An agent-based model for estimating consumer adoption of PHEV technology

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ABSTRACT
This study presents a prototype of a spatially-explicit and socially-embedded agent based model to study adoption of plug-in hybrid vehicle (PHEV) technology under a variety of scenarios. Heterogeneous agents decide whether or not to buy a PHEV by weighing environmental benefits and financial considerations (based on their personal driving habits, their projections of future gas prices, and how accurately they estimate fuel costs), subject to various social influences. Proof-of-concept results are presented to illustrate the types of questions which could be addressed by such a model, and how they may help to inform policy-makers and/or vehicle manufacturers. For example, our results indicate that simple web-based tools for helping consumers to more accurately estimate relative fuel costs could dramatically increase PHEV adoption.

4,824 words + 5 figures = 6,074 words total

INTRODUCTION

Plug-in hybrid electric vehicles (PHEVs) have been proposed as a logical next step in the evolution of sustainable transportation technologies (1). A recent joint report by the Electric Power Research Institute (EPRI) and the National Resources Defense Council (NRDC) (2) found that PHEVs have the potential to substantially reduce green house gas (GHG) emissions, assuming sufficient penetration into the market. From a consumer perspective, PHEVs offer the higher fuel efficiency of electric vehicles (EVs) within the electric assist range, but also the convenience and flexibility of traditional fuels and existing refueling infrastructure for longer trips. Based on average U.S. commuting distance (around 12 miles/day (3)), most daily consumer travel would be in the 30-40 mile electric assist range afforded by some current PHEV conversion kits (4), even if recharging is only available at home. Emissions from recharging PHEVs are significantly lower than for gasoline and diesel motor fuels, even for coal-fired electricity generation (assuming CO_2 storage and capture) (2), and as primary sources of power for the electric grid become greener in future years, emission reductions will be even further reduced.

Assuming that vehicle manufacturers are successful in introducing an array of OEM PHEVs within the near future, there will still be significant barriers to widespread early adoption of new PHEV technologies that must be overcome. In a 2008 survey, 69% of respondents reported little or no familiarity with PHEV technology (5). Many consumers are hesitant to adopt new technologies before they are tried and tested (6), and there may be significant consumer uncertainty about potential problems such as battery life and replacement costs, and vehicle recharging time, which would contribute to this hesitancy. Uncertainties in future petroleum prices, pricing and power sources for electricity generation (which vary regionally and by time of day), and trip lengths, make it difficult for consumers to accurately calculate the relative financial and/or environmental trade-offs of PHEVs relative to other vehicles. While awareness of global climate change is generally high in the U.S. (60% report worrying about this a great deal or a fair amount (7)), it is not clear how much consumers will weigh the environmental benefits of a vehicle against personal financial considerations when making a vehicle purchasing decision. To further complicate the matter, consumer choices are not necessarily rational (especially when these require difficult calculations), and are often influenced by others in their social and geographical networks.

In the coming years, both policy-makers and PHEV manufacturers will have a strong interest in gauging adoption rates of PHEV technology, and in determining ways to influence the market. Discrete choice models, in combination with logit analysis, have been a dominate framework in transportation for modeling consumer vehicle choice and use (*e.g.,* to ascertain the influence of feebate programs on fuel efficiency in new vehicle purchases (8, 9), in modeling consumer preferences for alternative-fuel vehicles (10, 11) and for measuring the influence of residential density of household's vehicle fuel efficiency and usage choices (12). Most of these statistically based approaches assume a static distribution of decision strategies and do not support changes in consumer behavior in response to social or other external pressures. Various logit models (13, 14, 15, 16) have also highlighted the importance of accounting for heterogeneity among vehicle consumers and have begun to incorporate some spatial and social influences on vehicle choice. In contrast, agent-based models (ABMs) stochastically simulate spatially-explicit interactions and behaviors of autonomous and heterogeneous agents in order to observe and study the emergence of coherent (but dynamic) system behaviors at larger scales in space and/or time. ABMs have become increasingly popular in transportation studies (17, 18, 19, 20, 21).

