An Agent-Based Decision Support System for Electric Vehicle Charging Infrastructure Deployment

Timothy Sweda and Diego Klabjan
Department of Industrial Engineering and Management Sciences
Northwestern University
Evanston, Illinois 60208, USA
E-mail: tsweda@u.northwestern.edu, d-klabjan@northwestern.edu

***Abstract*—The current scarcity of public charging infrastructure is one of the major barriers to mass household adoption of electric vehicles (EVs). Many drivers are reluctant to purchase EVs without convenient charging access away from home, but investors are also hesitant to build charging stations without underlying knowledge of EV demand realization. In this paper, an agent-based decision support system is presented for identifying patterns in residential EV ownership and driving activities to enable strategic deployment of new charging infrastructure. The Chicagoland area is used as a case study to demonstrate the model.**

I. Introduction

As consumers have become increasingly aware of the environmental impacts of gasoline-powered vehicles as well as the economic and political implications of the United States' dependence on foreign oil, the demand for alternative-fuel vehicles (AFVs) has risen over the past several years. Electricity has emerged as one of the most practical and feasible alternative-fuel solutions, and automakers have already begun releasing plug-in hybrid and battery electric vehicle (PHEV, BEV) models for the mass market. Most cities in the U.S., however, do not have a network of public charging infrastructure to support electric vehicles (EVs). This lack of infrastructure is one of the major barriers to mass household adoption of EVs [1].

At the same time, investors are hesitant to deploy charging infrastructure without underlying knowledge of EV demand realization. A number of different models have been developed to study the market potential of EVs and other AFVs. For example, nested multinomial logit models have been employed for forecasting the market share of AFVs in general [2] and also of hybrid EVs (HEVs) and diesel-powered vehicles [3]. Other models have attempted to capture changing consumer attitudes, such as the shift in perception of a new vehicle technology from risky and unique to safe and mainstream [4] and the effect of consumer learning on the market penetration rates of individual vehicle makes [5]. In addition, market simulation models for predicting PHEV adoption rates have been studied [6][7].

One common weakness of the previously mentioned models is that spatial patterns in the adoption of new vehicle technologies are not captured. Investors wanting to build new charging infrastructure for EVs need to know where EVs are likely to be concentrated and where they are likely to be driven. Agent-based modeling (ABM), a technique for studying the interactions among many autonomous and heterogeneous decision makers, has been used often in recent years to model the transition of passenger vehicle fleets to AFVs because of its ability to capture both spatial and temporal patterns. So far, researchers have primarily utilized ABM to examine transitions to hydrogen-powered vehicles, incorporating either generic environments [8][9] or actual geographic and demographic data [10][11]. However, it has also been used to study the grid impacts of PHEV ownership [12].

In this paper, an agent-based decision support system is presented for identifying patterns in residential EV ownership and driving activities to enable strategic deployment of new charging infrastructure. The Chicagoland area is used as a case study to demonstrate the model, which incorporates road network data to permit micro-level analyses of the market for EVs. This is the first known instance of utilizing street data to study a transition to AFV technology.

II. Model

The model used in this paper seeks to capture the activities and decisions of individual drivers who have the option of purchasing EVs. It is an ABM in which the agents represent drivers, and these agents can interact with each other to influence their vehicle purchasing behaviors. The agents all exist within an environment that consists of houses, where the agents live; workplaces, where the agents work; points of interest, or other destinations that the agents may visit; charging stations, where agents that own EVs can recharge their vehicles; and a road network, along which the agents travel. Such a setup allows more realistic travel behaviors that are not possible when agents are confined to a grid-based environment, especially when each cell in the grid represents a large area (e.g., one square mile, as in [10] and [11]).

Agents are assigned values for several different attributes, including income, preferred vehicle class (e.g., compact, midsize, luxury, etc.), level of range anxiety, and greenness. Each agent is also assigned a house and a workplace, as well as a vehicle with an initial age and a terminal age when it must be replaced. Because vehicle maintenance costs are not accounted for in the model, it is assumed that agents know ahead of time when to replace their vehicles.

Every simulation week, each agent receives a schedule of errands, or destinations to visit along with the time that must be spent at each location. The errands are classified into three types: local, distant, and work. Local errands are within a given radius of the agent's house, while distant errands require travel outside of the radius. The third errand type corresponds to the agent's workplace, which must be visited for a period of eight hours every simulation weekday. The other errands may be completed in any order and on any day of the week, but the agent has morning and evening curfews that must be obeyed, thereby limiting the number of errands that may be completed in one simulation day.

