An Agent-Based Information System for Electric Vehicle Charging Infrastructure Deployment

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Abstract

The current scarcity of public charging infrastructure is one of the major barriers to mass household adoption of plug-in electric vehicles (PEVs). Although most PEV drivers can recharge their vehicles at home, the limited driving range of the vehicles restricts their usefulness for long-distance travel. In this paper, an agent-based information system is presented for identifying patterns in residential PEV ownership and driving activities to enable strategic deployment of new charging infrastructure. Driver agents consider their own driving activities within the simulated environment, in addition to the presence of charging stations and the vehicle ownership of others in their social network, when purchasing a new vehicle. Aside from conventional vehicles, drivers may select among multiple electric alternatives, including two PEV options. The Chicagoland area is used as a case study to demonstrate the model, and several different deployment scenarios are analyzed.

Keywords: electric vehicles; charging stations; agent-based model; demand modeling

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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 electric vehicle (PEV) models for the mass market that can plug into the electrical grid to recharge. These include plug-in hybrid electric vehicles (PHEVs), which run on both gasoline and electricity, and battery electric vehicles (BEVs), which run solely on electricity. (Hybrid electric vehicles, or HEVs, also use electricity for propulsion, but they cannot connect to the electrical grid and are therefore not classified as PEVs.) Most cities in the U.S., however, do not have a network of public charging infrastructure to support PEVs. Even though most PEV drivers can recharge their vehicles at home, the limited driving range of the vehicles restricts their usefulness for long-distance travel. This lack of infrastructure is one of the major barriers to mass household adoption of PEVs (Klabjan and Sweda 2011).

At the same time, charging infrastructure providers are hesitant to deploy new charging stations without underlying knowledge of PEV demand realization. Stations that are capable of recharging a PEV in under an hour require significant up-front capital expenditures. If such charging stations are underutilized due to limited PEV ownership or poor placement (or both), then the payback period would be too long for most investors and would discourage future infrastructure investments.

In this paper, an agent-based information system is presented for identifying patterns in residential PEV ownership and driving activities to enable strategic deployment of new charging infrastructure. Driver agents commute from their homes to work and to other destinations within an environment. Their driving activities are captured at the street level implying a micro-level simulation. The drivers periodically replace their vehicles, choosing among both conventional and electric vehicles, based on their driving activity, their demographic information, the adoption rates of electric vehicles (EVs) within their social networks (specifically, neighbors and coworkers), and the locations of charging stations.

The contributions of this work include the following: (*i*) a simulation model of drivers transitioning to multiple different EV technologies with both public and at-home charging options; (*ii*) a study of the effect of charging infrastructure presence on PEV adoption; (*iii*) detailed street-level modeling of driving in the EV context; and (*iv*) an analysis of adoption trends of the different EV options (HEV, PHEV, BEV) when all three are available for purchase. The final contribution is especially important since many other studies focus on only a single AFV option and neglect to consider possible competition among multiple AFV types.

The remainder of the paper is organized as follows. Section 2 provides an overview of the literature pertaining to transitions to alternative fuels. In Section 3, the proposed model is described in detail. The model implementation is explained in Section 4, and simulation results are presented in Section 5.

Literature review

A number of different approaches have been used in the literature to study the market potential of PEVs and other AFVs. Discrete-choice models, which relate a decision maker's choice among a discrete set of alternatives to the attributes of the decision maker and of the alternatives, are particularly well suited for modeling vehicle purchasing decisions of consumers. Some examples in the literature of discrete-choice models applied to AFVs include logit models for AFV choices based on stated preference surveys of California drivers (Bunch et al. 1993; Golob et al. 1993; Ren et al. 1994; Brownstone et al. 2000), drivers from the other 47 contiguous states (Tompkins et al. 1998), and car buyers in Germany (Hackbarth and Madlener 2013); nested multinomial logit models for forecasting the market share of AFVs in the U.S. (Greene 2001) and Canada (Potoglou and Kanaroglou 2007) and also of hybrid electric vehicles (HEVs) and diesel-powered vehicles (Greene et al. 2004); and a multiple discrete-continuous choice model in which households may choose multiple AFVs and decide how often to use each vehicle (Ahn et al. 2008). Other discrete-choice 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 (Santini and Vyas 2005); the stimulation of AFV demand by word of mouth from drivers without AFVs (Struben and Sterman 2007); the effect of consumer learning on the market penetration rates of individual vehicle makes (Heutel and Muehlegger 2010); and the stability of attitudes before and after experiencing an EV (Jensen et al. 2013). The model of Struben and Sterman (2007) is compared to other similar dynamic diffusion models by McManus and Senter (2009) and is found to capture more realistic consumer choice behaviors. However, none of these models capture social interactions among consumers, which are shown by Axsen (2010) to have an effect on vehicle purchasing decisions. The models instead assume that consumers make decisions independently of each other and do not react to changes in the vehicle ownership of other drivers. The models are analytical forecasting models whereas the work presented in this paper is a comprehensive simulation methodology that, even when utilized purely for forecasting PEV demand, is more general since social interactions are captured.

Simulation models have also been developed to study transitions to AFV technologies. These models primarily employ agent-based frameworks, which have become popular in recent years for analyzing complex systems. In Sullivan et al. (2009), interactions among consumers, fuel producers, vehicle dealers, and the government are modeled to analyze the market penetration of PHEVs under different economic scenarios, and mechanisms for promoting AFV adoption are studied by Zhang et al. (2011), where the agents represent vehicle manufacturers and consumers. The grid impacts of household PHEV ownership are examined by Cui et al. (2012) and Waraich et al. (2013). In Cui et al. (2012), PHEV-owning households exert a neighbor effect on nearby households, creating hot spots for electricity demand, and in Waraich et al. (2013), an agent-based traffic simulation is used to generate daily electricity demand profiles. Other agent-based models (ABMs) focused on PEV adoption include Eppstein et al. (2011) and Shafiei et al. (2013), both of which also consider social interactions among agents. The aforementioned demand models all neglect to consider the influence of charging (or refueling) infrastructure accessibility on vehicle purchasing decisions, however. In the cases of hydrogen vehicles, PEVs, and other AFVs, a lack of sufficient infrastructure could make owning those vehicles entirely impractical for some drivers, and the placement of individual stations could greatly affect adoption rates. A distinguishing feature of the ABM proposed in this work is micro-modeling of driving, which also enables charging infrastructure placement at a granular level.