Real vehicle consumers weigh the costs and benefits of vehicle characteristics including fuel efficiency, seating and cargo capacity, safety, reliability, etc., when determining which vehicle to purchase (13). However, in the future, it is not unreasonable to assume that many comparable vehicle types will be available with and without a plug-in option. In this case, regardless of consumer preferences for other characteristics, the primary barrier to PHEV adoption would be the price premium due to the plug-in battery (as indicated in (22)). In order to avoid having to make up specifications for a wide range of potential PHEV models, and make a host of other assumptions regarding vehicle model selection, this study has opted to focus on modeling a subset of new-car buyers who have already narrowed their selection to a Prius-like HEV and PHEV, for which performance characteristics where easily obtained (4). Consumers agents thus make their decision based on perceived trade-offs between initial vehicle price, vehicle fuel efficiency, and environmental costs of the HEV and PHEV. In the future, as other types of PHEVs become available, one could add additional layers of vehicle selection criteria. This work is intended as proof-of-concept of insights that can be gained by such a model, how such information might be used to positively influence PHEV adoption, and what sorts of information must be gathered to make the model more realistic.

Table 1: Primary consumer agent attributes and how they are initialized. Attributes G,Y may increase dynamically; vehicle age is updated annually, and vehicle mpg is adjusted when a new car is purchased.

Consumer attribute	**Allowable ranges in current simulations and how initialized**
Annual salary	\$30K to \$250K, median \$65,000 (beta distributed, spatially-correlated); see 2a
Age	16 to 85, median 39 yrs (beta distributed; positively correlated with salary and threshold T)
Residential location	x,y coordinates in a $15 \times 15mi^2$ region (normally distributed overlapping towns of various sizes) ; see 2a
Expected number of years to own a car before buying one	mean 9 yrs (3), std 3 yrs (normally distributed; negatively correlated with salary and annual driving distance)
Annual driving distance	500 to 380K, median 12K miles (3) (log-normally distributed; weakly negatively correlated with salary) ; see 2c
Radius of spatial neighborhood	Annual driving distance/(3658)
Spatial radius of social network	0 to 5 miles (uniformly distributed)
Threshold for willingness to consider new PHEV technology (T)	mean = 0, std=0.2 (normal distribution; negatively correlated with salary, positively correlated with age); thus, roughly one half of new car buyers are initially willing to consider a PHEV (consistent with (22)).
Susceptibility of to social influence (SS)	0 to 1, median = 0.09 (beta distributed)
Greenness (G)	0 to 1, median 0.17 (beta distributed), see Figure 2(d)
Years of look-ahead in computing fuel operating costs (Y)	Ternary categories: 0, 1, or 2 (where 0 means 0 years, 1 means 1 year, and 2 means expected years of ownership of the car); initial distribution all agents 0, agents uniformly distributed from 0 to 2, all agents 2
Current vehicle age	Initialized to mean of 5 yrs, std 2 yrs (truncated to a non-negative normal distribution)
Current vehicle mpg	Initialized to mean of 25.1 mpg (23), std of 5.3 (normally distributed)

MODEL DESCRIPTION

Although space limitations preclude us from a thorough description of the model, Table 3 lists the primary attributes most relevant to the studies described here, roughly characterize how these distributions were initialized, and cite available data sources utilized. For simplicity, salary and age are treated as static attributes, and everything is assumed to be in inflation-adjusted 2009 dollars. The model accounts for non-normal distributions as well as spatial and inter-attribute correlations in agent demographics that may influence vehicle selection. Spatial correlation of salaries were generated using the turning-bands method (24), and the additional parameters that were correlated to salary were generated using multivariate normal distributions, which were subsequently transformed to the desired distributions. Beta distributed data was generated by transforming normally distributed data as described in (25).

Agents have heterogeneous social and geographic networks, and different agents have different susceptibilities to being influenced by others in their social network. The social network of an agent is demographically determined as the intersection of other agents who (a) live within that agent's spatial radius of their social network, (b) are of similar age ($\pm$ 5 years), and (c) have a similar salary ($\pm$ \$10,000); see Figure 1. This results in fat-tailed distributions, see Figure 1, which are typical for social networks (e.g., (26)). The neighborhood in which an agent is able to perceive the composition of the fleet is the union of agents in their social network and agents within their spatial neighborhood (which is based on their typical driving distance). Because of the heterogeneity in residence locations, social network sizes, and driving distances, there is considerable heterogeneity in the sizes of neighborhood fleets perceived by the agents.

