Using National Survey Respondents as Consumers in an Agent-Based Model of Plug-In Hybrid Vehicle Adoption

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Abstract—Plug-in hybrid electric vehicles (PHEVs) offer the potential to significantly reduce greenhouse gas emissions, if vehicle consumers are willing to adopt this new technology. Consequently, there is much interest in exploring PHEV market penetration models. In prior work, we developed an agent-based model (ABM) of potential PHEV consumer adoption that incorporated several spatial, social, and media influences to identify nonlinear interactions among potential leverage points that may impact PHEV market penetration. In developing that model, the need for additional data to properly inform both the decision-making rules and agent initialization became apparent. To address these issues, we recently conducted and analyzed an extensive consumer survey; in this work, we modify the ABM to reflect the survey findings. A unique aspect is a one-to-one correspondence between agents in the model and survey respondents, thus yielding distributions and cross-correlations in agent attributes that accurately reflect the survey population. We also implement a used-PHEV market, and allow agents to purchase new or used compact PHEVs or vehicles of their current type. Based on our prior survey response analysis, our modified model includes a PHEV-technology threshold component, a multinomial logistic prediction of willingness to consider a compact PHEV based on dynamically-changing attitudes, and agent-specific delay discounting functions that predict the amount agents are willing to pay up front for greater fuel savings. We thus independently account for agents’ discomfort with the new PHEV technology, their desire to drive a more environmentally friendly vehicle, and their willingness to pay a higher sticker price for a PHEV. Results of 10 survey-based ABM scenarios are reported with implications for policy-makers and manufacturers. We believe close integration of the design of consumer surveys and the development of ABMs is a key step in developing useful decision-support models; this work serves as an example of one way to achieve that.

Index Terms—Plug-in hybrid electric vehicles (PHEVs); agent-based model; market penetration; electric vehicle adoption; vehicle choice simulation, vehicle choice survey.

I. INTRODUCTION

Currently, transportation accounts for approximately one third of greenhouse gas (GHG) emissions in the U.S., and is its fastest growing source [1]. Plug-in hybrid electric vehicles (PHEVs) offer the potential to significantly reduce GHG emissions [2]-[4]. The degree to which this can occur depends on current regional electric power generation sources [5]-[6], smart grid technologies to improve grid efficiency and reduce peak demands [7]-[9], and power generation shifts from coal to cleaner sources, including natural gas and renewables (e.g., wind, solar) [10][11]. Potential vehicle-to-grid technologies could further reduce peak electricity demands [12][13] and, therefore, have a positive feedback on the grid efficiency. In addition, PHEVs have projected lifecycle costs that are lower than internal combustion engines [14]. From the consumer perspective, PHEVs can provide large savings in fuel costs without the range limitations of all-electric vehicles (EVs); the EPA/DOT sticker data for the 2013 Chevy Volt states that the vehicle “will save $6,850 in fuel costs over 5 years compared to the average new vehicle.”

Realization of these potential PHEV benefits ultimately depends on consumers’ willingness to adopt this new technology. Although public awareness of PHEVs is growing [15], consumers continue to have concerns regarding the new battery technologies in electric drive vehicles (EVs, PHEVs, and hybrid-electric vehicles) and the potential inconvenience of recharging [16]-[22]. While previous work indicates consumers are willing to pay a premium for greater fuel efficiency [22][23], initial Chevy Volt sales have fallen short of projections [24], and are outcompeted by the otherwise similar gas-powered Chevy Cruze [25].

Consequently, there is significant interest in modeling the potential market penetration of PHEVs (and other electric-drive vehicles) under a variety of scenarios (e.g., [26]-[36]; for a recent review see [37]) to understand the impacts of potential policies, incentives, energy prices, and other factors affecting consumer vehicle choice. However, despite this progress, there exists a need for greater micro-data to properly inform such models [30][38].
For example, in prior work [30] we developed an agent-based model (ABM) of potential PHEV consumer adoption that incorporated several spatial and social effects, including threshold effects [39], homophily [40], and conformity [41][42], as well as media influences, to identify nonlinear interactions among potential leverage points that may impact PHEV market penetration. In that work, the need for additional data to properly inform both the agent decision-making rules and agent initialization became apparent.