Another group of ABMs has studied the interrelation between refueling infrastructure placement and the adoption of hydrogen vehicles. The earliest of these appeared in Stephan and Sullivan (2004), which has since been extended and applied to a region in Los Angeles, California (Stephan et al. 2007; Mahalik et al. 2009; Mahalik and Stephan 2010), and it considers drivers in an urban environment who commute along roads to various destinations. Drivers can choose to purchase either conventional or hydrogen vehicles based on their own attributes and driving activities, the vehicle ownership of other agents, and the accessibility of hydrogen refueling stations. At the same time, investor agents can construct and demolish refueling stations based on actual or expected fuel sales at the station locations. Similar yet simpler models are used to study a transition to hydrogen vehicles in Germany (Schwoon 2007), analyze the effects of social networks and technological learning on hydrogen vehicle adoption (Huétink et al. 2010), and test the impacts of different parameter settings on the numbers of hydrogen stations and vehicles (Ning et al. 2010). In these models, however, refueling activities are not explicitly captured, thereby weakening the analyses.

A few papers in the literature have considered the problem of optimally locating charging stations. Ip et al. (2010) use a set covering model in which demand nodes represent regional traffic volumes and are assigned to charging stations based on a hierarchical clustering method. Chen et al. (2013) analyze vehicle parking information to determine the locations and durations of EV charging demand and formulate a mixed-integer program to minimize charging station access costs. Other models capture trip data for individual drivers and locate charging stations based on where the infrastructure is needed to enable those trips. For example, Andrews et al. (2012) develop a set of tours based on trip data from the Metropolitan Travel Survey Archive and isolate the ones with total distances greater than the maximum range of a BEV. The authors subsequently consider only the isolated tours when they implement their mixed-integer program to minimize the distance that drivers must travel to access charging stations. Another model by Hess et al. (2012) simulates PEV travel in Vienna, Austria and uses genetic programming to achieve optimal infrastructure deployments that minimize mean trip times. Although these location models are capable of providing optimal charging infrastructure deployments based on certain metrics, they are valid only when the population of PEV drivers is stationary in time, which is not the case in current markets where PEVs are available. Additionally, the expansion of public charging infrastructure will further spur demand for PEVs and thereby render obsolete any previously optimal deployment solution.

This paper extends the preliminary work of Sweda and Klabjan (2011). To the best of the authors' knowledge, there is no other study in the literature that explores the effect of charging station locations on the adoption of PEVs. Unlike non-electric AFVs and even conventional vehicles, PEVs are unique in that they can be recharged at the driver's home as well as at stand-alone charging stations. PEV drivers therefore have multiple recharging options available to them, and some drivers may never need to visit a charging station if their driving patterns allow them to always recharge at home. This paper is also the first to study the adoption of different PEV types (PHEVs and BEVs), each with its own specific recharging requirements, in such a setting. Whereas BEVs can never run out of charge, PHEVs may deplete their batteries in the middle of a trip since they also use gasoline.

Model

The model developed 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 to influence each other's vehicle purchasing behaviors. An agent-based approach was selected over other alternatives since it captures such interactions as well as spatial information, both of which can influence vehicle purchasing decisions, and allows agents to react to changes in their environment. In particular, social interactions among neighbors and coworkers are explicitly taken into account, which is possible only through spatial modeling. In the model, 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 PEVs 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 (as in Stephan et al. (2007), Mahalik et al. (2009), and Mahalik and Stephan (2010)).

Houses and workplaces are located randomly in the environment using given density functions that are based on data from the U.S. Census and other sources, and each agent is uniquely assigned to one of each (additional details provided in Section 4). The locations of points of interest and charging stations, as well as the nodes and arcs of the road network, are given. It is assumed that all components of the environment (not including the agents) are fixed during the course of each run (a period of ten simulated years), and none can be modified, added, or destroyed. In addition, agents never change their houses or workplaces during a run. When traveling from one location (its home, its workplace, a point of interest, or a charging station) to another, an agent identifies the points in the road network closest to its origin and destination and finds the shortest path between the two points.

Agents are assigned values for several different attributes – income, preferred vehicle class (compact, midsize, luxury, SUV), and greenness – that remain constant during each simulation. The greenness attribute is intended to capture drivers' environmental concerns and is defined as the additional amount that an agent will pay for a BEV than for a conventional vehicle, all else equal. Each agent is also assigned 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. Another simplifying assumption is that each agent represents a single-occupant, single-vehicle household that uses its vehicle as its sole means of transportation. Thus, vehicle purchasing decisions do not include considerations for households with multiple drivers or multiple vehicles, or that utilize public transit for some or all of their commuting needs.

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, to which the agent commutes every weekday. The other errands may be completed after work on weekdays or throughout the day on weekends, but the agent has morning and evening curfews that must be obeyed, thereby limiting the number of errands that may be completed in one 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.) Charging stations offer fast recharging, but agents prefer to recharge at home if they have no more errands to run during the day. It is worth noting that because of the mandatory curfews, all PEVs will automatically recharge overnight. This corresponds to the expected recharging behavior of actual PEV drivers, especially if time-of-usage electricity rates are in effect.

The following algorithm summarizes the daily routine of each agent with time resolution of 15 minutes.

```
if today is a weekday then
    when time = work start time − time to drive from home to work
        go to work (following the shortest path from home to work)
    when time = work end time
        if agent has errands to run then
            run errands (explained in the next paragraph)
        else
            go home (following the shortest path from work to home)
        end if
else if today is a weekend then
    when time = morning curfew time
        if agent has errands to run then
            run errands
        end if
```

end if

If the current simulation day is a weekday, then the agent leaves home for work to arrive by the work start time, and at work end time the agent leaves work. The agent completes any errands that it has after work, or if it has no errands, then it heads straight home. On weekends, the agent can begin running errands at the morning curfew time and departs from home rather than from work. It is assumed that agents who drive PEVs do not need to recharge when traveling from home to work, which is reasonable since most PEV owners recharge their vehicles overnight and have a full charge when they depart for work in the morning. They may, however, need to recharge their vehicles while running errands, as shown next.

The "run errands" function consists of the following actions.

while agent still has errands to run **and** time $<$ evening curfew time **do**
  if agent's vehicle is a BEV **then**
    if vehicle's charge level $<$ min$\{$threshold, energy required to reach next errand$\}$ **then**
      go to nearest charging station (following the shortest path from the agent's current location to the station)
      set vehicle's charge level $=$ maximum charge level
    end if
  end if
  go to next errand (following the shortest path from the agent's current location to the errand)
  remove the errand from the agent's list of errands
end while
go home (following the shortest path from the agent's current location to home)

If the agent drives a BEV, then before attempting its next errand it must decide whether or not to recharge at a charging station first. If its vehicle's charge level is below a threshold or is insufficient to reach the next errand, then the vehicle must be recharged; otherwise, the agent may complete the errand. (It is assumed that whenever an agent visits a charging station, its vehicle is completely recharged.) The agent returns home after all of its errands for the day have been completed, or when the current simulation time equals the evening curfew time, in which case any errand in progress is interrupted. Such a myopic algorithm does create scenarios in which a BEV becomes stranded (i.e., the vehicle cannot reach either the next errand or its nearest charging station without traveling some distance on an empty battery), but the model does not penalize miles traveled by a BEV on an empty battery. A more sophisticated routing algorithm could be designed to address this issue, but it would be more difficult and computationally expensive to implement.