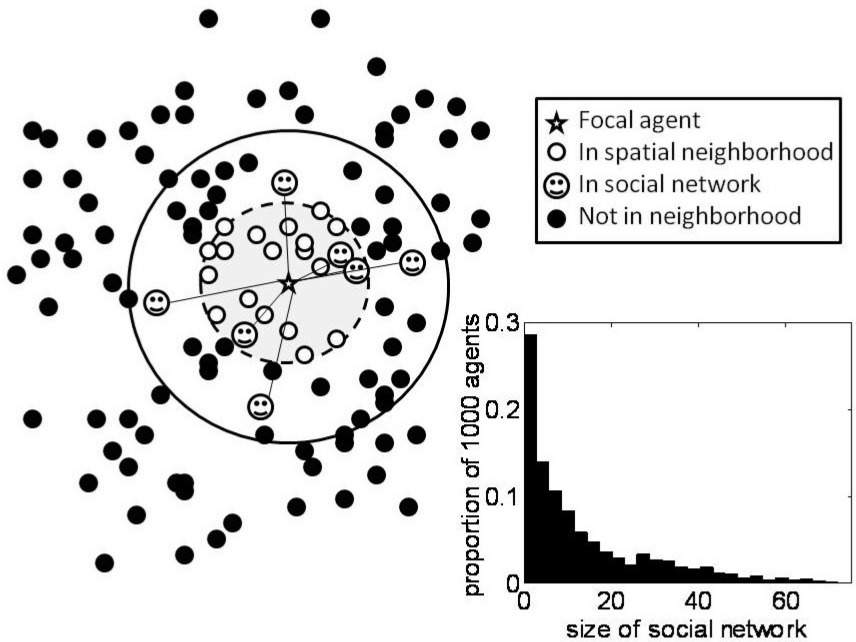

Figure 1: Example social network and geographical network of a representative focal agent (shown with a star). All other agents within the focal agent's unique spatial radius (dashed circle) are in its spatial neighborhood (open circles), and all agents that are within the focal agent's unique maximum social network radius (dotted circle) and have similar age and salary demographics are in its social network (faces). The resulting degree distribution (*i.e.*, number of friends per agent) of a representative social network for 1000 agents.

Agents are updated asynchronously on an annual basis, as follows: For each year in the simulation

1) For each agent (in random order), update attributes based on social influences
2) For each agent (in random order)
   a) Stochastically determine whether to consider buying a car
   b) If the agent decides to buy a new car this year
      i) If the proportion of PHEV's in the vehicle fleet perceived by this agent exceeds this agent's adoption threshold
         1) Determine the cost C of the HEV and PHEV, based on purchase price and fuel costs estimated for either 0 yrs, 1 yr, or the expected number of yrs that the agent would own their next vehicle, according to the agent-specific variable Y.
         2) Determine the relative costs RC of the two vehicles as
            $RC = (C_{PHEV} - C_{HEV})/C_{PHEV}$
         3) Determine the amount of gas per year GPY used by each vehicle, accounting for time on plug-in electric-assist range
         4) Determine the relative environmental benefits REB of the available vehicles as
            $REB = (GPY_{HEV} - GPY_{PHEV})/GPY_{HEV}$
         5) Determine the relative desirability D of the two vehicles as
            $D = G \times REB - (1 - G) \times RC$
         6) If $D > 0$, buy the PHEV, else if $D < 0$ buy the HEV (else choose randomly)
      ii) Otherwise, buy the HEV
   c) Otherwise keep current car and age it by one year

The probability of buying a car in a particular year in Step 2a is based on a normal cumulative distribution probability curve centered on the expected number of years this agent likes to own a car, but an agent will not buy earlier than its preferred time unless there is a vehicle available for purchase that is sufficiently more efficient than the currently owned car. In step 2bi, the agent determines the proportion of PHEVs in its neighborhood, and only if that exceeds that agent's personal threshold will the agent consider adopting the new PHEV technology (as in the threshold based influence models of (27, 28). In all cases, simulations were started the year that PHEVs are introduced, so that some early adopters are required or no one will buy the PHEV.

In step 2bi1, the agent assesses the anticipated cost of each vehicle (C). If their ternary attribute $Y = 0$, only the purchase price of the vehicle is considered. Otherwise, the agent also estimates fuel costs over the next year (if $Y = 1$) or over the expected duration of ownership (if $Y = 2$), taking into account the number of miles they expect to drive each day, one of three projected gas price scenarios (see Figure 2b) and PHEV recharging costs at $0.11 per kwh (29). Based on data reported at (4), the HEV's fuel economy is assumed to be 45 mpg, while the PHEV's is assumed to be 105 mpg when running in plug-in battery assist mode and 45 mpg otherwise, with a 5 kWh plug-in battery with a range of 35 miles and a 5.5 hr charging time. Environmental costs incurred by electricity generation vary widely by region and time of recharging, and are not currently considered in the model; rather the environmental benefit of the PHEV is assumed to be the proportionate reduction in the projected amount of gasoline used (step 2bi4). In step 2bi5, greenness (G) is used to weight the relative perceived environmental benefits vs. the relative estimated financial costs of the two vehicles in deciding which vehicle to purchase (step 2bi6). Both Y and G may be stochastically increased through social influence, based on (a) whether a randomly selected agent from the social neighborhood (selected proportionate to the Euclidean distance between certain agent attributes, in keeping with conformity theories (30, 31)) has a higher greenness value and (b) the agent's susceptibility to social influence.