To address these issues, in a joint collaboration between the University of Vermont and Sandia National Laboratories, we performed an extensive online survey of 1,000 adult U.S. residents using the Amazon Mechanical Turk (AMT) crowdsourcing platform [43] in July, 2011. AMT has emerged as a reliable and relatively inexpensive survey tool [44]-[48]. Our AMT survey, designed in large part to specifically inform and improve the ABM first presented in [30], comprised 105 questions regarding consumer demographics, purchasing decisions, factors influencing vehicle choice (including PHEVs), attitudes toward the environment and energy, and discounting questions that assessed how much a respondent would be willing to pay up front for a vehicle that would provide various levels of future benefits. After extensive quality control (described in [49]), 911 out of the 1000 responses were deemed reliable and included in subsequent analyses. Survey respondents were fairly representative of national demographics (e.g., see Table 1 and Fig. 1 in [49]). For example, the number of participants that responded from 47 states across the U.S. was proportional to each state’s 2010 census population ($R^2=0.91$), and the distribution of vehicle number per household was very similar to national data [50]. Although many survey respondents came from households with multiple vehicles (they reported an average of 1.7 vehicles per household) and possibly multiple drivers, they were directed to answer questions regarding their personal driving habits and the vehicle (past, present, or future) available for their primary use. Other than household income, questions on demographics and attitudes related to the survey participant, not the household. To minimize participation bias, we specifically ordered the questions so that participants were not aware that the survey was related to vehicle purchasing attitudes until the third of six sections, and the PHEV focus was not revealed until the fifth section.

Our AMT survey yielded several useful results. For example, more AMT participants (86%) stated that financial benefits due to fuel savings would be very important in considering the purchase of a PHEV than those (55%) who stated that reducing greenhouse gas emissions would be very important; this is consistent with [17][51][52], who found that most consumers prioritize financial benefits over environmental benefits. However, our survey analysis also showed that those who are most concerned about climate change had 44.4 times greater odds of being willing to consider purchasing a PHEV than those least concerned, whereas those who felt that fuel savings were very important had only 15.25 times greater odds to consider purchasing a PHEV than those who ranked this as relatively unimportant. Like other recent studies that found strong correlations between pro-environmental attitudes and stated preferences for alternative fuel vehicles [53][54], this implies that environmental benefits may actually be a more powerful motivator for PHEV adoption than financial benefits, for those who place high importance on environmental concerns. These findings provide motivation for properly modeling dynamically changing environmental attitudes when predicting PHEV market penetration. The complete survey and all participant-level survey responses are available online [55]. See [49] for distributions and correlations between consumer attributes and attitudes, and an in-depth statistical analysis on several factors we found most influential and predictive of consumer willingness to consider PHEVs.

In this work, we used the AMT survey results to improve the ABM decision-making rules for potential PHEV adoption, and we populate the ABM with 911 agents, each based directly on the individual responses of one of the 911 survey participants. ABMs are typically initialized by drawing from statistical distributions of attributes, informed by survey data where known. However, data on cross-correlation of many attributes are rarely available and, even if known, it is challenging to create random populations that respect distributions and cross-correlations between all attributes. By assigning each agent with the attributes of an actual consumer, distributions and cross-correlations of agent attributes accurately reflect those in the survey population. We use the modified ABM to study potential PHEV market penetration under various scenarios with different incentives, fuel costs and model assumptions, to illustrate how the improved model can provide useful insights to policy-makers and manufacturers. This close integration of consumer survey design, analysis, and agent-based modeling is an important advance in creating useful decision-support models for planning in transportation and other fields.

II. AGENT-BASED MODEL

We adapted the ABM of [30] to closely reflect the findings of the PHEV survey [49], both in terms of agent attributes and agent vehicle-purchasing decision options and rules. In this ABM, agents are models of vehicle consumers. To clearly distinguish when we are referring to simulated vehicle consumers in the model and actual vehicle consumers in the AMT survey, we generally refer to the former simply as “agents” and the latter as “AMT participants or respondents”. Readers are referred to [30] for many of the details and rationale behind the original ABM. Below, we focus on relevant modifications to this model based on the AMT survey.

A. Agent Initialization

We built a population of 911 agents directly modeled on the 911 survey respondents, thus obtaining data-driven distributions and cross-correlations of all agent attributes. After quality control, 3.8% of the 911 surveys had a few missing values (specifically, for the attributes used here, there were 31 respondents with 1 missing attribute, 3 respondents with 2 missing attributes, and 1 respondent with 4 missing attributes). Rather than discard these 35 surveys, we opted to replace the missing values with the median response category for that question. Most of the survey responses were ordinal or
categorical. For survey responses selected from ordinal bins, agents were assigned real values drawn from a uniform random distribution over the selected answer’s bin range to obtain more continuous distributions of attributes. For daily per capita vehicle miles traveled (VMT), the bin ranges were skewed slightly higher than those specified in the survey so that the resulting distribution more closely matched U.S. averages [50]. We felt the latter was important in determining the distance agents might drive in the all-electric range of a PHEV.

