A multi agent-based framework for simulating household PHEV distribution and electric distribution network impact

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ABSTRACT

The variation of household attributes such as income, travel distance, age, household member, and education for different residential areas may generate different market penetration rates for plug-in hybrid electric vehicle (PHEV). Residential areas with higher PHEV ownership could increase peak electric demand locally and require utilities to upgrade the electric distribution infrastructure even though the capacity of the whole regional power grid is under-utilized. Estimating the future PHEV ownership distribution at the residential household level can help us understand the impact of PHEV fleet on power line congestion, transformer overload and other unforeseen problems at the local residential distribution network level. It can also help utilities manage the timing of recharging demand to maximize load factors and utilization of existing distribution resources. This paper presents a multi agent-based simulation framework for 1) modeling spatial distribution of PHEV ownership at local residential household level, 2) discovering "PHEV hot zones" where PHEV ownership may quickly increase in the near future, and 3) estimating the impacts of the increasing PHEV ownership on the local electric distribution network with different charging strategies. In this paper, we use Knox County, TN as a case study to show the simulation results of the agent-based model (ABM) framework. However, the framework can be easily applied to other local areas in the U.S.

Key Words

Plug-in hybrid electric vehicle, agent-based model, electric distribution network, synthetic population

1. Introduction

By introducing Electric Vehicles (EV) that can operate in a full electric mode and be powered by the electricity grid will largely reduce the Green House Gas (GHG) emission and reduce the U.S. dependence on the foreign oil import (Parry, 2007). However, anxiety by consumers from battery travel range is a major concern for potential electric vehicle buyers. When electrical charge stations are not widely deployed for convenience battery recharge, fear of being stranded in an electric vehicle due to insufficient battery capacity will be a major deterrent for wide-spread acceptance of the EV in current period.

Plug-in hybrid electric vehicles (PHEV) received considerable attention in recent years (Denholm and Short, 2006). A PHEV is different from an EV whose battery is the only energy source for propelling the vehicle and which needs the electric recharge station on the road for refuel, a PHEV can be viewed as a regular hybrid electric vehicle (HEV) with bigger battery capacity and a recharge capability from power grid. Drivers can fill the PHEV up at the gas station on the road and also plug it in for recharging at home (Parks et al., 2007). The energy stored in the PHEV battery pack will be used first like an EV for local commute travel, and the gas will be used for greater distance travel and backup. The PHEV can operate in charge sustaining mode like a regular HEV should the driver need to drive longer distance and there are no battery recharge stations available on the road.

The electric recharge capability of PHEV offers more promise to replace a significant portion of the nation's current fuel-based light vehicle fleet and alleviate dependence on petroleum fuels before the EV battery recharging infrastructure is fully deployed nationwide. The burden of an undeveloped recharging infrastructure is transferred to the power grid that supplies electricity to the residence. 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. In principle, this under-utilized capacity could effectively power a national fleet of PHEVs with little need to increase the energy delivery capacity of the existing grid infrastructure. Kintner-Meyer et al. (Kintner-Meyer et al., 2007) indicated that existing electric power generation plants would be used at full capacity for most hours of the day to support up to 84% of the nation's cars, pickup trucks and SUVs for a daily drive of 33 miles on average. However, the assumption does not consider that PHEV users will most likely charge their vehicles when convenient, rather than waiting for power grid off-peak periods. For example, drivers will plug in for recharging their PHEVs in early evening when they return home from work.