If an agent drives a PHEV or BEV, then the vehicle must be recharged periodically. Recharging can occur at the agent's home, at a destination on the errands list with charging access, or at a stand-alone charging facility. (Gasoline stations are assumed to be ubiquitous in the model, and thus refueling activities for gasoline-powered vehicles do not need to be considered.) Recharging at a charging facility is quick but expensive, so agents will prefer to recharge elsewhere at a lower cost whenever possible. It is worth noting that because of the mandatory curfew, all EVs will automatically recharge overnight. This corresponds to the expected recharging behavior of actual EV drivers, especially if time-of-day electricity rates are in effect.

Agents with BEVs also accumulate inconvenience and worry associated with their recharging activities. Inconvenience refers to the added driving distance incurred by seeking recharging, and worry increases as the agent drives while the charge level of the vehicle is below a certain threshold. Worry is related to the agent's level of range anxiety, as an agent with high range anxiety is more likely to accumulate worry than an agent with low range anxiety. Agents with PHEVs, on the other hand, have neither worry nor inconvenience because their vehicles can run on gasoline after they exhaust their all-electric range. They recharge if charging access is nearby but do not venture out of their way just to keep their batteries fully charged.

An important component of the ABM described in this paper is the ability of agents to interact with each other. Every agent observes the purchasing decisions of those around it, and as the proportion of EV owners in its social network grows, it becomes more likely to purchase an EV as its next vehicle. Two such spheres of influence are included in the present model: neighbors and coworkers. Since the number of agents in the simulation is likely to be small relative to the size of the population being modeled, it is improbable that two agents will live sufficiently close together to be classified as neighbors in the physical sense. It is therefore necessary to define a neighbor relation as a function of the distance between two agents. Two agents living near each other would have a strong neighbor relation, for example, and two agents living far apart would have a weak neighbor relation. A similar notion is used to define coworker relations among agents, where the relations are a function of the distance between the workplaces of agents.

When the time comes for an agent to purchase a new vehicle, the agent has a choice among four types of vehicles: internal combustion engine (ICE) vehicle, HEV, PHEV, and BEV. Only vehicles from the agent's preferred vehicle class are considered. For each vehicle, the agent takes into account the purchase price, the expected fuel costs (based on past driving activity, future expected fuel prices, and the vehicle's fuel efficiency), the agent's own greenness, and any influences from neighbors and coworkers. Furthermore, when considering either a PHEV or BEV, the agent must penalize the new vehicle based on the availability of charging infrastructure. If the agent is discarding a BEV, then the penalty is measured as a function of the agent's accumulated inconvenience and worry; otherwise, the agent estimates the penalty by observing where charging stations are located.

For an agent a, the optimal vehicle choice $y(a,t)$ at time t satisfies the expression

$$\begin{aligned} y(a,t) = \operatorname*{argmin}_{v \in V(a)} \big\{ & Price(v,t) + E[FuelCost(v,a,t)] \\ & - GreenBonus(v,a) - SocialInfluence(v,a,t) \\ & + LongDistancePenalty(v,a) \\ & + E[InfrastructurePenalty(v,a,t)] \big\}. \end{aligned}$$

Here, $V(a)$ is the set of vehicles available to agent a. The price of a new vehicle is denoted by $Price(v,t)$ (used vehicles are not considered in the model), and $E[FuelCost(v,a,t)]$ is the total expected cost of fuel (either gasoline or electricity) for the vehicle over its lifetime based on the agent's past driving activity. Subtracted from these are $GreenBonus(v,a)$, a function of the agent's greenness and income that is greatest for vehicles with the least reliance on gasoline, and $SocialInfluence(v,a,t)$, which increases for the EV options as more of the agent's neighbors and coworkers purchase EVs. The term $LongDistancePenalty(v,a)$ equals zero for ICE vehicles and HEVs but is positive for PHEVs and BEVs, and it is greatest if an agent regularly travels long distances (such as from home to work) where the range of EVs is inadequate. The final term, $E[InfrastructurePenalty(v,a,t)]$, can be calculated exactly if the agent has accumulated inconvenience and worry but must be estimated otherwise, in which case it is smallest when there are plenty of charging stations near the agent's home and workplace. The vehicle v that minimizes the bracketed expression is the agent's optimal vehicle choice.