Each agent in the ABM has several associated demographic attributes modeled directly after survey responses of exactly one AMT participant, including individual age, annual household income, residential location (rural, suburban, urban), and location in the political spectrum (11% far left, 32% left, 33% center, 19% right, 4% far right). Each agent also has vehicle attributes modeled after the responses of its corresponding AMT participant, including:

(i) The typical number of years of car ownership;
(ii) Personal Daily VMT;
(iii) Age of the vehicle currently available for their primary use;
(iv) Current vehicle class reported as either compact (24.1%), midsized (29.5%), full-size (10.3%), minivan or SUV (20.1%), full-size van or pickup (5.5%). There were an additional 10.5% reported as no vehicle, motorcycle, or other; rather than discard these surveys, we assigned them to the compact vehicle class;
(v) The manufacturer suggested retail price (MSRP) of their current vehicle;
(vi) The fuel type (in this study, recorded only as PHEV or non-PHEV), all-electric range (if any) and miles per gallon (MPG) when not in all-electric mode; and
(vii) Whether they purchased their most recent vehicle new (32%) or used (60%); of the remaining 8% who said they had never owned a vehicle, we assigned 4% to new and 4% to used.

Rather than asking AMT survey participants to self-report the original MSRP and fuel efficiency of their current vehicles (which we thought would likely be highly unreliable), we approximated the values for vehicle MSRP and MPG from the database located at www.cars.com, based on AMT respondents’ self-reported make, model, and year. MSRP was averaged over all styles brought to 2011 U.S. dollar equivalents, assuming 3% annual inflation. MPG was averaged over all driving modes. See Table I for initial agent population means for several of the survey-based variables.

In addition, agents have survey-based attitudinal characteristics representing their levels of concern regarding GHG emissions, U.S. energy independence, transportation fuel costs, the importance of projecting one’s environmental image through vehicle choice, and the potential inconvenience of recharging. All of these attitudinal characteristics (except environmental image) are subject to change through social and/or media influences. We inferred the degree to which agents are susceptible to media influences (6% low, 39% medium, 56% high) and social influences (59% low, 33% medium, 9% high), based on survey responses to a series of questions asking to what degree various factors had influenced their current opinions regarding U.S. transportation energy usage.

Agents were assigned a PHEV-comfort threshold $T$ based on survey participants’ responses to the question, “Assuming you were buying a new vehicle, what is your comfort level in purchasing/leasing the new PHEV technology rather than a more established type of vehicle, assuming it had all the other features you desired and was within your budget?” The participants responded by selecting their comfort threshold, phrased as a percentage range of PHEVs they would have to see around them before they would be comfortable considering a PHEV. The distribution of responses in each range was similar to that of an identically binned Gaussian distribution with a mean of 25% and a standard deviation of 48% [49], as shown in Fig. 1. In our initial agent population, 32% had a 0% threshold (innovators), another 4% had a threshold 0 < $T$ ≤ 5% (early majority adopters), and only 7% would never consider a PHEV.

Agents were assigned a separate probability of “willingness to consider a compact PHEV” attribute ($W$) reflecting whether survey respondents stated they “would definitely” (28%), “might” (51%), or “would not” (21%) consider purchasing a compact PHEV, respectively. Agents corresponding to the “would definitely” group were assigned $W = 1$, but for the remainder we dynamically estimated this probability every time step, based on a multinomial logistic model described in the next section.

Finally, survey respondents indicated how much they would be willing to pay up front for a vehicle (not necessarily a PHEV) that achieves 6 different specified dollar amounts in fuel savings per year. These delay discounting responses were associated with individual agents and used to interpolate the maximum price premium agents would pay for PHEVs to achieve estimated annual fuel savings based on projected gasoline and electricity prices over the agent’s expected years of vehicle ownership and daily VMT.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Mean Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household Income</td>
<td>$54,231</td>
</tr>
<tr>
<td>Age</td>
<td>34 years</td>
</tr>
<tr>
<td>Daily VMT</td>
<td>43.5 km</td>
</tr>
<tr>
<td>Age of Initial Primary Vehicle</td>
<td>8.5 years</td>
</tr>
<tr>
<td>Expected duration of car ownership</td>
<td>7.0 years</td>
</tr>
<tr>
<td>Fuel Efficiency of Initial Primary Vehicle</td>
<td>10.2 km/L</td>
</tr>
<tr>
<td>MSRP of Initial Primary Vehicle</td>
<td>(24 mpg)</td>
</tr>
<tr>
<td></td>
<td>$28,585</td>
</tr>
</tbody>
</table>
Fig. 1. Histogram of AMT survey responses of self-reported PHEV comfort threshold ranges, superimposed with a truncated normal distribution binned the same way.