In recent years, it has been recognized that the need to increase the electric capacity for large PHEV acceptance by consumers can be mitigated by several factors including market penetration and distribution of the PHEVs, and the vehicle charging time. A number of studies have modeled the impact of different scales of PHEV market penetration on the power grid (Denholm and Short, 2006; Lemoine et al., 2007; Parks et al., 2007). Hadley and Tsvetkova (Hadley and Tsvetkova, 2009) indicated that most regions would need to build additional generation capacity to meet the added electric demand when PHEVs are charged in the evening. Lilienthal and Brown (Lilienthal and Brown, 2007) showed that uncontrolled charging strategy of PHEVs would place increased pressure on power grid. No additional generation capacity would be required for a large penetration of PHEVs only when all charging cycles start in the off-peak periods. Lemoine et al. (Lemoine et al., 2007) also mentioned that the system generation requirements were calculated for 1, 5, and 10 million PHEVs charging from the

California grid, assuming an effective charging rate of 1Kw. Letendre and Watts (Letendre and Watts, 2009) have looked at the charging loads of three different PHEV penetration rates (i.e., 50k, 100k, and 200k) and three different charging scenarios such as uncontrolled charging, delayed charging, and off-peak charging.

Most current research is focused on PHEV charging load impacts on state and regional electric grids based on total electric generation capacity level. The PHEV charging loads are computed based on different charging strategies that the future PHEV fleet may adopt. By aggregating all PHEVs' charging consumption and comparing the result with the total state or regional electric grid's maximum, the researchers can validate if there is sufficient electric capacity for assumed PHEV penetration rate. However, those research efforts have made the assumption that newly purchased PHEVs in the future will be evenly distributed across residential areas and ignores the possibility of imbalanced PHEV penetration in different residential areas. Practically speaking, since the PHEV penetration rate has a correlation with household demographic attributes such as income, travel distance, age, household member, education and neighborhood effect, the variation of these household demographic attributes in different residential areas may generate different PHEV penetration rate patterns. In this case, if a region with the total electric generation and power grid capacity are under-utilized and too many consumers on a given circuit recharge their plug-in vehicles simultaneously, it could increase peak electric demand locally and require utilities to upgrade the electric distribution infrastructure.

Understanding the impact of the PHEV fleet on electric line congestion, transformer overloads and other unforeseen problems with the electric distribution network at the local residential level and estimating potential "PHEV hot zones" are challenges faced by today's utilities system. These residential distribution networks will experience the new load as a significant impact even if PHEV acceptance is small in the beginning. 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. At the substation levels, the demands are less aggregated. As a result, the electrical grid substations are more sensitive to the usage patterns of a few customers. Understanding the future potential "PHEV hot zones" and estimating the "PHEV hot zones'" impact on local electric distribution network can help utilities manage the timing of recharging demand to maximize load factors and utilization of existing distribution resources.

To evaluate the impact on the local electric distribution network, it is necessary to estimate several factors including the distribution of PHEVs, owner driving behavior and charging pattern at the individual household level. The objective of this research is to develop an agent-based framework for 1) modeling spatial distribution of PHEV household adoption in residential areas, 2) evaluating the impacts of PHEVs charging load on a residential electric distribution network with different charging strategies, and 3) discovering "PHEV hot zones" where PHEV ownership may quickly increase in the near future. We use Knox County, TN as a case study to show the simulation results of the proposed agent-based model (ABM) framework. However, the framework can be easily applied to any other local area in the U.S. The framework use multi agent-based simulation to produce possible global outcomes (the PHEV distribution and PHEV charge load) given sets of assumptions of how individual agents decide about adoption of new technology for their future vehicle and charge pattern for their PHEV. The simulation results from this framework may help utilities to prioritize investments given electric load growth projections.

This paper is organized as follows: Section 2 describes the agent-based PHEV household adoption model for estimating PHEV ownership distribution in local residential areas. Section 3 discusses synthetic household data generated at the block groups level and household locating process and how the data are used for estimating individual household's PHEV choice behavior. Section 4 presents the agent-based simulation platform for modeling the households in the Knox County and the PHEV ownership. This section also discusses the imbalanced PHEV ownership distribution and the existing of local PHEV hot zones. Section 5 deals with the potential PHEV charging impact because of the imbalanced PHEV ownership distribution in the local area. Section 6 discusses the model verification and validation and final conclusions are given in Section 7.