III. Implementation

The current version of the model is implemented in Repast, which was selected over other ABM platforms because of its ease of use and open-source code. Repast takes as inputs shapefiles containing geographic information systems data to define the environment. Additional Java routines have been implemented to initialize the agents and define their behaviors, and the timesteps in the simulation correspond to 15-minute intervals in order to enable tracking of individual agents as they move within the environment. Data from the Chicagoland area (Cook, DuPage, Lake, and Will counties) are used to demonstrate the model (see Figure 1).

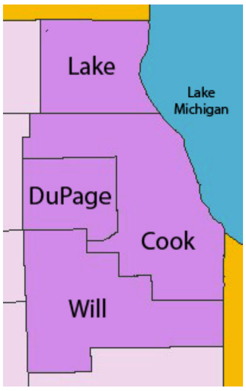

Fig. 1. Map of the Chicagoland region used in the implementation of the model, which includes Cook, DuPage, Lake, and Will counties.

To synthesize the environment, shapefiles from the U.S. Census containing road data, zip code tabulation area (ZCTA) data, and points of interest were imported into Repast, and houses were located based on ZCTA population data. The houses were populated with drivers (agents), who were randomly assigned to workplaces in accordance with county workflow data. Initial charging infrastructure deployments included both existing and proposed layouts. The agent population within the region was usually on the order of hundreds or thousands (sometimes with as many as 10,000 agents), which was sufficient to capture interaction effects among agents.

IV. Results

A. Charging Station Coverage

Coverage statistics, which measure how effectively a given deployment of charging stations serves potential EV purchasers, are illustrative since they can be computed prior to running the simulation and compared across different infrastructure deployment strategies. Examples include the average distance from an agent's house to the nearest charging station, the average number of charging stations within a given distance from an agent's house, and the probability that an agent selected at random has at least one charging station within a given distance from its house. These statistics are summarized in Tables I-III for three charging station deployment scenarios: a base case (consisting of the nearly 20 publicly accessible charging stations currently deployed in the Chicagoland area) and two proposed deployments, each with approximately 70 additional charging stations.

TABLE I
Average Distance to Nearest Charging Station

Scenario	Dist. (mi.)	Std. Error (mi.)
Base	10.50	0.06
Prop. 1	5.01	0.05
Prop. 2	4.37	0.03

Based on the values in the tables, it can be observed that the first of the proposed deployment scenarios is targeted more towards densely populated areas than the second one.

TABLE II
Average Number of Nearby Charging Stations

Scenario	# Within X mi. (Std. Error)			
	X = 5	X = 10	X = 15	X = 20
Base	0.92 (.03)	3.35 (.05)	5.85 (.06)	7.91 (.07)
Prop. 1	3.69 (.08)	12.52 (.13)	23.00 (.16)	33.14 (.18)
Prop. 2	3.49 (.08)	12.21 (.13)	22.20 (.14)	32.21 (.16)

TABLE III
Probability of Nearby Charging Station

Scenario	Prob. Within X mi. (Std. Error)			
	X = 5	X = 10	X = 15	X = 20
Base	0.157 (.004)	0.517 (.005)	0.821 (.004)	0.938 (.002)
Prop. 1	0.633 (.005)	0.889 (.003)	0.949 (.002)	0.987 (.001)
Prop. 2	0.671 (.005)	0.948 (.002)	0.983 (.001)	0.995 (.001)

While the number of nearby charging stations is greater on average for the first scenario than for the second scenario, the average distance to the nearest charging station is greater and the probability of living within a given radius of at least one charging station is lower. Other coverage statistics that take into account consumer incomes along with additional demographic information could be studied as well to analyze further how well each deployment provides coverage to potential EV purchasers.

B. Inconvenience to BEV Drivers

It is also important to observe the impacts of deployment decisions on EV driving behavior. Table IV summarizes the inconvenience experienced by BEV drivers, or the extra distance they must travel to visit charging stations, in addition to the cost of electricity for traveling this extra distance. The cost was obtained by multiplying the annual inconvenience by \$0.03667, assuming an electricity price of \$0.11 per kilowatt-hour (kWh) and a battery efficiency of 3 miles per kWh. In the implementation, it is assumed that EV drivers can recharge at either public charging stations or their houses, but not at their workplaces (because workplace charging accessibility is extremely limited presently), which is why the values may seem high. If recharging at workplaces is permitted, then the annual inconvenience would be much lower.

