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Simulating the household plug-in hybrid electric vehicle distribution and its electric distribution network impacts

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ABSTRACT

This paper presents a multi agent-based simulation framework for modeling spatial distribution of plug-in hybrid electric vehicle ownership at local residential level, discovering "plug-in hybrid electric vehicle hot zones" where ownership may quickly increase in the near future, and estimating the impacts of the increasing plug-in hybrid electric vehicle ownership on the local electric distribution network with different charging strategies. We use Knox County, Tennessee as a case study to highlight the simulation results of the agent-based simulation framework.

1. Introduction

The electric recharge capability of plug-in hybrid electric vehicles (PHEVs) offers promise to replace a significant portion of the US's current fuel-based light vehicle fleet before electronic vehicle battery recharging infrastructure is fully deployed nationwide. The general assumption is that the electric power grid is built to support peak loads and, as a consequence, suffers from low asset utilization rates in off-peak periods. However, this assumption does not consider that vehicle users will most likely charge their vehicles when convenient, rather than waiting for power grid off-peak periods.

The PHEV charging loads are computed based on charging strategies that the future vehicle fleet might adopt. Hadley and Tsvetkova (2009), for example, find that most US regions would need to build additional generation capacity to meet the added electric demand when PHEVs are charged in the evening, while Lilienthal and Brown (2007) showed an uncontrolled charging strategy of PHEVs would place increased pressure on power grid but no additional generation capacity would be required if PHEVs charging cycles started in the off-peak periods. Equally, Letendre and Watts (2009) concluded that variability in charging times for vehicles may have a critical impact on the local electric grid infrastructure.

These efforts, however, ignore the possibility of spatially variable PHEV penetration in residential areas. Given the vehicle penetration rate is expected to vary with household demographic and socioeconomic attributes such as income, travel distance, age, household size, education, the variation of these household demographic attributes in residential areas will generate PHEV penetration rate patterns. There may be specific points along some electric distribution lines that face congestion if local patterns of electricity demand change significantly because of PHEV recharging. As a result, the electrical grid substations will be more sensitive to the usage patterns of a few customers. Hence in a region the overall electric generation and grid capacity may be under-utilized but if too many consumers on a given circuit recharge their plug-in vehicles simultaneously, it could increase peak electric demand locally causing system disruptions and require upgrading of the electric distribution infrastructure.

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Here we develop an agent-based framework for modeling spatial distribution of PHEV household adoption in residential areas, evaluating the impacts of vehicles charging load on a residential electric distribution network with different charging strategies, and discovering "PHEV hot zones" where PHEV ownership may quickly increase in the near future. We use Knox County, Tennessee as a case study to show the simulation results of an agent-based model (ABM) framework.

2. Agent-based PHEV ownership model

Existing PHEV adoption and market penetration models provide an estimate of future vehicle market share and percentage of vehicle at broad geographic scales. To understand the PHEV charging load impact on a local residential distribution network, it is necessary to build a vehicle ownership distribution model at such high resolution level. The PHEV ownership distribution pattern in a residential community is determined by the (choice) behavior of individual households for new vehicle selection. Since different demographic attributes of individual household can affect the household vehicle purchase decision, the probability of an individual household choosing a PHEV as their next new vehicle is likely different. It is useful, therefore, to develop an explicit vehicle ownership distribution model at spatially high resolution that reflects the individual household's PHEV choice at local scale.

Social units (e.g., individuals, households, firms, or nations) now form the basis of many theories of group phenomena that underlie computational models of global structures produced by their interactions (Lazer et al., 2009). Agent-based modeling (ABM) explores complex social macro dynamic behaviors emerging from the interactions of autonomous and interdependent individual actors (agents) within this approach (Epstein, 2006). This models social structures from the 'bottom-up' by simulating individuals with virtual agents and creating emerging organizations from the operation of rules that govern interactions among agents.

Like many other social phenomena, household level PHEV adoption or ownership distribution has a spatial–temporal dimension and involves dynamic decisions made by individuals. We use an ABM to combine household demographic and socioeconomic characteristics of Knox County with nationwide vehicles sale, cost and energy cost prediction data from US Energy Information Administration's Annual Energy Outlook 2010 report for scenario driven forecasting of PHEV ownership distribution in Knox County households for 2011–2020.