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 an agent drives while the charge level of its vehicle is below a certain threshold. 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 (it is assumed that PHEVs always operate in charge-depleting mode, using gasoline only when their batteries have no charge remaining). They recharge if charging access is available at their current location 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 may be much smaller than the size of the population being modeled, it is possible that no 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. The expression used in the model is

$$Neighbor(a,b) = \frac{MaxDistance - Distance(a,b)}{MaxDistance},$$

where a and b are agents, $Distance(a,b)$ is the distance between the houses of the two agents, and $MaxDistance$ is the maximum value of $Distance(a,b)$ for which a and b may be considered neighbors. The value of $Neighbor(a,b)$ approaches one as a and b live closer together, and it equals zero when a and b live at least $MaxDistance$ away from each other. A similar notion is used to define coworker relations among agents ($Coworker(a,b)$), 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: an 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

$$\begin{aligned} y(a,t) = \operatorname*{argmin}_{v \in V(a)} \big\{ & Price(v,t) + E[FuelCost(v,a,t)] - GreenBonus(v,a) + \\ & SocialInfluence(v,a,t) + WorkPenalty(v,a) + \\ & E[InfrastructurePenalty(v,a,t)] + VehiclePenalty(v,a) \big\}. \end{aligned} \tag{1}$$

Here, $V(a)$ is the set of vehicles available to agent a. The terms on the right-hand side of the expression are as follows, where all parameter values are given in the Appendix.

- $Price(v,t)$: This term represents the sticker price of vehicle v at time t when purchased new (used vehicles are not considered in the model).

- $E[FuelCost(v,a,t)]$: This term measures the total expected cost of fuel (either gasoline or electricity) for vehicle v calculated by agent a at time t. The odometer reading of the agent's current vehicle is used to estimate the total distance that the agent will travel in the new vehicle over its lifetime, and the expected proportions of gasoline and electric miles (100%/0% for ICEs and HEVs, 20%/80% for PHEVs, and 0%/100% for BEVs) as well as the fuel consumption rates of vehicle v are multiplied together to determine the total expected gasoline and electricity consumption of the new vehicle. These quantities are then multiplied by their respective fuel prices, and also by a factor of 0.61 based on evidence from Allcott and Wozny (2010) that consumers will only pay \$0.61 to save \$1.00 on future fuel costs, and then summed to obtain the total expected cost of fuel.

- $GreenBonus(v,a)$: This is an incentive for agent a to purchase vehicle v that depends on the agent's greenness and also the vehicle's reliance on gasoline

- $SocialInfluence(v,a,t)$: This term captures the effect of agent a's social network on the agent's decision to purchase vehicle v at time t. It is calculated as

$$SocialInfluence(v,a,t) = \alpha(v,a)\left(\left(1 - \frac{\sum_{b\in\mathcal{N}(a)} Neighbor(a,b)\cdot Influence(b,t)}{\sum_{b\in\mathcal{N}(a)} Neighbor(a,b)}\right) + \left(1 - \frac{\sum_{b\in\mathcal{C}(a)} Coworker(a,b)\cdot Influence(b,t)}{\sum_{b\in\mathcal{C}(a)} Coworker(a,b)}\right)\right),$$

  where $\alpha(v,a)$ is a vehicle-dependent coefficient that equals 0 for ICE vehicles and is positive for EVs, $\mathcal{N}(a)$ and $\mathcal{C}(a)$ are the neighbors and coworkers of a, respectively, and $Influence(b,t)$ is a value between 0 (if b owns an ICE vehicle at time t) and 1 (if b owns a BEV at time t). The value of this term represents a penalty for purchasing an EV due to limited EV ownership within the agent's social network and ranges from 0 (if all of the agent's neighbors and coworkers own BEVs) to $2\alpha(v,a)$ (if there are no EV owners within the agent's social network). It reflects the idea that an agent becomes more familiar with EVs and less reluctant to purchase one as more of its neighbors and coworkers become adopters themselves.

- $WorkPenalty(v,a)$: This is a penalty term that is arbitrarily large if v is a BEV and the range of the vehicle would not permit agent a to complete a round trip between its home and workplace without recharging somewhere in the middle, and equals 0 otherwise.

- $E[InfrastructurePenalty(v,a,t)]$: This term is a penalty representing the perceived burden to agent a at time t of driving vehicle v due to the lack of public charging infrastructure. Naturally, it is only positive if v is a BEV (and 0 otherwise). If the agent does not currently own a BEV, then the value of this term is calculated as

$$E[InfrastructurePenalty(v,a,t)] = \frac{P(a,t)}{(1+k_h StationsNearHome(a,t)+k_w StationsNearWork(a,t))^2},$$

where $StationsNearHome(a,t)$ and $StationsNearWork(a,t)$ count the number of stations near a's home and workplace, respectively, $P(a,t)$ is the penalty when there are no charging stations close to the agent's home (i.e., when $StationsNearHome(a,t)$ equals 0 and $StationsNearWork(a,t)$ equals 0), and k_h and k_w are scaling coefficients. The denominator is squared so that the penalty decays rapidly as the number of stations near the agent's home and workplace increases. If the agent currently owns a BEV, then the term is calculated as

$$E[InfrastructurePenalty(v,a,t)] = \beta_i Inconvenience(a,t) + \beta_y Worry(a,t),$$

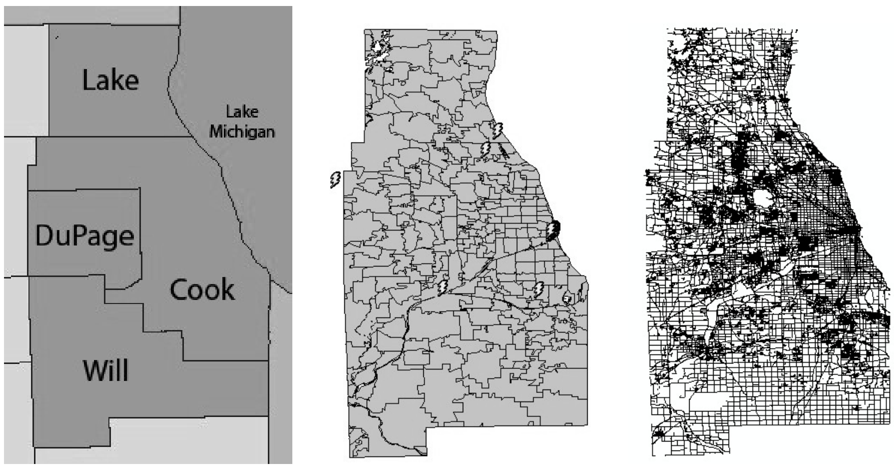
where β_i and β_y are weighting coefficients for the inconvenience ($Inconvenience(a,t)$) and worry ($Worry(a,t)$) experienced by a, respectively.