EXPERIMENTS

Preliminary experiments were designed to illustrate the types of questions which could be addressed by such a model, and how they may help policy-makers and/or vehicle manufacturers to assess potential influences on adoption of PHEV technology.

Representative Run

The first experiment is merely a representative run to show annual PHEV purchases, and reasons for purchase, using the 10,000 agents shown in Figure 1, a low (possibly subsidized) PHEV price premium of $5000, moderately increasing gasoline prices (as shown in Figure 2b, middle line, which indicate an increase to $4.87/gallon in year 14), heterogeneous but mild susceptibilities to social influence (beta distributed between 0 and 1 with a median susceptibility of only 0.09), and initially heterogeneous (uniformly distributed) fuel cost lookahead (Y) by the agents. That is, at year 0 one third of the agents ignored potential fuel cost savings by the PHEV and only considered the price premium in assessing the financial implications of a vehicle purchase ($Y = 0$), one third of the agents computed potential fuel savings for 1 year only ($Y = 1$), and the remaining third computed potential fuel savings for the number of years they anticipate owning the vehicle ($Y = 2$).

Gasoline prices, premiums and projected fuel costs

The second set of experiments was designed to highlight the potential increase in PHEV purchases when consumers are accurately able to forecast savings in fuel costs, as a function of gasoline price projections (ranging from low to medium to high, as shown in Figure 2b) and PHEV price premiums of $5000 (low) and $10,400 (the latter being the current cost of an available PHEV conversion kit (4)). Here, the two extremes of how agents compute fuel savings projections were modeled, ranging from populations of agents who all computed projected fuel costs over the expected duration of ownership of the vehicle ($Y = 2$) to populations of agents who all ignored fuel costs and only considered the initial price premium in computing relative vehicle costs ($Y = 0$). For computational efficiency in these simulations we used populations of 1000 agents each, as prior experimentation had showed that results were very similar between 1,000 and 10,000 agent simulations. Note that recharging costs are small relative to gasoline costs, so the model is relatively insensitive to potential increases in electricity costs, and the later was not explicitly varied.

RESULTS

Representative Run

Figure 3 shows the results from the representative run described above. The top line in Figure 3 illustrates how many agents considered buying a car in a given year (dotted line with circles). Since PHEVs are assumed to be introduced