We use a few simple, theory-based logical rules to guide the behavior and decision of the individual agents. The interactions of individual households in the model produce the emerging PHEV ownership patterns. In addition, individual households in the ABM are able to make dynamic decisions based on changing information, such as gasoline price, existing PHEV ownership and government policies. In this agent-based household PHEV ownership distribution model, we have integrated a consumer choice model (Lin and Greene, 2010) with University of Michigan Transportation Research Institute (UMTRI) model (Sullivan et al., 2009) for estimating the time when consumers start searching for a new car and a stigmergy-based neighborhood effect model (Cui et al., 2009) for estimating the probability of consumer's selection for different PHEV.

The consumer vehicle choice probability model is based on consumer's socioeconomic attributes, the cost and performance of the vehicle, gasoline and other energy cost, and the government policies. The core of this model is the Nested Multinomial Logit (NMNL) module that estimates the users' choice probability on 13 kinds of advanced vehicle technologies. In this model, the US market is divided into 1458 market segments and the market share of technologies is aggregated from the market segments into the national level. The model is capable of estimating the consumer's vehicle choice probability results from 2005 to 2020. Since our interest is estimating the ownership distribution of kinds of PHEV and their impact on local community power supply, we used four categories to represent the domain of advanced vehicles consumer can choose from (i.e., PHEV-10, PHEV-20, PHEV-40 and others, which include hybrid electric vehicles and traditional Internal Combustion Engine (ICE) vehicles) rather than using 13 advanced vehicle technologies listed in the original model. This consumer choice model is used as the individual agent decision rule for selecting the vehicle from available PHEV choices. The model can be represented in following mathematical equations.

$$P_{ij} = \frac{e^{\sum_{A} \beta_{ja} x_{ja}}}{\sum_k e^{\sum_{A} \beta_{ka} x_{ka}}} \quad \sum_j P_{ij} = 1 \tag{1}$$

where i is the household index, j is the vehicle index, k is the index of all other vehicles, a is the index of observed household and vehicle attributes, A is the household attributes that have correlation with the probability of consumer's decision for choosing vehicle j, x_a is the attributes of household and vehicle, and β is the parameter determining the impact fact of the vehicle attributes to consumer's choosing.

On the other hand, the consumer transportation budgets serve a major role in UMTRI model (Sullivan et al., 2009) for estimating the time when agents start to actively search for a new vehicle. According to the description of UMTRI model, all consumers will stay within their consumer transportation budgets which are comprised of fixed and variable terms as follows:

$$\text{Budget} = C1 + C2 + C3 \tag{2}$$

where $C1$ is the monthly vehicle payment, $C2$ is the monthly fuel cost and $C3$ is the vehicle maintenance cost.

In our agent-based household vehicle ownership model, the UMTRI model is used for modeling the agent household's decision to buy another car. For every time period, the household agents will review their transportation budget status and decide whether or not it is time to buy another vehicle. We augmented the consumer vehicle choice model with a "neighborhood effect". Epstein et al. (2010) and Sullivan et al. (2009) have used the neighborhood effect as one attribute for predicting the consumer's vehicle choice. But how the "neighborhood effect" numerically contributes on the consumer's decision for their new vehicle is still an un-answered question. Here we used the individual behavior or contribution is described in the following equations:

$$P_d^{t+1} = P_d^{t+1} + \gamma \tag{3}$$

$$P_d^{t+1} = P_d^{t+1} \times \varepsilon^{-\tau} \tag{4}$$

$$P_d = \frac{(P_d^{t+1} + K)^F}{\sum_{i=1}^{N} (P_i^t + K)^F} \tag{5}$$

P_d is the positive effect for one kind of vehicle. For this kind of vehicle ownership in neighborhood or other social network connected by areas, the positive effect P_d is incremented by a constant, γ, as shown in Eq. (3). At the same time, the positive effect P_d will decay as time passes. The decay rate $\varepsilon^{-\tau}$ will be applied on P_d every time cycle as shown in Eq. (4). Eq. (5) describes the vehicle d's probability ρ_d of being chosen. N is the number of advanced vehicle technologies available for consumers. The constants F and K are used to tune the consumer's vehicle selection behaviors.