Fig. 2. Synthesized spatial correlations across the 38.9 km² (15 mi²) simulated domain in normalized values of (a) household income, where red is highest income and blue is lowest, (b) education level, where red is highest education and blue is lowest, and (c) political leaning, where red indicates far right and blue indicates far left; (d) agent residence locations (white dots) are generated to be sparse in the rural region (red background), have intermediate spacing in the suburban region (green background), and are dense in the urban region (blue background).
All attributes described so far were, for each agent, based directly on survey responses of one AMT participant, thus respecting the distributions and cross-correlations of these attributes as observed in the survey population. However, since survey respondents came from 47 states across the U.S., and given our desire to model spatial and social effects, we synthesized agent locations in a simulated 38.9 km² (15 mi²) domain. To do this, we used 10 iterations of a Kohonen self-organizing map (SOM) [56] to locate the 911 agents in space based on the normalized values of 4 attributes. This was done to generate spatial correlations in household incomes (Fig. 2a), education levels (Fig. 2b), political leanings (Fig. 2c), and appropriate spacing and grouping of agents based on respondents from urban, suburban, and rural regions (Fig. 2d). The resulting spatial correlations (Fig. 3a) do not alter the observed cross-correlations between these 4 attributes (Fig. 3b), since individual agents were mapped to various locations without changing their attributes.

Each agent computes a perceived PHEV market share given vehicles owned by agents in its individual “social neighborhood”. We defined the latter to include all agents within each agent’s daily VMT/4, based on the assumption that consumers who drive more perceive more vehicles. The resulting spatial neighborhoods had a minimum of 31 agents, a median of 476 agents, and a maximum of 910 agents. Similarly, social influences were computed within an agent’s “social neighborhood,” defined to include all agents in its spatial neighborhood that have annual household incomes within ±$10,000 and age within ±15 years of its own attribute values, based on the principle of homophily [40]. The resulting social neighborhoods had a minimum of 5 agents, a median of 49 agents, and a maximum of 190 agents.

B. Agent Decision-Making
During each simulated annual time step, all agents are updated asynchronously in random order. Prior to making any vehicle purchasing decisions, certain agent attitudes are updated subject to both external and internal influences. Specifically, concerns regarding GHG emissions $G$ and U.S. energy independence $E$ are updated by adding the product of the average annual change in media coverage conveying the need to reduce transportation energy and the agent’s susceptibility to media influence $S_M$. In our simulations, the level of media coverage was stochastically increased from 0.05 to 0.3 over the 14 years of the simulation, based on the assumption that the increase in energy and climate-related impacts will be reflected by an increase in media coverage. Similarly, concern regarding fuel costs $F$ is updated by adding the average annual change in gasoline prices times $S_M$, where gasoline prices are stochastically increased from $0.911/L$ ($3.45/gal$; the 2011 U.S. average) to various projected values in 2040 (EIA, 2013). Electricity prices are assumed to increase linearly from $0.099/kWh$ in 2011 to $0.108/kWh$ in 2040 [58]. Four of the attitude attributes (political leaning, concerns regarding GHG emission, concerns regarding U.S. energy independence, and concerns regarding the potential inconvenience of recharging) are also modified through social influences, subject to the attitudes of other agents in their social network and their level of social susceptibility using the social update procedure described in [30].

Following its attitude updates, an agent probabilistically decides whether to consider purchasing a new vehicle during the current year, based on the age of its current vehicle and a normal probability distribution centered on the agent-specific number of years the agent expects to own the vehicle. The agent then estimates the expected annual fuel-cost savings of a PHEV relative to a vehicle of its current type over the expected number of years of vehicle ownership, based on its daily VMT and the projected gasoline and electricity cost (this
rational computation assumes that consumers will take advantage of the increasing number of web tools (e.g., [59][60]) that provide easy access to this information), and the maximum expected annual cost of ownership of these two vehicle types, including loan payments after trading in their current vehicle. The assumptions regarding vehicle financing and depreciation are described in [30].

The agent next selects between five vehicle purchasing options in the following order: (1) a new compact PHEV similar to a Chevy Volt (with a pre-incentive sticker price of $40,000, an all-electric range of 61 km (38 mi), an average of 16 km/L (38 mpg) when running on gasoline, and a 16 kWh battery), (2) a new vehicle similar in type to its current vehicle, (3) a used compact PHEV similar to a Chevy Volt (that is not as old as its current vehicle), (4) a used vehicle of the same type as its current vehicle (but not as old), or (5) no vehicle purchase. We selected the Chevy Volt as representative of a first-generation PHEV targeted toward the general public and with a relatively high all-electric range, sufficient for the U.S. average daily VMT of 47 km (29 mi) [50].