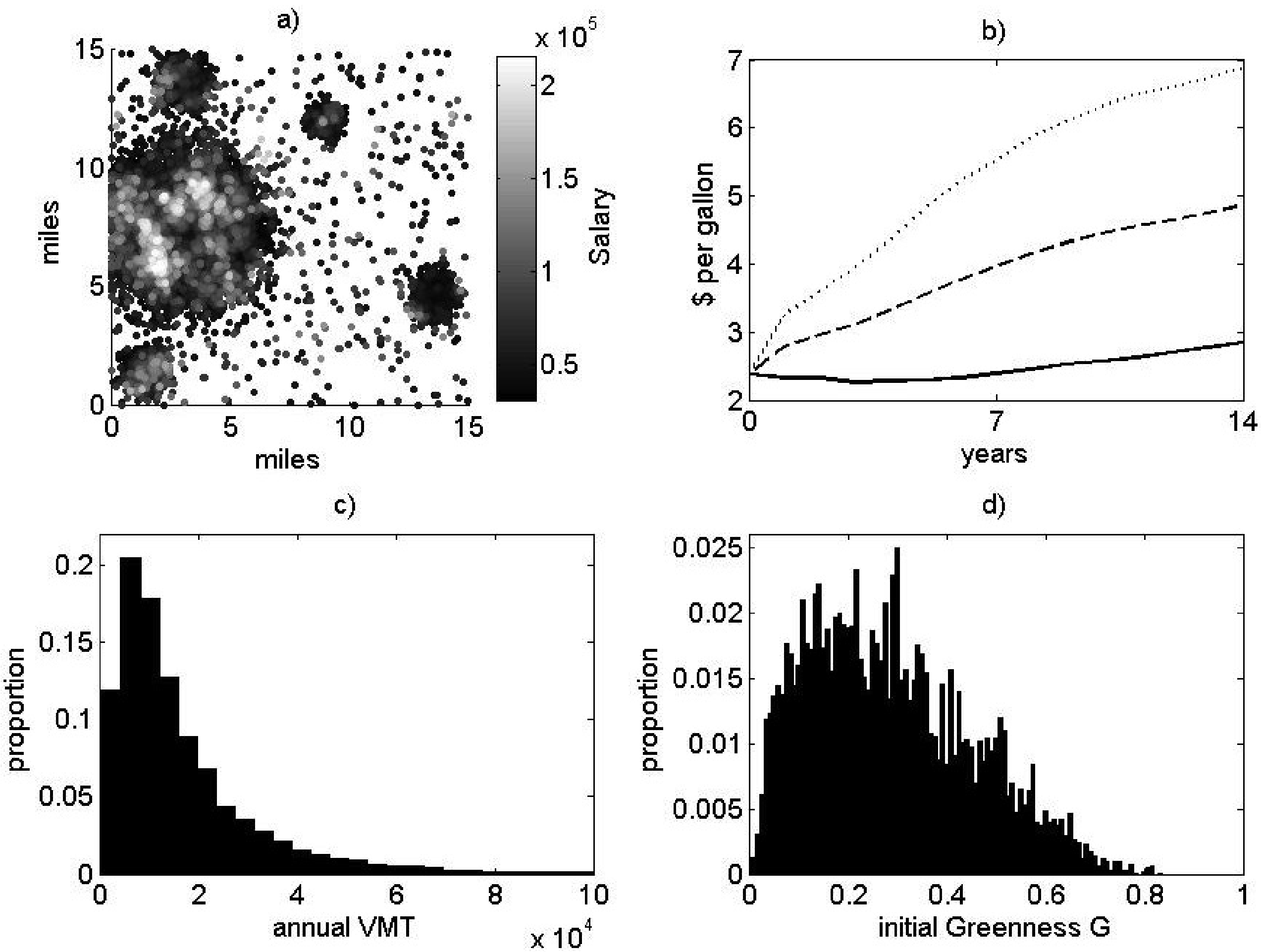

Figure 2: (a) Residential locations and spatial distribution of annual salaries for the representative 10,000 member population reported on in the Results Section; b) three gas price projection scenarios (high and low scenarios taken from (29)); c) histogram of annual vehicle miles traveled (VMT) for the 10,000 agents (0.6% of agents had maximum VMT greater than 100,000 miles, but here the x-axis has been truncated for visual clarity); d) initial greenness G of the 10,000 agents are beta distributed with a median of 0.2.