- $VehiclePenalty(v,a)$: This is a penalty term that is positive if vehicle v lacks particular features that are characteristic of agent a's preferred vehicle class and 0 otherwise. For example, if the agent prefers SUVs, then this term may be positive for PEVs since they lack the cargo space typically found in SUV models.

The vehicle v that minimizes the bracketed expression in (1) is the one that the agent will purchase.

Implementation

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 system data to define the environment. Additional Java routines were 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). The simulation was executed on a Windows 2008 server with twelve cores; however, the simulation does not run in parallel and uses a single core for each sample. For one sample over a period of ten years, approximately four hours of computation time is required.



(a) County map (b) ZCTA map (with charging stations) (c) Street map

Figure 1: Maps of the Chicagoland area used in the implementation of the model

To synthesize the environment, shapefiles from the U.S. Census (www.census.gov) 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 generated layouts. The agent population within the region was one thousand, which was sufficient to capture interaction effects among agents. (Using a larger number of agents increased the computational time significantly without a noticeable change in the results.)

Calibration of the model was accomplished by inputting historical gasoline prices for the city of Chicago, removing PEV options from the vehicle market, and adjusting the other parameters so that the simulated pattern of HEV adoption aligned with the actual observed HEV adoption curve of the past decade. Due to the lack of historical data on PEV sales and driving activities, it was not possible to validate every aspect of the model. Many of these aspects, however, are supported elsewhere in the literature, including social influences on PEV purchases (Axsen 2010), greenness (Kahn 2007), inconvenience (Sperling and Kitamura 1986), and worry (Chéron and Zins 1997). Parameters for such features of the model were assigned values that seemed sensible and yielded reasonable simulation output (see Appendix for the list of parameter settings used). Sensitivity analysis of some of the model parameters was also performed, and these results are presented in the next section.

Results

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 Figures 2–4 for seven charging station deployment scenarios: a base case (consisting of the 18 publicly accessible charging stations deployed in the Chicagoland area at the time this work was started) and six generated deployments, each with either 70 or 200 additional charging stations located based on weights of population (P), population squared (Q), or randomly with no weights (R).

From the figures, it can be observed that locating charging stations according to the Q weighting scheme increases the average number of stations near each agent, but doing so also increases the average distance between an agent and its nearest station and decreases the probability of an agent having a charging station near its house. Interestingly, the average numbers of stations within five miles of each agent in the Base+70Q and Base+200R scenarios are essentially the same. This implies that under such a coverage metric, clustering 70 stations in highly populated

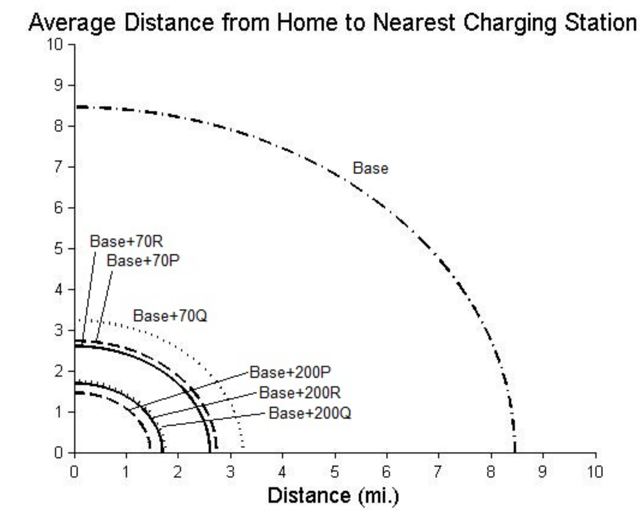


Figure 2: Average distance from an agent's house to the nearest charging station

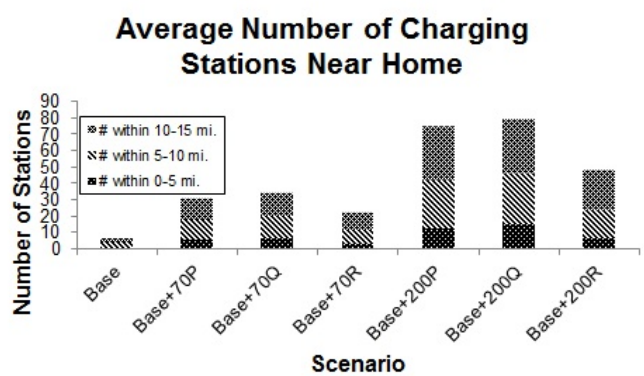


Figure 3: Average number of charging stations near an agent's house

areas can be just as effective as installing nearly triple the number of stations randomly throughout the region without considering population at all. Another observation worth noting is that the average distance between an agent and its nearest charging station is lowest with the R weighting scheme when 70 stations are added to the base case, but when 200 stations are added, the P weighting scheme yields the lowest value. For cases where this coverage metric is used, Figure 2 suggests that the best strategy for locating charging stations based on population data depends on the number of stations being located.