Part of the agent decision-making process depends on whether the agent is even willing to consider purchasing a compact PHEV; this is considered true if either the agent has a willingness value of \( W = 1 \) or if a uniform random number is less than the probability predicted by a multinomial logistic model estimating its likelihood of seriously considering a compact PHEV, based in part on its dynamically changing attitudes. Specifically, we used multiple ordinal logistic regression to build a predictive model of survey respondents who reported they “would definitely” or “would not” consider a compact PHEV based on 7 attributes: the agent’s political leaning, their attitudes regarding the environment and energy, their concerns regarding fuel costs and recharging, their desire to project an environmental image through vehicle ownership, and their current vehicle class, the latter reflecting their willingness to potentially switch vehicle classes to purchase a compact PHEV (since most first generation PHEVs are compact vehicles). In our previous PHEV survey analysis [49], these 7 attributes were the most predictive set we found; five-fold cross-validation yielded an average of 80% positive predictive value when testing the survey data. The logistic prediction was incorporated into agent decision-making as described below.

An agent will purchase a new compact PHEV if all of the following are true:

(i) The age of the used PHEV is less than the age of its current vehicle,

(ii) The difference in price between the used PHEV and the used vehicle of its current type under consideration falls within the agent’s willingness to pay extra,

(iii) The agent is willing to consider a compact PHEV, and

(iv) The number of PHEVs owned by agents within its spatial neighborhood exceeds its threshold \( T \) (except in Scenario 2 where we did not use the threshold).

If the agent does not purchase a new PHEV, it then decides whether to purchase a new vehicle similar in type to its current vehicle based on whether (a) the agent is willing to consider buying a new car, and (b) the vehicle is affordable.

If the agent does not purchase a new vehicle, it then assesses whether to purchase a used vehicle, either a compact PHEV or a conventional vehicle of the same type as its current vehicle. We assume that used vehicles of the current vehicle type are available for all years under consideration, and the agent considers the most recent used model that is affordable (based on the vehicle depreciation formula in [30]). For used compact PHEVs, we implement a used PHEV market; we track which PHEV model years have been traded in and allow only these years to be purchased as used PHEVs. The agent considers the most recent used PHEV that is both available and affordable.

The agent will purchase the used PHEV if all of the following are true:

(i) The price premium of a new PHEV (less any available rebates) is within the agent’s willingness to pay extra (linearly interpolated from their delay discounting attributes based the amount of fuel costs they expect to save annually),

(ii) The maximum annual cost of ownership is affordable (defined as \( \leq 20\% \) of the annual household income, a common rule of thumb [61]),

(iii) The agent is willing to consider a compact PHEV (estimated from the logistic function as described above),

(iv) The agent is willing to consider buying a new car, and

(v) The number of PHEVs owned by agents within its spatial neighborhood exceeds the agent’s threshold \( T \) (except in Scenario 2 where we did not use the threshold).

If the agent does not purchase a new PHEV, it will purchase the used vehicle similar in type to its current vehicle, provided the vehicle age is less than the age of its current vehicle. Otherwise, the agent does not buy any vehicle and retains its current vehicle during this time step.

III. RESULTS

We report on 10 scenarios after 14 years of simulation, starting from 0% compact PHEVs in 2011 to projected market penetration in 2025 (Fig. 4, Table II). Similar to the findings in [30], we did not observe qualitative differences in the results of different stochastic runs (as evidenced here by the relative smoothness of the curves in Fig. 4), so individual runs of each of the 10 scenarios were used to illustrate the relative model sensitivities to the different parameters in these scenarios. Since, on average, agents consider buying a vehicle every 7 years, this simulation period corresponds to approximately 2 vehicle purchases per agent. In the base case scenario, we assumed all agents will consider purchasing a new car, agent thresholds \( T \) and initial vehicle classes are as reported by survey participants; gas prices stochastically trend upward toward the Annual Energy Outlook 2013 reference gasoline price projection [58] of $1.14/L ($4.32/gal) in 2040 (in 2011 dollars); and we assume that PHEV incentives exist for the duration of the 14-year simulation in the form of a $7,500 federal tax rebate (as currently exists in the U.S.), a
manufacturer rebate (as existed for the Chevy Volt in June, 2013), and a $1,500 state tax rebate (as currently exists in California). Each of the remaining scenarios varies in exactly one parameter, as follows. Scenario 2 omitted the use of the threshold $T$ in the agent decision-making process. Scenario 3 assumed that agents who had purchased their most recent vehicle used would not consider purchasing their next vehicle new. Scenario 4 assumed that all agents were compact