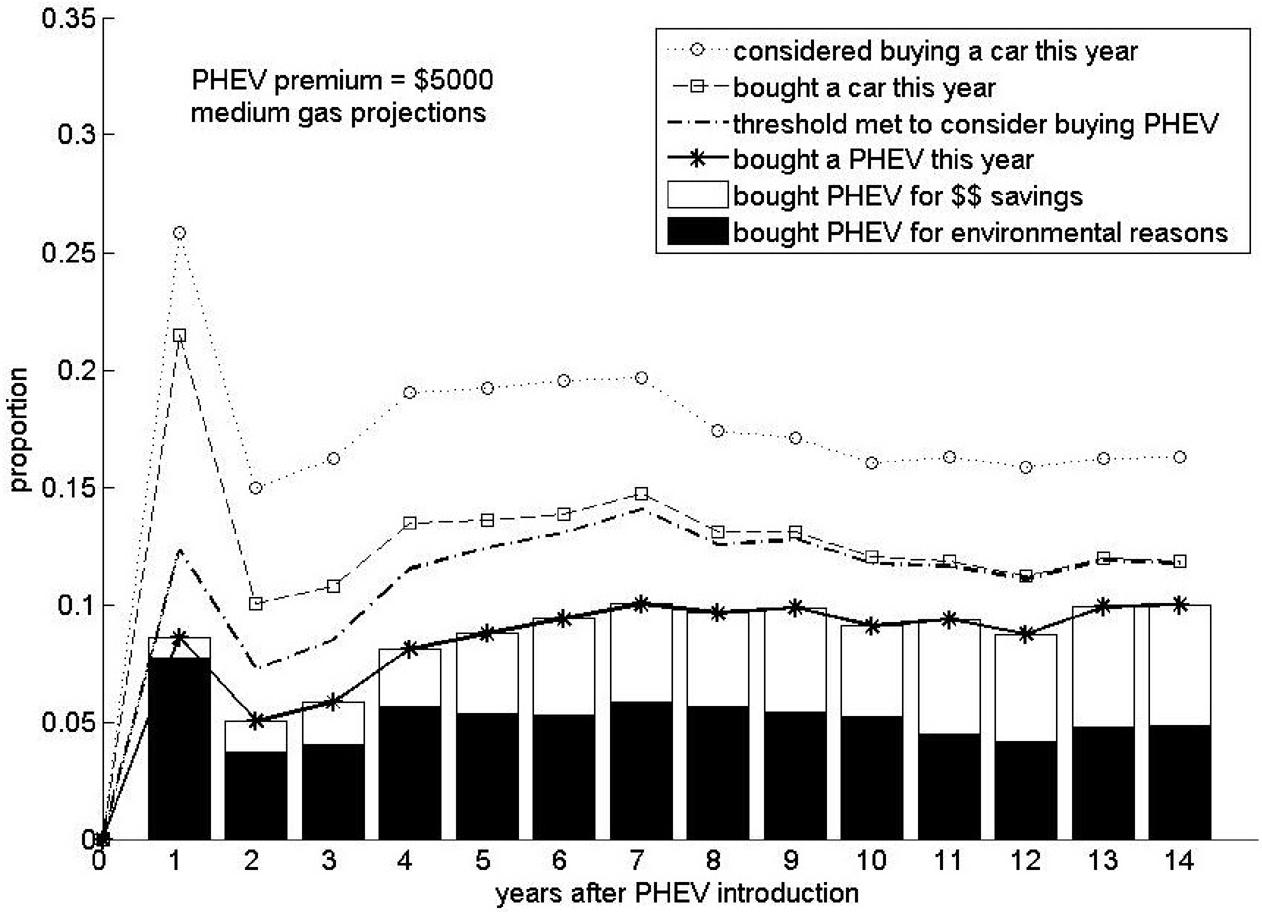

Figure 3: Representative results for one simulation using the 10,000 member population shown in Figure 2a,c,d with the middle gas price projection shown in Figure 2b. Other specifications of the simulation are described in the text. The y-axis denotes proportion of the population.

in year 1, and the initial mpg of the fleet is set to 25.1, the large increase in fuel efficiency of the PHEVs relative to the initial fleet results in a spike in the number of vehicle owners willing to consider buying a new car in year 1. Of these, 83% actually went through with a vehicle purchase (dotted line with squares), although of these 60% selected the HEV and only 40% selected the PHEV (solid line with asterisks at the top of the stacked bars). Agents who opted to purchase an HEV over a PHEV did so for one of two reasons: (a) only 57% of the initial buyers in this simulation were willing to be early adopters of the PHEV technology (the dash-dot line shows the proportion of these potential vehicle purchasers who were above their personal thresholds for considering a PHEV), and (b) only 10% of new car buyers perceived the PHEV as a better financial deal, since gasoline prices were still relatively low and most consumers only computed fuel costs for 0 or 1 year ahead. This is reflected by the composition of the stacked bars, where the black portion of each bar indicates consumers who were swayed by their greenness G to purchase the PHEV, even though they thought it was more expensive in the long run, whereas the white portion of each bar reflects the PHEV purchasers who actually perceived the PHEV as cheaper in the long run, and so purchased it regardless of their greenness attribute G.

As the simulation proceeds, the proportion of new car buyers that selected the PHEV over the HEV increases monotonically from 40% at year 1 to 84% at year 14. This shift occurs for 3 reasons: (a) as the number of PHEVs in the fleet increases, the number of vehicle purchasers who were above their threshold for considering a PHEV approaches those who actually bought a car (note how the dash-dot line converges on the dashed line with squares), so the threshold becomes less and less a limiting factor in the decision, (b) due to social influence, the proportion of this population who calculate fuel costs over the anticipated number of years of ownership of a vehicle increases from 33% at year 0 to 64% at year 14, meaning that more consumers appreciate the true fuel costs savings of the PHEV; thus, the PHEV purchasers who selected the PHEV for perceived lower net costs rises from 10% at year 1 to 52% by year 11 and remains there through year 14, (c) due to social influence, the environmental greenness G of the population increases from 17% at year 0 to 27% at year 14, so more consumers were swayed by the environmental benefits of the PHEV, even when they perceived the net costs of the PHEV higher than that of the HEV. At the end of the 14 year simulation, only 19% of HEV owners had calculated fuel costs for the expected duration of vehicle ownership, as contrasted with 67% of PHEV owners. Similarly, by year 14 all HEV owners had a median greenness of 0.13, whereas PHEV owners had a median greenness of 0.22.