The three coverage statistics computed in this section represent just a sample of the many different ways in which the coverage of charging stations can be measured. Other statistics that take

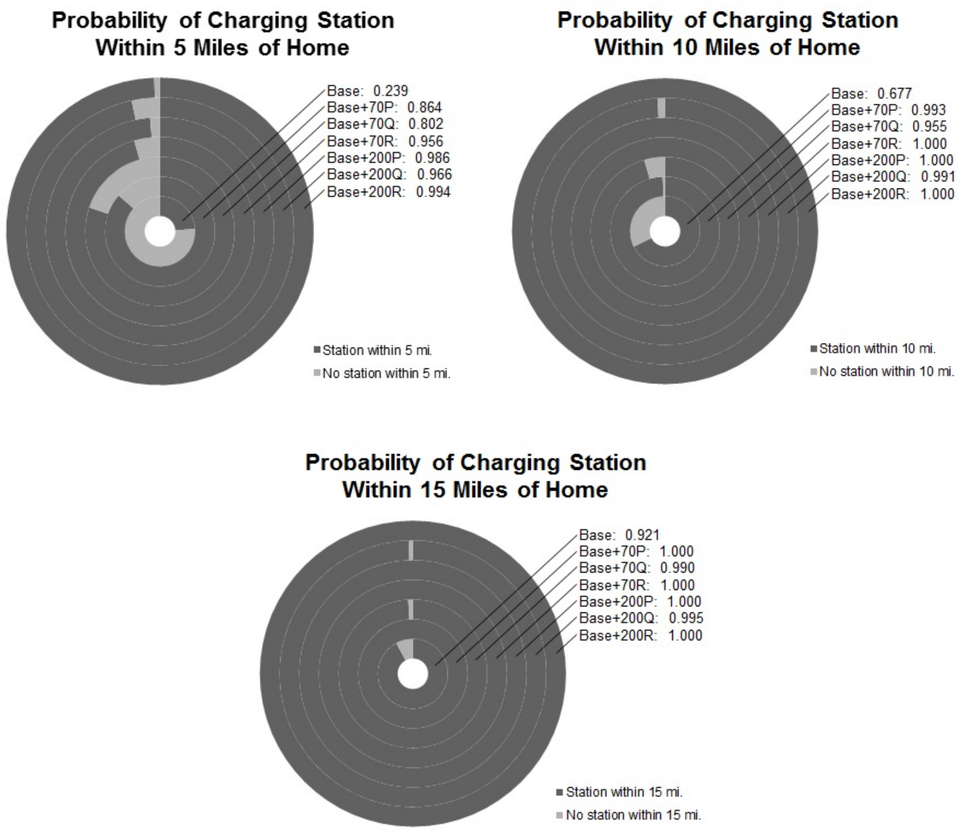


Figure 4: Probability of at least one charging station within 5, 10, and 15 miles of an agent's house

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 PEV purchasers.

BEV Driver Statistics

It is also important to observe the impacts of deployment decisions on BEV driving and recharging behaviors. Figures 5 and 6 summarize the inconvenience experienced by BEV drivers as well as their annual visits to charging stations, respectively. In the implementation of the model, it is assumed that PEV drivers can recharge at public charging stations or at their homes, but not at their workplaces (because workplace charging accessibility is extremely limited presently (Axsen and Kurani 2008)). If recharging at workplaces is permitted, then both inconvenience and charging station visit frequencies would be much lower.

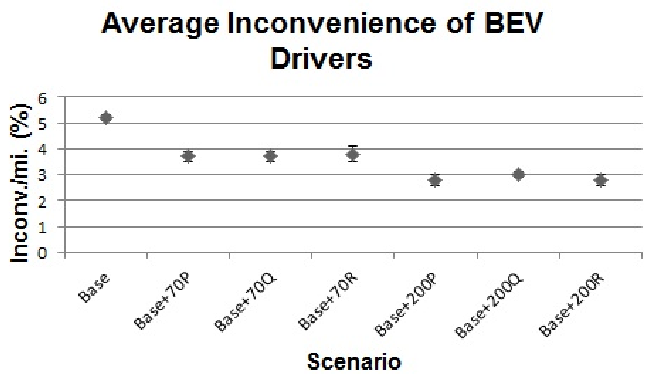


Figure 5: Average inconvenience of BEV drivers, measured as the percentage of total miles driven that is due to recharging activities

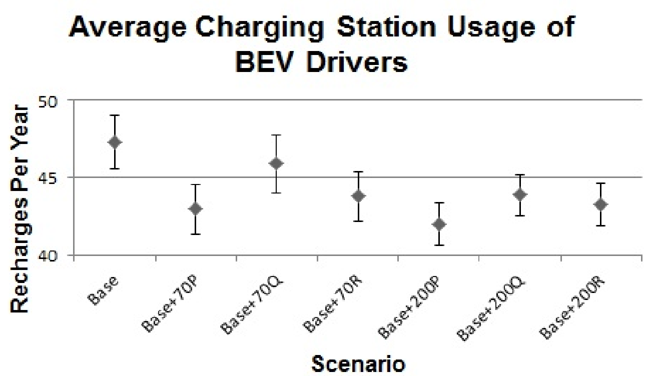


Figure 6: Average number of charging station uses per BEV driver per year

The figures show that BEV drivers go less out of their way to recharge as the availability of charging stations increases, and also that their frequency of visiting charging stations decreases (though not significantly) as more stations open. This relation makes sense intuitively, as less inconvenience for BEV drivers corresponds to less time on the road and therefore less of a need for public charging. For charging infrastructure providers, though, it suggests that building additional charging stations can cannibalize sales at existing stations. A station owner would need to be able to offset these costs by monetizing the decrease in inconvenience for BEV drivers or gaining new customers from the station's area of influence in order to justify the opening of the station. Likewise, if an infrastructure provider has multiple stations in its portfolio, it might consider closing some of its stations to *increase* inconvenience. Making public charging infrastructure more scarce would be detrimental in the long run to BEV adoption, but it could make financial sense to an infrastructure provider seeking to increase demand for its charging stations.

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 various model parameters impacts long-term trends in the adoption rates of the different types of EVs relative to each other, and also how the presence of charging infrastructure affects BEV adoption. In each of the following sets of experiments, only the indicated parameter is varied while all other parameter values are as listed in the Appendix, and the default infrastructure scenario is the base case.

Effect of gasoline prices

Figure 7 shows the rates of EV adoption over a period of ten years when gasoline is priced at $4, $6, and $8 per gallon. The adoption rates by the end of the ten-year period are illustrated in Figure 8. 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.

HEVs are the most popular EV choice in all three scenarios. They rapidly gain market share near the beginning of the simulation and then taper off, eventually reaching a plateau. HEVs are attractive to many drivers because they offer improved fuel economy over ICE vehicles in exchange for only a moderate premium on the purchase price. They are also more likely to be bought by consumers with high greenness or who have social networks with high levels of EV ownership.

After a few years, however, the number of first-time HEV buyers diminishes and existing HEV owners begin swapping their vehicles for BEVs and PHEVs. This results in HEV ownership reaching an equilibrium level and even beginning to decline when the number of new HEV owners is surpassed by those who replace their HEVs with PEVs. As this trend continues, PEV adoption increases at a steady rate since growing social influences increase the likelihood of future buyers choosing PEVs.