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Use Threshold $T$?</th>
<th>All will consider new cars?</th>
<th>All initially compact car owners?</th>
<th>Predicted gasoline price in 2040</th>
<th>Rebate amounts (Federal + Manuf. + State)</th>
<th>Rebate duration</th>
<th>% compact PHEVs in 2025</th>
<th>% change compared to Base case</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Base case</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>$1.14/L ($4.32/gal)</td>
<td>$7,500 + $4,000 + $1,500</td>
<td>NA</td>
<td>17.8%</td>
<td>NA</td>
</tr>
<tr>
<td>2) No threshold</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>$1.14/L ($4.32/gal)</td>
<td>$7,500 + $4,000 + $1,500</td>
<td>NA</td>
<td>33.9%</td>
<td>+16.1%</td>
</tr>
<tr>
<td>3) Some used-only buyers</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>$1.14/L ($4.32/gal)</td>
<td>$7,500 + $4,000 + $1,500</td>
<td>NA</td>
<td>8.0%</td>
<td>-9.8%</td>
</tr>
<tr>
<td>4) All compact buyers</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>$1.14/L ($4.32/gal)</td>
<td>$7,500 + $4,000 + $1,500</td>
<td>NA</td>
<td>21.2%</td>
<td>+3.4%</td>
</tr>
<tr>
<td>5) High gas prices</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>$1.64/L ($6.19/gal)</td>
<td>$7,500 + $4,000 + $1,500</td>
<td>NA</td>
<td>18.6%</td>
<td>+0.8%</td>
</tr>
<tr>
<td>6) Very high gas prices</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>$2.11/L ($8.00/gal)</td>
<td>$7,500 + $4,000 + $1,500</td>
<td>NA</td>
<td>19.6%</td>
<td>+1.8%</td>
</tr>
<tr>
<td>7) No state rebate</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>$1.14/L ($4.32/gal)</td>
<td>$7,500 + $4,000 + $0</td>
<td>NA</td>
<td>14.8%</td>
<td>-3.0%</td>
</tr>
<tr>
<td>8) No state or manufacturer rebate</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>$1.14/L ($4.32/gal)</td>
<td>$7,500 + $0 + $0</td>
<td>NA</td>
<td>9.9%</td>
<td>-7.9%</td>
</tr>
<tr>
<td>9) No rebates</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>$1.14/L ($4.32/gal)</td>
<td>$0 + $0 + $0</td>
<td>NA</td>
<td>5.3%</td>
<td>-12.5%</td>
</tr>
<tr>
<td>10) Rebates end after 5 years</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>$1.14/L ($4.32/gal)</td>
<td>$7,500 + $4,000 + $1,500</td>
<td>5 yr</td>
<td>12.7%</td>
<td>-5.1%</td>
</tr>
</tbody>
</table>
car owners (as in the scenarios reported in [30]). Scenario 5 assumed a more rapid rise in gasoline prices based on a high gasoline price projection [58]. Scenario 6 assumed an even higher rise in gasoline prices (e.g., such as might occur with an increase in gasoline tax). Scenario 7 assumed there was no state rebate. Scenario 8 assumed no state rebate and no manufacturer rebate; and Scenario 9 assumed no PHEV rebates at all. Scenario 10 assumed that all rebates were terminated after 5 years. PHEV market penetration for the 10 scenarios is shown in Fig. 4, with details summarized in Table II.

IV. DISCUSSION

Market penetration of PHEVs (and other EVs) is still very low and highly variable across the 50 U.S. states, ranging in 2013 from a low of essentially 0% of new car registrations in Mississippi to a high of 1.6% in Washington and Hawaii [62]. Thus, proper model validation is impossible with such low numbers, especially considering that agents are based on survey respondents from 47 states. Furthermore, our ABM is intentionally relatively simple; for example, we do not attempt to model other types of EVs (or any other vehicles not owned by our 911 survey respondents) or make any attempt to account for future unknown changes in the technology or how this might impact PHEV price or consumer willingness to adopt. Our intent with this ABM is not to make accurate or quantitative predictions, but rather to better understand potential barriers and leverage points that may impact PHEV market penetration by improving our originally proposed PHEV model [30] using agent decision-making rules and initialization based on data from the recently published PHEV survey [49].

Since 911 surveys passed our quality-control standards, we elected to limit our simulated populations to exactly 911 agents with a one-to-one correspondence between survey respondents and agents, thus preserving distributions and cross-correlations of respondent attributes. One could conceivably scale-up this model using multiple copies of these 911 agents in different spatial locations. However, in our previous work [30], we found no qualitative differences between simulations with 10,000 agents and those with 1,000 agents, or between different stochastic runs with the same parameters. Thus, for this study, we judged that 911 agents were sufficient to identify trends and sensitivities. Ideally, the model could be scaled up by conducting a larger survey within a limited geographical region of interest; however, given our choice to perform the survey using AMT, we could not limit the geography of respondents beyond specifying they must be within the U.S.