Individual households with different characteristics are represented by agents. The combination of the three decision models described above will help each agent make an independent choice about whether to buy a PHEV or not and the kind of PHEV to buy. If each agent household is geo-located, the global behavior about the spatial distribution PHEV ownership can be generated from the interaction and independent decision of individual agents in the simulation.

3. Synthetic household characteristics and locating process

Accurately generating PHEV ownership distribution in a local community needs high fidelity household characteristics and individual locations that can be used in the ABM simulation for estimating each individual household (agent) vehicle choice behavior. The high fidelity input data for agent-based simulation is the primary assurance for the simulation to generate meaningful results. Collecting the individual household characteristics and location information of the targeted community is extremely important for understanding the local community PHEV distribution and their impact on local electric distribution network. Nevertheless, because of ineffective survey based strategy (privacy concerns, high cost, and low response rate) obtaining high resolution, spatially explicit household and personal characteristics are usually challenging. One solution is using population synthesizers to reconstruct methodologically rigorous estimates of household characteristics and their location from survey data and high-resolution geospatial data, such as Public Use Microdata Sample (PUMS) (American Community Survey, 2010), Census Summary Files 3 (SF3) (US Census Bureau, 2003), Census Transportation Planning Products (CTPP) (US Department of Transporation, 2011) and high resolution (90 m) population distribution data LandScan USA (Bhaduri et al., 2007).

Most of simulations suffer from a shortage of accurate data of local residency. Without accurate data, the usability of the results generated from the simulation is limited. The first step is to allocate local household data for the simulation. Here, the virtual Knox County households are generated from the copula-based household synthesizer, in which the households have the same attributes with known local distributions (i.e., SF3 statistics) at each census block groups (BGs) while having similar inter-variable correlations as observed in the PUMS and distributed throughout the study area by integrating LandScan USA.[1]

Fig. 1 shows the study area's 234 BGs and three PUMAs (i.e., 01301, 01302, and 01400). Since the PUMA and BGs boundaries are not always co-located in Knox County, when one BG corresponds to multiple PUMAs, it is assigned to the largest PUMA for simplification. Overall, 190,965 virtual households (368,666 members) are synthesized. Considering PHEV purchasing and usage, several potentially relevant household demographic variables are extracted, including: household income in 1999, number of household member, number of workers, number of vehicles, household highest educational attainment, and household travel time to work, derived from individual records.

Since the household is assumed to be the decision-making unit for automobile purchasing, only family and non-family households are considered in this paper (i.e., group quarters are excluded). For each PUMA, a unique copula-based synthesizer is constructed. Copulas have been a novel statistical tool that can be applied to construct multidimensional probability model with arbitrary marginal distributions in a flexible manner. Recently application of copulas in transportation can be

[1] Our copula-based virtual household synthesizer is based on detailed demographic samples from PUMS that are based on a 5% sampling rate and are grouped in geographical units named Public Use Microdata Areas (PUMAs). The PUMA is determined in a way that it must contain approximately 10,000 households from a population of 200,000, so the privacy of each survey respondent is well-protected. However, it also results in coarse spatial extent and hence is a disadvantage for regional-specific studies. Local summary tables are obtained from SF3, which are in the geographical units called Block Groups (BGs). The SF3 information is based on the Census long forms (16.7% sampling rate) and further adjusted by short forms data (100% sampling rate). Here, the copula-based virtual households are derived from PUMS and then locally fitted to SF3 summaries.