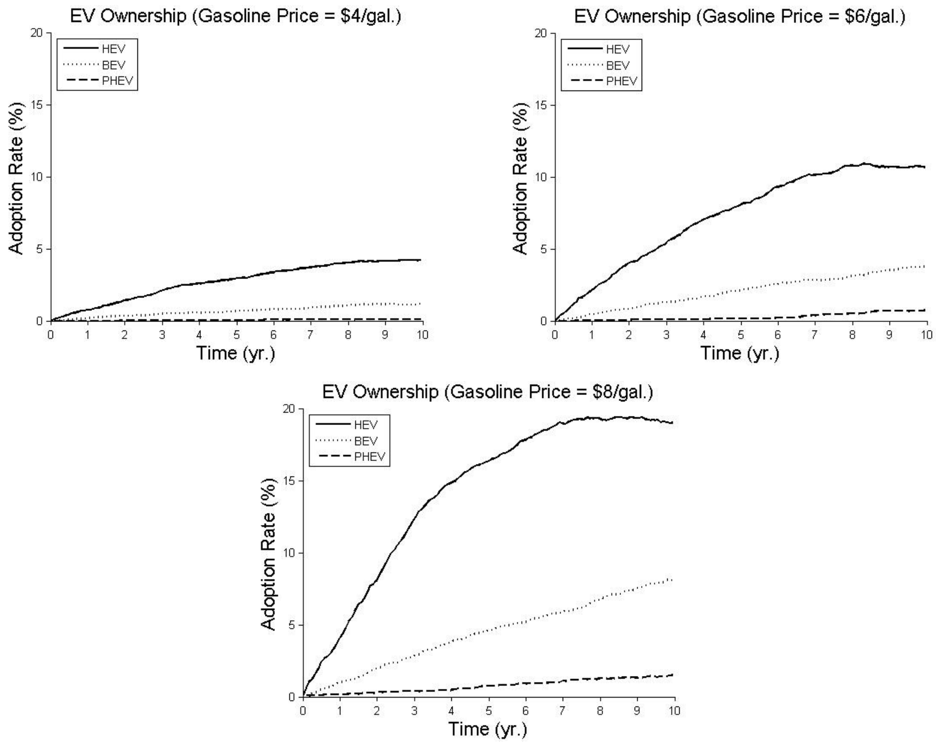


Figure 7: EV adoption curves when gasoline is priced at $4, $6, and $8 per gallon

Among the two PEV alternatives, buyers tend to prefer BEVs over PHEVs, as observed by the difference in adoption rates. PHEVs are often marketed to appeal to consumers who would like to own a PEV but are concerned about the limited driving range of BEVs. They are touted as a compromise between fuel-efficient HEVs and electric-only BEVs, but Figure 8 suggests that this characteristic could be a detriment to PHEV adoption. PHEVs have lower fuel efficiencies than HEVs when they use gasoline instead of electricity, and their batteries are smaller than those found in BEVs. On top of these factors, PHEVs also cost more than either HEVs or BEVs. It is for these reasons that PHEV adoption does not gain traction in the same way as HEV and BEV adoption.

Effect of greenness

Greenness is another factor influencing the likelihood of an agent purchasing an EV. Figure 9 shows the rates of EV adoption over time for the base case infrastructure scenario when each

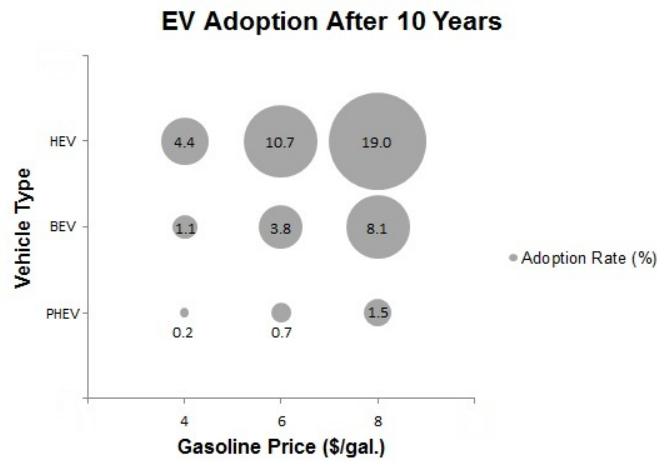


Figure 8: EV adoption rates after ten years

agent's greenness is multiplied by a factor of 0, 0.5, and 1.5. In the case of zero greenness, agents place no monetary value on the environmental aspects of EVs and the $GreenBonus(v, a)$ term in equation (1) is effectively removed. It can be seen that PEV adoption increases as greenness increases, and this is especially true for HEVs when greenness values are multiplied by 1.5. For regular greenness values, HEVs are a competitive alternative to ICE vehicles for a substantial number of agents but are suboptimal by only a few hundred dollars. Boosting greenness values by even a small amount makes HEVs the more attractive option.

Effect of social influence

EV adoption rates when each agent's social influence ($SocialInfluence(v, a, t)$ in equation (1)) is multiplied by factors of 0, 0.5, and 1.5 are shown in Figure 10. Having zero social influence implies that unfamiliarity with EVs based on limited EV ownership within an agent's social networks is not factored into vehicle purchasing decisions. The effect of social influence is the opposite of that of greenness, so EV adoption decreases as the multiplying factor increases. As social influence goes to zero, both HEV and BEV adoption rates rise significantly. Comparing the case of zero social influence to the case of 1.5 greenness, the overall rate of EV adoption is similar, although BEVs have a greater market share when there is no social influence. This difference can be attributed to the fact that the social influence penalty for BEVs is 10 times that of HEVs (based on the definition