TABLE IV
Average Annual Inconvenience Incurred by BEV Drivers

Scenario	Inconv. (mi./yr.)	Std. Error (mi./yr.)	Elec. Cost
Base	1,239	91	\$45.43
Prop. 1	757	44	\$27.76
Prop. 2	667	34	\$24.46

The data in Table IV suggest that EV ownership extends beyond the most densely populated areas, as BEV drivers incur greater inconvenience under the first proposed deployment scenario than under the second. This makes sense because individuals with higher incomes, who are more likely to purchase EVs, tend to live in less densely populated communities. The lower inconvenience also implies that there are likely to be more repeat BEV buyers since agents consider their inconvenience when selecting a new vehicle.

C. EV Adoption

The model can be used to identify EV adoption patterns based on different case scenarios, and these patterns in turn can be used to select the best strategies for deploying new charging infrastructure. The results in this section illustrate how adjusting the price of gasoline reveals long-term trends in the adoption rates of the different types of EVs relative to each other.

Figures 2-4 show the rates of EV adoption over a period of ten years when gasoline is priced at \$4, \$6, and \$8 per gallon, respectively. All other parameters are held constant and are chosen to encourage EV adoption for demonstration purposes. For example, agents tend to underestimate the inconvenience of owning a BEV, and they consider the fuel savings over the lifetime of a new vehicle as opposed to just over a short time horizon. Not surprisingly, the overall rate of EV adoption increases as the price of gasoline increases, but a number of interesting trends among the different EV types emerge.

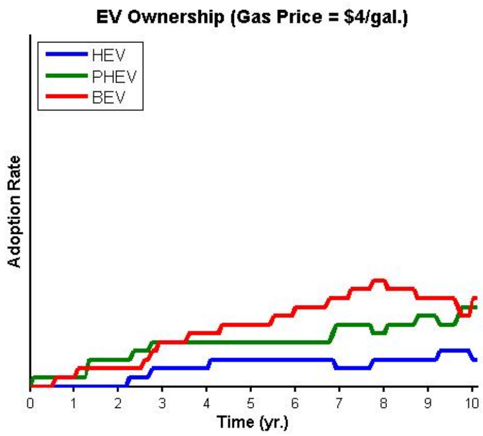

Fig. 2. Adoption of EVs over time with the price of gasoline fixed at \$4 per gallon.

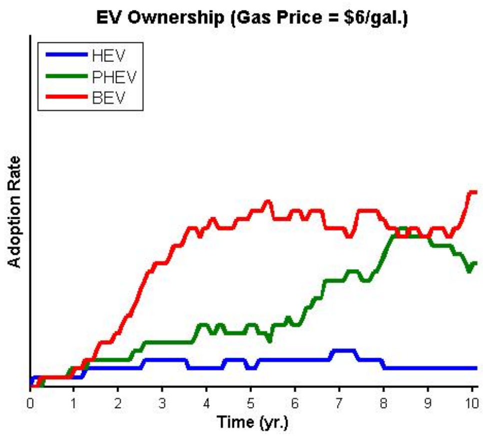

Fig. 3. Adoption of EVs over time with the price of gasoline fixed at \$6 per gallon.

Considering first the BEV sales, represented by the red curves, it is evident that the transition to BEVs occurs most

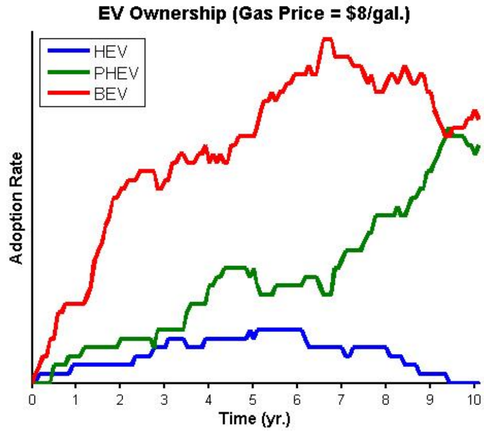

Fig. 4. Adoption of EVs over time with the price of gasoline fixed at \$8 per gallon.