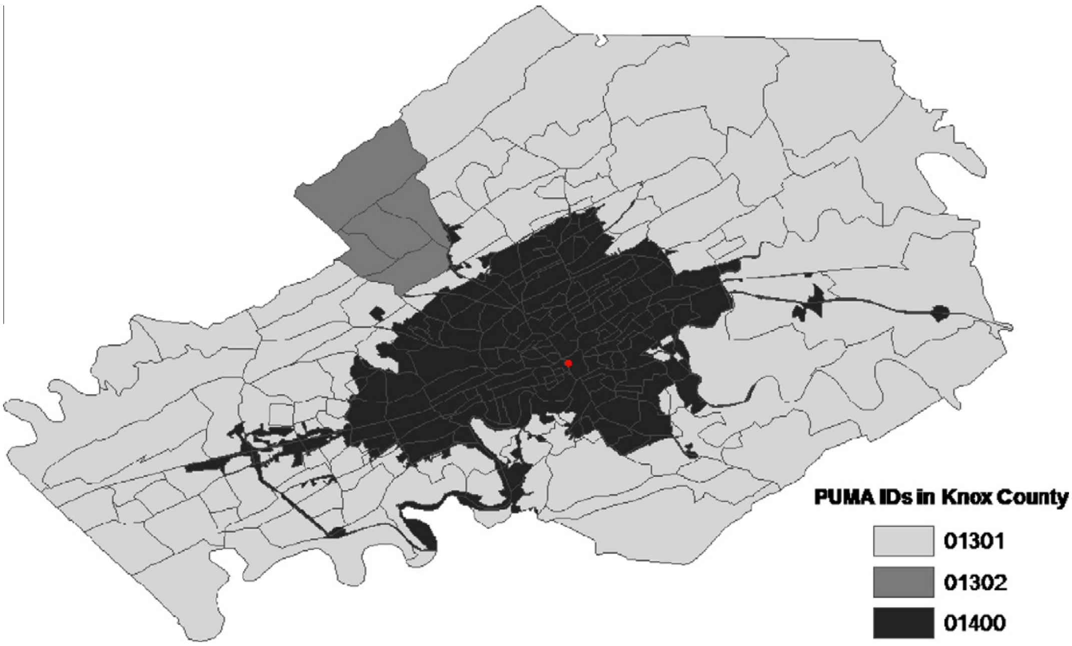

Fig. 1. Illustration of three PUMAs and 234 census block groups in the Knox County.

found in (Spissu et al., 2009). The marginal distributions $u_j = F_{x_j}(x_j) = 1, \ldots, 6$ are derived by non-parametric kernel density functions, in which the discrete–continuous transformation is considered for the average household income, household size, number of workers, number of vehicles, educational attainment, and household travel time to work. The correlation matrix Σ is computed by Spearman's r, and then corrected for formatting issues with the tolerance ε set at 0.002. The Gaussian copulas $C_{U_1,\ldots U_d}$ are then used to synthesize virtual households.

At the local level, Form SF3 summaries for each BG are collected and treated as constraints. However, not every variable has a corresponding local summary and some variables have different universes and to avoid making extraneous assumptions, we only take income and person numbers summaries as two local constraints. Following the local fitting procedures, virtual households are assigned for each BG.

However, since the minimum spatial resolution dealt with by the household synthesizer is the block groups, it might be difficult to study the microscopic spatial distribution of PHEV in the block groups. Thus, another procedure to place individual synthetic households at the specific map coordinates has been developed, employing the personal travel time data of workers to work from SF3, number of workers commuting between census tracks from CTPP, and high resolution (90 m) population distribution data with LandScan USA.

4. The ABM simulation platform

We used the NetLogo multi-agent simulation tool to develop our model. In this tool, agents move around in a virtual world and interact with other agents. There is no centralized control or coordination of the agents' actions. Agents are responsible for maintaining their own state and performing their own actions asynchronously and as rapidly as they can. In such agent-based simulation, the overall behavior of the system is an emerging property of the individual, independent interactions of the agents.

One agent represents one household. Each household agent is created with certain attributes extracted from the synthetic household data discussed in Section 3. Each agent has specific rules of behavior to determine how the households select when and what kind of vehicle. There are 190,965 households in the Knox County, which means 190,965 agents are created in this simulation platform. Once all agents are initialized, the model proceeds according to internal clocks. Essentially, all agents are engaged in PHEV selection activity during each time period (1 calendar month). Simulated household and its geo-locations, as well as the current status of the vehicle (such as the age of vehicle and the mileage) are updated each simulation period (1 calendar month).