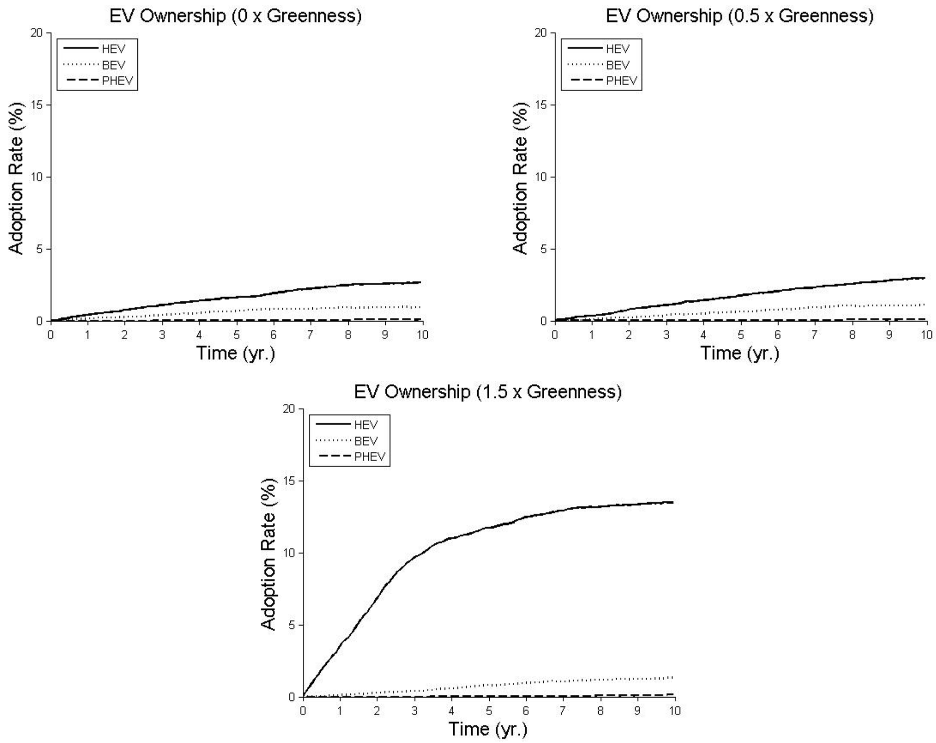


Figure 9: EV adoption curves when greenness is multiplied by 0, 0.5, and 1.5

of $\alpha(v, a)$ in the Appendix) whereas $GreenBonus(v, a)$ is only twice as great for BEVs than for HEVs.

Effect of PEV prices

One main obstacle to PEV adoption is the prices of the vehicles themselves, which are much higher than those of ICE vehicles. In recent years, however, the prices of PEVs have declined. Figure 11 depicts the EV adoption curves for PEV prices from 2011 ($40,300 for PHEVs, $32,800 for BEVs) and 2014 ($34,200 for PHEVs, $29,000 for BEVs). All other vehicle prices remain the same. In both cases, HEVs are the most popular EV option, although their market share is lower when PEV prices are lower. PHEVs are relatively unpopular even with 2014 prices, but they still manage to captulre nearly 1% market share after ten years.

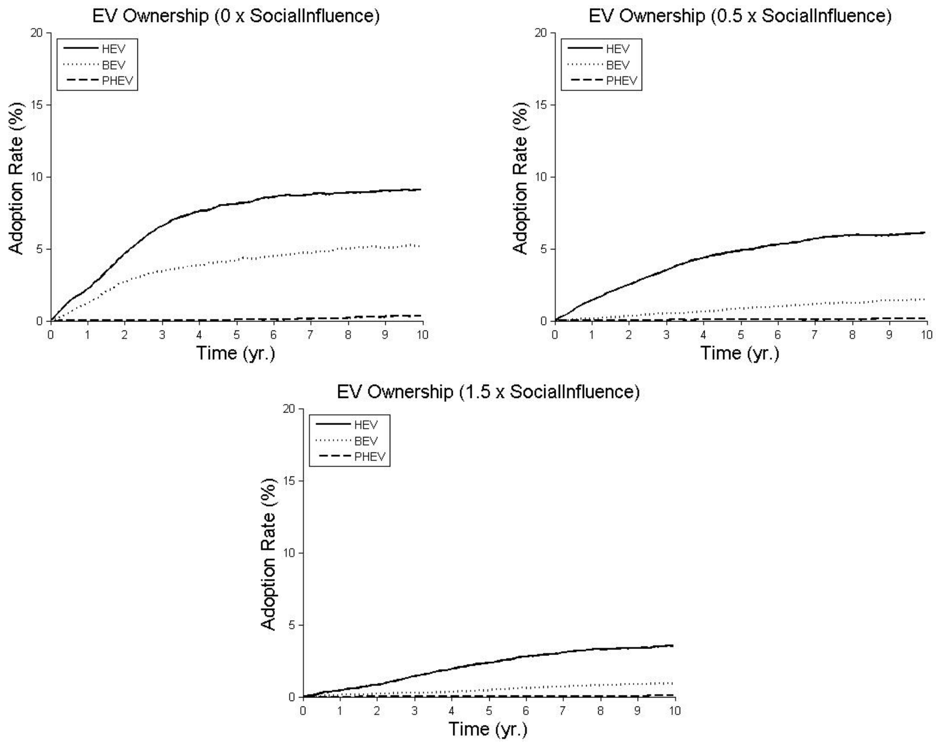


Figure 10: EV adoption curves when social influence is multiplied by 0, 0.5, and 1.5

Effect of number of charging stations

It is also worth observing the relation between the deployment of charging stations and the market penetration of BEVs. Figure 12 summarizes the data for all seven infrastructure deployment scenarios. As expected, there appears to be a slight positive correlation between the numbers of charging stations and BEV drivers. The difference in BEV adoption relative to the base case is significant for all scenarios except for Base+70R. The effect of increasing the number of charging stations from 70 to 200 is not significant, however. This pattern of decreasing marginal benefits of additional stations suggests that alternative policy measures having a more direct effect on the price of BEVs relative to ICE vehicles, such as incentive programs or gasoline taxes, may be more effective at stimulating BEV adoption.

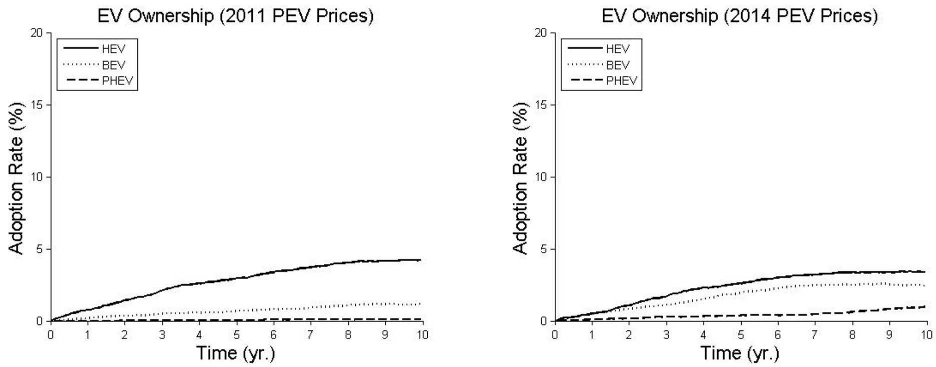


Figure 11: EV adoption curves with 2011 and 2014 PEV prices

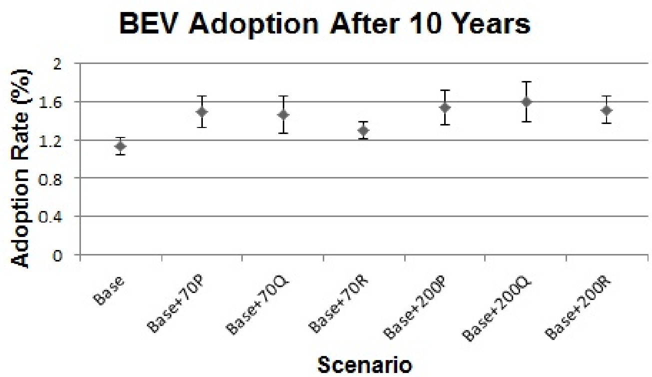


Figure 12: BEV adoption rates by scenario

Conclusions and Future Work

In this paper, an agent-based decision support system has been presented for identifying patterns in residential PEV ownership and driving activities to enable strategic deployment of new charging infrastructure. It successfully captures the recharging behaviors of PEV drivers when both public and home charging options are available as well as EV adoption when different vehicle types are available in the market. The model has been implemented using data from the Chicagoland area and tested with multiple charging station deployment scenarios. It is demonstrated that the availability of public charging infrastructure can indeed affect consumers' vehicle purchasing decisions and should be considered when modeling infrastructure deployment for alternative fuels.