Gasoline prices, premiums and projected fuel costs

Figure 4 depicts the cumulative PHEV adoption in this population (z-axis) over time (x-axis) as a function of the projected gasoline prices (y-axis) and PHEV price premium (surfaces a and c assume the $5000 premium, and surfaces b and d assume the $10,400 premium), for the two extremes in the rationality of how agents computed fuel cost projections. In surfaces a and b all the agents computed projected fuel costs over the expected duration of ownership of the vehicle (Y=2), whereas in surfaces c and d all the agents ignored potential fuel savings and only considered the initial price premium in computing their cost-benefit analysis (Y=0). Consequently, surfaces c and d show no change in PHEV adoption as a function of gas prices; for these two surfaces, 100% of PHEV purchasers did so for their environmental benefits, as costs were never perceived lower for the PHEV when fuel savings were ignored. In contrast, PHEV adoption increases with increasing gas prices in surfaces a and b, although the sensitivity of PHEV adoption to rising gas prices is markedly lower when the initial price premium is reduced from $10,400 (surface b) to $5000 (surface a).

DISCUSSION

The preliminary results presented here serve to illustrate the types of questions that could be addressed by an agent-based model assessing how much consumers are willing to pay for a PHEV, in exchange for projected savings in fuel costs and/or perceived environmental benefits. Such simulations could potentially be used to inform policy-makers and/or vehicle manufacturers as to which types of policies or features may have the most effect on adoption of PHEV technology. For example, the large difference between surfaces a and b, and between c and d in Figure 4 indicate the large increase in PHEV adoption that could be achieved by reducing the price premium from $10,400 (the cost of the current Hymotion PHEV Prius conversion kit (4)) down to $5000 (which could be achieved by governmental incentives and/or improvements in battery manufacturing technology). Regardless of the price premium, the differences between surfaces a and c, and between b and d, illustrate that helping consumers to more accurately estimate fuel cost savings over their anticipated duration of ownership of a vehicle can dramatically increase PHEV adoption; this could be relatively easily accomplished through simple web-based calculators (or in kiosks in dealerships) into which consumers enter some basic information regarding their typical VMT, expected years of ownership, etc., and

