on 20 October 2014, at `http://www.zurich.ibm.com/news/12/battery500.html`.
19. John Voelcker. Reduce, Reuse, Recycle: Average Vehicle Now 11.4 Years Old, Oldest Since WW2. Accessed on 10 March 2014, at `http://www.greencarreports.com/news/1086136_reduce-reuse-recycle-average-vehicle-now-11-4-years-old-oldest-since-ww2`.
20. Jae D. Kim and Mansour Rahimi. Future energy loads for a large-scale adoption of electric vehicles in the city of los angeles: Impacts on greenhouse gas (ghg) emissions. *Energy Policy*, 73(0):620 – 630, 2014.
21. MapQuest. Directions Web Service - MapQuest Platform. Accessed on 18 March 2014, at `http://www.mapquestapi.com/directions/#matrix`.
22. Jeremy Neubauer and Eric Wood. The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility. *Journal of Power Sources*, 257(0):12 – 20, 2014.
23. Lydia O'Connor. San Francisco and Los Angeles Account for 35 Percent Of Nation's Electric Vehicle Sales, Data Finds. Accessed on 17 January 2014, at `http://www.huffingtonpost.com/2013/09/03/california-electric-cars_n_3862972.html`.
24. Phillip Paevere, Andrew Higgins, Zhengen Ren, Mark Horn, George Grozev, and Cheryl McNamara. Spatio-temporal modelling of electric vehicle charging demand and impacts on peak household electrical load. *Sustainability Science*, 9(1):61–76, 2014.
25. Michael B Pellon, Margaret J Eppstein, Lance E Besaw, David K Grover, Donna M Rizzo, and Jeffrey S Marshall. An agent-based model for estimating consumer adoption of phev technology. *Transportation Research Board (TRB)*, pages 10–3303, 2010.
26. Recargo. PlugShare - EV Charging Station Map. Accessed on 09 March 2014, at `http://www.plugshare.com/`.
27. Malte Schwoon. Simulating the adoption of fuel cell vehicles. *Journal of Evolutionary Economics*, 16(4):435–472, 2006.
28. Ehsan Shafiei, Hedinn Thorkelsson, Eyjólfur Ingi Ásgeirsson, Brynhildur Davidsdottir, Marco Raberto, and Hlynur Stefansson. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from iceland. *Technological Forecasting and Social Change*, 2012.
29. JL Sullivan, IT Salmeen, and CP Simon. Phev marketplace penetration: An agent based simulation. 2009.
30. Timothy Sweda and Diego Klabjan. An agent-based decision support system for electric vehicle charging infrastructure deployment. In *Vehicle Power and Propulsion Conference (VPPC), 2011 IEEE*, pages 1–5. IEEE, 2011.
31. US Environmental Protection Agency. Federal Tax Credits for Electric Vehicles Purchased in or after 2010. Accessed on 17 March 2014, at `http://www.fueleconomy.gov/feg/taxevb.shtml`.
32. US Environmental Protection Agency. Fuel Economy. Accessed on 18 March 2014, at `http://www.fueleconomy.gov/`.
33. Ingo Wolf, Tobias Schrder, Jochen Neumann, and Gerhard de Haan. Changing minds about electric cars: An empirically grounded agent-based modeling approach. *Technological Forecasting and Social Change*, (0):–, 2014.