5. Experimental design and results

We use the two scenarios, Base Case and FreedomCARGoals Case defined in Lin and Greene (2010), to illustrate the household PHEV distributions in the Knox County. The same energy prices are used in the two cases. We use Lin and Greene's output for PHEV distribution model calibration to confirm that the proposed model generates similar estimated vehicle sales each year from 2011 to 2020. We aggregate the individual household PHEV based on the census block group (234 BGs in the Knox County) in which individual households are located. By using ownership distribution model and the synthetic household data, we are able to estimate the vehicle type for each household in each simulation month. For demonstrating the vehicle distribution in the local community and discovering the "PHEV hot zone" – the highest PHEV ownership concentration – we aggregate the individual household PHEV based on the BGs. The distribution of the PHEV in Knox County for 2020 based on the two scenarios is seen in Fig. 2. We only display the distributions of ownership.

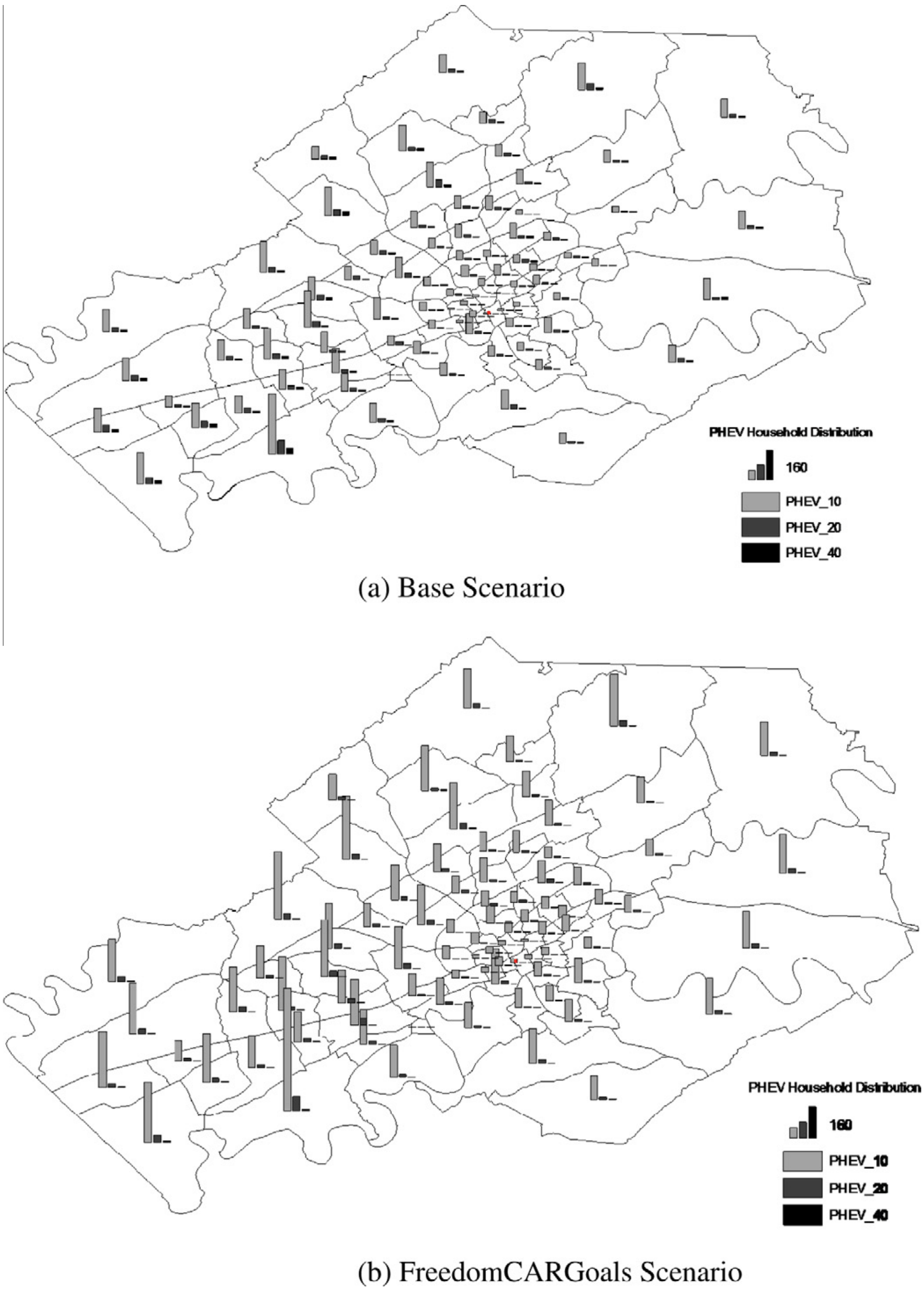

Fig. 2. PHEV distributions for Basic and FreedomCARGoals scenarios (2020).