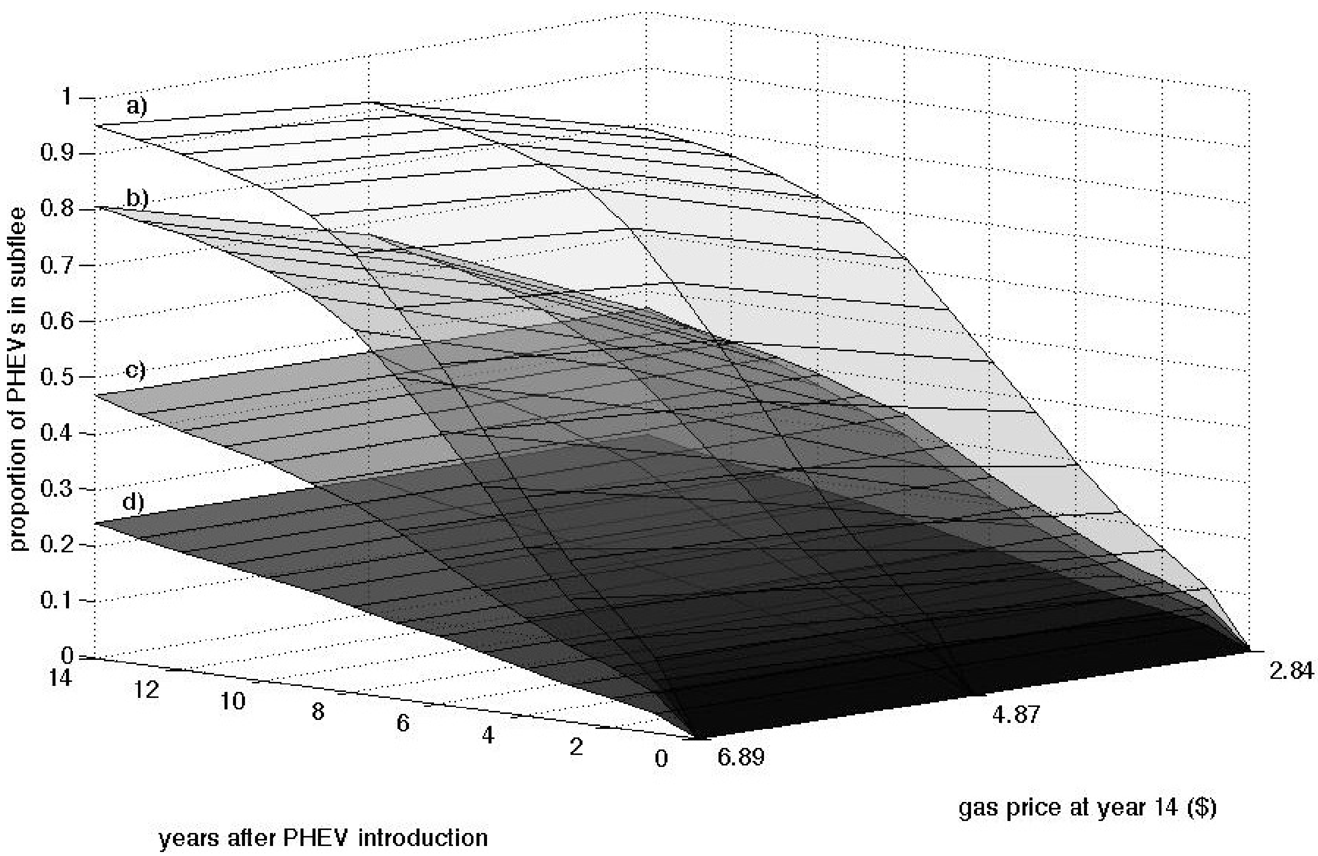

Figure 4: Time series proportion of PHEV adoption into a 1000 member population run under the three gas price projections shown in Figure 2b (denoted here by the projected price at the end of the simulation). Surfaces a) and c) assumed a $5000 PHEV price premium, while surfaces b) and d) assumed $10,400 PHEV price premium. For surfaces a) and b) all agents computed projected fuel savings for the expected duration of ownership of the vehicle, whereas for surfaces c) and d) all agents ignored potential fuel savings. The z-axis represents the proportion of PHEVs in each 1000 member population (representing the sub-population of vehicle consumers who have already narrowed their next vehicle purchase to a Prius-like HEV or PHEV).

which then report the amortized costs of various vehicles under different estimates of gas price increases. If such a tool were available, Figure 4 also shows how increases in gas prices (e.g., through a gas tax) could then influence PHEV adoption. Additionally, programs could be put into place to lower the thresholds at which consumers feel comfortable considering a PHEV, such as through warranties on batteries or battery exchange programs that could help to alleviate consumer uncertainties about the lifetime and replacement costs of the PHEV battery packs.

Some aspects of the system are more difficult to directly manipulate, such as the degree that social influence has on particular agents. However, new viral marketing techniques (32) can capitalize on the social diffusion of innovation, and this model could be used to explore various marketing strategies. Additionally, once the model has been extended to include feedbacks between manufacturing outputs, dealer inventories, and consumer purchasing, the spatially-explicit nature of the model can be used to explore the impacts of various spatial distributions of inventory which may facilitate regionally localized rapid PHEV adoption that could ultimately increase profitability for manufacturers and system-wide PHEV penetration.

In summary, this study has presented a prototype for a stochastic, socially-embedded, spatially-explicit agent-based model for investigating adoption of PHEV technology. This model can help to identify pressure points where the system can be most impacted by governmental and/or manufacturer policies. In addition, by helping to identify relative sensitivities of underlying assumptions and parameters this model helps to identify which types of data will be most important to collect in future studies, in order to make such a model more representative of U.S. vehicle consumer purchasing behaviors. In order to facilitate scaling the model up to a potentially nationwide scale, work is ongoing to explore the feasibility of training recurrent artificial neural networks on city-wide agent-based models, and then using these as rapid response functions that would interact with each other (and with dealer and manufacturer agents) on a nationwide scale. The results presented there also highlight the sensitivity of the model to spatial and social heterogeneity (33).

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