rapidly and within a greater proportion of the population when the price of gasoline is expensive relative to the price of electricity. At some point, however, the adoption rate levels off since BEVs are not suitable for all agents, especially those in low-income households, those that drive compact or other fuel-efficient vehicles, and those for which the limited driving range is problematic. The process of leveling off is smoothest when gasoline is modestly priced. When gasoline is inexpensive, BEV adoption occurs gradually and can take a long time to stabilize. On the other hand, expensive gasoline makes BEVs very attractive to consumers, causing an early surge of adopters. The resulting social influence encourages further adoption, but a period of disownment follows as agents that have accumulated too much inconvenience and worry replace their BEVs with other vehicles. These trends can be large in magnitude because of the high number of BEV owners, and such volatility can impede the stabilization of BEV adoption.

PHEV sales, represented by the green curves, exhibit a curious behavior relative to BEV sales. While the two seem to increase at similar rates at the beginning of the time horizon (especially when gasoline is the least expensive), sales of PHEVs tend to lag behind those of BEVs until the end of the time horizon, at which point they are once again similar. Because the simulation parameters for the implementation in this section cause agents to underestimate the inconvenience of owning a BEV, agents tend to purchase a BEV before they purchase a PHEV. However, agents that own BEVs usually also favor PHEVs, and if they decide to sell a BEV, they often replace it with a PHEV. Such a tendency allows the adoption rate of PHEVs to catch up to that of BEVs, which explains why the two curves eventually meet up in each of the plots.

The sales of HEVs, represented by the blue curves, are interesting as well. Regardless of the price of gasoline, they never grow as quickly as the sales of BEVs and PHEVs. In [6], a similar phenomenon is observed for PHEVs, where smaller, more fuel-efficient ICE vehicles become preferable as the price of gasoline increases. The smaller vehicles gain market share, whereas PHEVs only retain theirs. A different vehicle market is used in the model implementation in this section, and HEVs lose market share to plug-in vehicles rather than to compact ICE vehicles (due to vehicle class restrictions on agents). In fact, HEV owners almost always replace their vehicles with BEVs or PHEVs. This transition occurs most rapidly when gasoline prices are highest, and thus the adoption rate of HEVs can actually decrease back to zero.

V. Future Work

This model has not yet been used to analyze spatial patterns in EV adoption, which will be the focus of the next stage of research. In addition to how many, investors will want to know where new charging stations should be deployed. The deployment strategies will also depend on the investor. For example, an investor seeking to maximize station utilization will tend to place more stations near densely populated or frequently visited areas, whereas another investor interested in expanding public charging access may prefer to target regions that are less busy and not adequately served by the existing charging infrastructure. Understanding how EV adoption occurs with respect to geography as well as to demographics will prove critical to determining the most effective charging infrastructure deployment strategies.

Another research avenue worth pursuing is the development of a framework for optimizing the deployment of charging infrastructure. In its current form, the model takes as input a fixed plan for charging station deployment and does not attempt to make modifications either dynamically or iteratively. A more sophisticated simulation optimization algorithm would enable better decision making by providing deployment recommendations instead of only evaluating given deployments.

One limitation of the ABM proposed in this paper is the lack of data regarding PHEV and BEV sales as well as the behaviors of drivers of such vehicles. While the current implementation has been calibrated with historical HEV sales data, several parameters have been adjusted without the guidance of actual figures, such as the impact of social influence on EV adoption, the ratio of electric miles driven to gasoline miles driven by PHEV drivers, and the level of range anxiety of BEV drivers. As these data become available, more thorough calibration will be possible to allow for better projections of future EV ownership.

VI. Conclusion

In this paper, an agent-based decision support system has been presented for identifying patterns in residential EV ownership and driving activities to enable strategic deployment of new charging infrastructure. The Chicagoland area is used as a case study to demonstrate the model, which incorporates road network data to permit micro-level analyses of the market for EVs. Three different charging station deployment scenarios are analyzed, and patterns of HEV, PHEV, and BEV adoption are explored.

Further investigation into the causes of these adoption patterns will permit more specific recommendations to investors on how best to deploy new charging infrastructure. As a next step, spatial analysis of EV adoption patterns utilizing demographic and geographic data will be performed to gain insights into the evolution of the residential EV market.

Acknowledgment

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