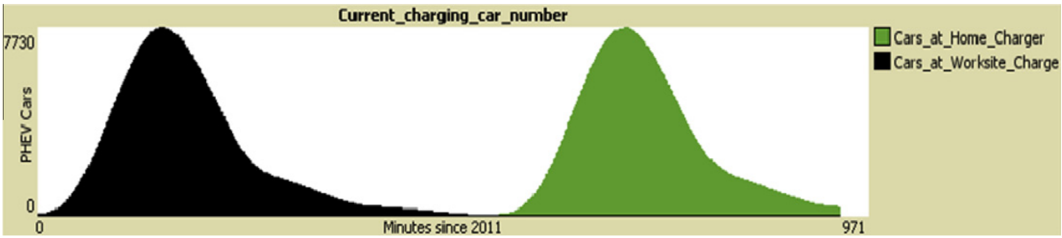

Fig. 3. Charging load for uncontrolled PHEV charging system.

The height of the bars in different BGs represents the number of PHEVs in the corresponding BGs. The longer the bar is, the more vehicles are in the corresponding BGs. As shown in Fig. 2, the FreedomCARGoals scenario will have a higher PHEV market penetration than Base Case. However, both have very similar vehicle distribution patterns in Knox County; that is, both scenarios indicate that the southwest portion of the county (which is the Town of Farragut) will have the highest PHEV concentration. This area is considered as the "PHEV hot zone". We also see that PHEV-40 ownership within the Base Case is higher than that for the FreedomCARGoals scenario. The possible reason is because under the FreedomCARGoals scenario, more households are capable and willing to buy basic level PHEV vehicle, PHEV-10. Because of the neighborhood effect, more households are attracted to buy a PHEV-10 instead of a PHEV-40 which is more expensive than PHEV-10.

Using the PHEV residence ownership distribution result for the FreedomCARGoals Scenario we are able to conduct preliminary analysis of battery charge load impacts on the local electric distribution network. PHEVs under this Scenario will reach 8192 in 2020 in the county. Taking the worst scenario of all vehicles simultaneously recharging during the grid peak time, each vehicle will consume 1.45 kW during the recharge, with the peak load for all PHEVs being 11,878 kW. In most cases, because drivers have different travel patterns and charge time schedules, the maximum load pattern for uncontrolled evening charging will be similar to Fig. 3. Under this scenario, it is reasonable to assume that the vehicle owner begins charging the vehicle upon arriving at work in the morning and upon returning home from work. The black area represents the charge load at work and gray area indicates the load while at driver's residence. Charging start times are decided by the PHEV driver's commute time from work to home and from home to work. The PHEV-10, PHEV-20 and PHEV-40 need to be charged from 2 to 6 h continuously.

Four census block groups (46, 57, 58 and 62) with 2670 vehicles each, from the 234 BGs in Knox County, have the highest estimated PHEV penetration under the FreedomCARGoals Scenario. According to the simulation output, the evening peak charging load for these BGs can reach 3625 kW, 32.6% of the vehicle charging load generated by the fleet in the Knox County. These BGs can be considered as the "PHEV hot zones".

6. Conclusions

In this paper, we have modeled the high-resolution spatial distribution of vehicle ownership in local residential areas at a county scale and evaluated the impacts of PHEVs charging load on the residential electric distribution network. Our approach for generating synthetic household characteristics and locating them is described. Knox County, TN is used as a case study to show the simulation results of the proposed ABM framework. The variation of household attributes such as income, travel distance, age, household member, and education, for residential areas may generate different vehicle market penetration rates. Residential neighborhoods, where multiple PHEV consumers share a given circuit to recharge their plug-in vehicles, could increase peak demand locally and require utilities to upgrade the distribution infrastructure.

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