Of the parameters tested, the PHEV technology comfort threshold $T$, reflecting consumer uneasiness with the new PHEV technology, is shown to be the largest barrier to potential PHEV market penetration, depressing potential PHEV sales by nearly 50% in 14 years of simulation (Fig. 4 and Table II, compare Scenarios 2 to Scenario 1). Note that our implementation of this social thresholding effect is motivated by the classic works of [39] and [62]. In [64] the authors took an alternative approach by discretizing time into 3 sequential phases and assigning innovators and early adopters to the first phase (which assumed 0.1% EV market penetration), early majority adopters to the second phase (5% EVs), and late majority and traditionalists to the third phase (10% EVs). In contrast, our implementation assigned percentage thresholds to agents within the self-reported ranges of their corresponding AMT survey respondents. Thus, agents naturally considered whether to purchase a PHEV after market penetration had exceeded their personal comfort threshold and the same agent could make more than one vehicle purchase during the course of a simulation. Although many of the survey-based agents were willing to be early adopters of the PHEV technology, after 14 years the total market penetration only exceeded the thresholds for 47% of the agents in Scenario 1. In these simulations, we assumed the heterogeneous agent-specific threshold values were static; it is possible that as PHEV technology becomes more widely advertised and familiar to consumers, these threshold values may decline over time. Furthermore, we did not model PHEV adoption by commercial operators, such as taxis, company vehicles, etc. It is possible that PHEVs may make more rapid inroads into these commercial fleets and thus impact the market penetration level perceived by consumers. Certainly, our results indicate that aggressive steps are needed by manufacturers (e.g., through educational advertising and strong battery warranties) and policy-makers (through public service announcements, development of public recharging infrastructure and policies, and through well-publicized incentives) to help consumers feel more comfortable with the PHEV technology.

If the PHEV market penetration exceeded an agents’ personal comfort threshold and the multinomial logistic model predicted that the agent would seriously consider purchasing a PHEV, we then assessed whether they were willing to pay the PHEV sticker price, assuming it was within their budget. Rather than inferring an agent’s willingness to pay extra for a more fuel efficient vehicle from indirect indicators (e.g., as in [64]), we used the individual delay discounting functions self-reported by survey respondents. Thus, our model independently accounts for agents’ discomfort with the new PHEV technology, their desire to drive a more environmentally friendly vehicle, and their willingness to pay a higher sticker price for a PHEV.

When no consumer agents were willing to switch from used-car buyers to new-car buyers, PHEV purchases dropped by 55% (Fig. 4 and Table II, compare Scenario 3 to Scenario 1). Since PHEVs are likely to be scarce in the used-car market for some time (and consumers may be even more uncomfortable purchasing a used PHEV, due to a fear of expected degradation in the battery capacity), and since economic pressures are causing some U.S. consumers to switch from new car buyers to used car buyers [65], this will be a major impediment to increasing the proportion of PHEVs in the U.S. light-vehicle fleet.

Interestingly, when we increased the number of agents who initially owned compact cars from 35% to 100% (Fig. 4 and Table II, compare Scenario 4 to Scenario 1), compact PHEV market penetration only increased by 3.4% over 14 years. This is because our agents were modeled after our survey population, of which a surprising 18% of the survey respondents indicated they would definitely, and another 39%...
stated that they might, consider switching car classes to purchase a compact PHEV. On the one hand, these results indicate the limited number of car classes in first generation PHEVs may not, in itself, be a large barrier to PHEV market penetration. On the other hand, they also imply that future availability of PHEVs in more vehicle classes may not have a huge impact on overall PHEV market penetration.

While we elected to use known attributes of the Chevy Volt as representative of available PHEV technology throughout each simulation, one could easily incorporate hypothetical improvements in PHEV technology over time (e.g., as in [64]) and/or increased availability of PHEV models over time. However, unless such changes succeed in dramatically lowering the PHEV comfort thresholds of many consumers (something we can only guess at), our results indicate that they may have relatively little impact on predicted PHEV market penetration. Thus, since we have no way of knowing what those future changes might be or how they may affect consumer purchasing decisions, we judged that adding such assumptions (which are not founded on data) into the model would introduce unnecessary complexity. We also assumed a constant 2011 vehicle price throughout the simulations, a standard assumption in engineering economics. In reality, one would hope that as PHEV rebates are phased out there will be a reduction in the MSRP of PHEVs relative to conventional vehicles due to improvements in battery technology and manufacturing and economy of scale.

Large increases in gasoline prices (Fig. 4 and Table II, compare Scenarios 5 and 6 to Scenario 1) had surprisingly small effects on PHEV market penetration in these simulations. However, our model assumed that vehicle consumers used rational computations of fuel costs savings (such as those now easily obtained through various websites). In reality, many consumers do not base vehicle purchasing decisions on financially accurate assessments of alternatives [23], so a more rapid rise in gasoline prices and/or higher gasoline taxes, and associated press coverage, may cause a disproportionately high psychological effect that stimulates PHEV adoption at a greater rate than rational fuel cost savings would warrant.