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 PEV adoption patterns utilizing demographic and geographic data could be performed to gain insights into the evolution of the residential PEV market. 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 PEV 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 PEV 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 PEV 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 PEV ownership.

Acknowledgment

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Appendix

Simulation settings

Parameter	Value
Number of drivers	1,000
Length of each simulation	10 yr.
Length of each timestep	15 min.
Vehicle driving speed	20 mph
Radius for short-distance errands	5 mi.
Gasoline price	$4/gal.
Electricity price	$0.11/kWh

Notes:

- Vehicle driving speed is low to account for stops a vehicle might make under actual driving conditions due to traffic signals, other vehicles, etc. (in the model, vehicles always travel at a constant speed until they reach their destination).
- Gasoline and electricity prices are assumed to be time invariant.
- Gasoline price is based on the average price in Chicago during 2011 (www.chicagogasprices.com); electricity price is based on the average Illinois residential rate during 2010 (www.eia.gov).

Vehicle characteristics

Type	Class	Price ($)	Miles Per Gallon	Miles Per kWh	Battery Capacity (kWh)
ICE	Compact	13,600	31	–	0
ICE	Midsize	21,900	29	–	0
ICE	Luxury	27,500	25	–	0
ICE	SUV	27,200	23	–	0
HEV	Compact	19,000	40	–	0
HEV	Midsize	25,200	39	–	0
HEV	Luxury	32,600	38	–	0
HEV	SUV	31,200	31	–	0
PHEV	All	40,300	37	2.5	16
BEV	All	32,800	–	3	24

Notes:

- Because both PEV models are not considered to belong to a specific vehicle class, any agent may consider them when purchasing a new vehicle.
- Prices and Miles Per Gallon for ICE vehicles and HEVs were obtained by averaging data from Motortrend (www.motortrend.com); data for the PHEV and BEV models are based on the 2011 Chevrolet Volt (www.chevrolet.com/volt-electric-car) and Nissan Leaf (www.nissanusa.com/leaf-electric-car), respectively.

Driver characteristics

Parameter	**Value**
Vehicle ownership length (yr.)	Uniform(6,12) (income<\$20,000) Uniform(4,8) (\$20,000≤income<\$40,000) Uniform(2,4) (income≥\$40,000)
Greenness (\$)	250·Uniform(0,2) (income<\$20,000) 1250·Uniform(0,2) (\$20,000≤income<\$40,000) 2500·Uniform(0,2) (income≥\$40,000)
Initial vehicle age (yr.)	Uniform(0,Vehicle ownership length)
Initial vehicle type	ICE
Preferred vehicle class	Compact w/ prob. 0.244 Midsize w/ prob. 0.325 Luxury w/ prob. 0.091 SUV w/ prob. 0.340
Worry threshold	3 kWh
Short-distance errands per week	Uniform(0,10)
Long-distance errands per week	Uniform(0,2)

Notes:

- Preferred vehicle class probabilities were obtained using data from Motor Intelligence (www.motorintelligence.com).
- If the agent drives a BEV, its worry increases for every mile that it travels while the charge level of its vehicle is below the worry threshold.

- The numbers of errands that an agent has vary from week to week but follow the given distributions.

Parameter values

Parameter	Value
Work start time	9:00 AM
Work end time	5:00 PM
Morning curfew time	8:00 AM
Evening curfew time	12:00 AM
Recharging threshold	6 kWh
Maximum charge level	24 kWh
$MaxDistance$	5 mi.
k_h	1
k_w	0
β_i	\$1/mi.
β_y	\$0.10/mi.

Note:

- The coefficient k_w is set equal to 0 since most of an agent's errands are near the agent's house, and also to avoid double counting charging stations that are near both the agent's home and workplace.

Functions

$$GreenBonus(v,a) = (a\text{'s greenness}) \cdot \begin{cases} 0, & v = \text{ICE} \\ 0.5, & v = \text{HEV} \\ 0.9, & v = \text{PHEV} \\ 1, & v = \text{BEV} \end{cases}$$

$$\alpha(v,a) = \$5{,}000 \cdot \begin{pmatrix} 0, & v = \text{ICE} \\ 0.1, & v = \text{HEV} \\ 0.9, & v = \text{PHEV} \\ 1, & v = \text{BEV} \end{pmatrix} \cdot \begin{pmatrix} 0.1, & a\text{'s income} < \$20{,}000 \\ 0.5, & \$20{,}000 \leq a\text{'s income} < \$40{,}000 \\ 1, & a\text{'s income} \geq \$40{,}000 \end{pmatrix}$$

$$Influence(b,t) = \begin{cases} 0, & b \text{ drives an ICE vehicle} \\ 0.5, & b \text{ drives an HEV} \\ 0.9, & b \text{ drives a PHEV} \\ 1, & b \text{ drives a BEV} \end{cases}$$

$$P(a,t) = \$0.10 \cdot (\text{total number of miles driven in } a\text{'s previous vehicle})$$

$$\begin{aligned} StationsNearHome(a,t) = {} & (\text{number of stations within 0-5 miles of } a\text{'s house}) + \\ & 0.5 \cdot (\text{number of stations within 5-10 miles of } a\text{'s house}) \end{aligned}$$

$$\begin{aligned} StationsNearWork(a,t) = {} & (\text{number of stations within 0-5 miles of } a\text{'s workplace}) + \\ & 0.5 \cdot (\text{number of stations within 5-10 miles of } a\text{'s workplace}) \end{aligned}$$

$$VehiclePenalty(v,a) = \begin{cases} \$20{,}000 \text{ w/ prob. } 0.9, & v = \text{BEV and } a\text{'s preferred vehicle class is SUV} \\ \$0, & \text{otherwise} \end{cases}$$