Our simulations illustrate the importance of governmental and manufacturer rebates in making PHEVs competitive (Fig. 4 and Table II, compare Scenarios 7-10 to Scenario 1). Again, we assumed that agents took all rebates into account when making vehicle purchasing decisions. However, even when these rebates are in place, many consumers may be unaware of them, particularly manufacturer rebates (that change frequently, vary with consumer credit ratings, and are often poorly advertised), and state rebates (which many consumers may not be familiar with). If PHEVs are to successfully penetrate the U.S. transportation market to a large extent, it may be necessary to continue and widely advertise such rebates until the MSRP of PHEVs can become more cost-competitive, unless improvements in PHEV technology and consumer education efforts are successful in significantly reducing consumers’ PHEV comfort thresholds.

V. CONCLUSIONS

Our prior PHEV market penetration work [30] left us frustrated with the lack of sufficient data to properly inform agent vehicle-purchasing decision rules or populate the ABM with realistic distributions and cross-correlations of agent attributes. For example, although we employed the well-established sociological Gaussian distribution to model the technology adoption lifecycle [66], we could not find data to properly estimate the mean and standard deviation of this distribution for new PHEV technology consumer adoption. We also could not find quantitative data to help predict which vehicle consumers were likely to seriously consider a PHEV, especially if this meant switching vehicle class to obtain a first generation PHEV. Additionally, even if consumers were willing to consider purchasing a PHEV, we found little information to help quantitatively predict how much extra they might be willing to spend up front to obtain greater fuel savings in the future.

To address these issues, we recently conducted and analyzed an extensive consumer survey designed, in large part, to specifically inform our PHEV market penetration ABM [49]. In the current study, we modified our ABM to reflect the survey results. Rather than generating a synthetic population based on the statistical distributions and cross-correlations found in the survey (a non-trivial task because of the multitude of cross-correlated and non-linearly related variables), we created an agent population with a one-to-one correspondence between survey respondents and agents, with each agent’s attributes based as directly as possible on the responses of one survey participant, including a variety of attitudes and susceptibility to social and media influences. Survey questions were carefully phrased to tease out different aspects of potential PHEV adoption barriers, including fear of new PHEV technology independent of other vehicle features or cost (and where consumers saw themselves on the PHEV technology adoption lifecycle), willingness to pay more up front to achieve various savings in fuel costs down the road (independent of the fuel type), attitudes regarding the environment and energy, stated willingness to consider a first generation PHEV with the understanding that they would only come in compact models, etc. We then redesigned the ABM to independently include these complementary aspects into agent vehicle purchasing decisions. Our revised model includes a PHEV-technology comfort threshold component, a previously validated multinomial logistic prediction of willingness to consider a compact PHEV [49], based on consumer attitudes including environmental and energy concerns (which could dynamically change in our model, subject to social and media influences), and agent-specific delay discounting functions that predict the amount agents are willing to pay up front for greater fuel savings.

Some of the survey responses were contrary to our original assumptions. For example, it is worth noting that, while our survey results confirmed that the comfort threshold $T$ could reasonably be modeled with a truncated Gaussian distribution (Fig. 1), the observed 48% standard deviation of this distribution was much larger than the 20% standard deviation assumed in our previous work [30]. The higher standard deviation reflects many potential early adopters, but also
implies that adoption rates will remain slow since many consumer may not consider a PHEV until market penetration is already quite high. Cross-correlations in many attributes (e.g., Fig. 3b) were also lower than initially assumed in [30]. In this work we have avoided the necessity to make assumptions on these distributions and cross-correlations by modeling the attributes of individual agents on those reported by individual survey respondents.

We report insights from several simulated scenarios. Our results indicate the fear of new PHEV technology remains a large barrier to widespread PHEV adoption among new car buyers. To date, there has been relatively little advertising or media attention designed to educate or allay consumer fears regarding this technology. Since a growing majority of U.S. vehicle purchasers elect to buy used rather than new cars, this will greatly limit the rate of PHEV market penetration, since PHEVs are not likely to become a large part of the used-car market in the near future. Surprisingly, our agent population was relatively insensitive to our restricting available PHEVs to compact cars and was also relatively insensitive to rising gasoline prices. However, our simulations confirm that governmental and manufacturer rebates will remain necessary to make PHEVs competitive until the sticker price of these vehicles comes down.

ABM predictions will always be subject to a wide range of uncertainties associated with various assumptions. Nonetheless, since manufacturers and policy-makers are required to make decisions in the face of such uncertainties, models can be useful decision support tools, if adequately grounded in data [67]. We believe that close integration of consumer surveys and the design of agent-based models is a key step in the development of useful decision-support models in the transportation research community and beyond.

In their recent review of electric-drive vehicle market penetration models, [37] recommend that there needs to be a greater connection between consumer surveys and electric-drive vehicle adoption rate modeling. This study illustrates how one can make that connection.

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