2. PHEV ownership distribution model

Existing PHEV adoption models and market penetration models provide an estimate of future PHEV market share and percentage of total vehicle at the national level. There are no published research efforts that can provide a PHEV ownership distribution model at the local residential household level. To understand the PHEV charging load impact on a local residential distribution network, it is necessary to build a PHEV ownership distribution model at the local household level. The PHEV ownership distribution pattern of a residential community is a group phenomena determined by the choice behavior of individual households for new vehicle selection. Since different demographic attributes of individual household can affect the household PHEV purchase decision, the probability of an individual household to choose PHEV as their next new vehicle may be different. There is a research needed to build a PHEV ownership distribution model at the macro level from the individual household's PHEV choice at local level.

A growing realization across the social sciences is that one of the best ways to build useful theories of group phenomena is to create computational models of social units (e.g., individuals, households, firms, or nations) and their interactions, and observe the global structures produced by their interactions. ABM and its computer simulation of human behavioral and social phenomena is a successful and rapidly growing interdisciplinary area. The ABM is a new approach that aims to model the complex social macro dynamic behaviors emerging from the interactions of autonomous and interdependent individual actors. ABM builds 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 (Bonabeau, 2002).

Like many other social phenomena, PHEV household adoption or ownership distribution has a spatial-temporal dimension and involves dynamic decisions made by individuals. Our research effort uses an agent-based model to combine household demographic information in Knox County, TN with nationwide vehicles sale, cost and energy cost prediction data from U.S. Energy Information Administration (EIA)'s Annual Energy Outlook (AEO) 2010 report (DOE, 2005) for generating the possible PHEV ownership distribution in Knox County households for the time period of 2011 – 2020.

The model offers deeper understanding of how various factors at the household level shape PHEV distribution and charging patterns in electric distribution network.

In the ABM simulation approach, the households are not treated in the same manner when choosing their new vehicle. Each household will have different tastes and preferences in terms of performance, energy efficiency, price, cargo space or seating available, etc. In general, the ABM model offers a simplified representation of reality by attempting to capture the most important elements of the phenomenon under study. We use a few simple, theory-based 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, government policies, etc. In the agent-based household PHEV ownership distribution model, we have integrated the ORNL consumer choice model (Lin and Greene, 2010), University of Michigan's UMTRI model (Sullivan et al., 2009) for estimating the time when consumer start searching for a new car and a new stigmergy-based neighborhood effect model (Cui et al., 2009) for estimating the probability of consumer's selection for different PHEV.

The ORNL model is used for estimating the consumer's vehicle choice probability based on consumer's attributes, the cost and performance of the vehicle, gasoline and other energy cost, and the government policies. The core of the ORNL model is the Nested Multinomial Logit (NMNL) module that estimates the users' choice probability on 13 different kinds of advanced vehicle technology. In the ORNL model, the U.S. market is divided into 1458 market segments and the total market share of different 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 – 2020. Since our interest is estimating the ownership distribution of different kinds of PHEV and their impact on local community power supply, we used four different categories to represent the domain of advanced vehicles consumer can choose from (i.e., PHEV-10, PHEV-20, PHEV-40 and others, which include HEV 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.

$$p_{ij} = \frac{e^{\sum_A \beta_{ja} x_{ja}}}{\sum_k e^{\sum_A \beta_{ka} x_{ka}}} \qquad \sum_j p_{ij} = 1 \tag{1}$$

where,

i: the household index

j: the vehicle index

k: the index of all other vehicles

a: the index of observed household and vehicle attributes

A: the total household attributes that have correlation with the probability of consumer's decision for choosing vehicle j

x_a : the attributes of household and vehicle

β : the parameter determining the impact fact of the different vehicle attributes to consumer's choosing.

On the other hand, the consumer transportation budgets serve a major role in UMTRI model 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. Consumer transportation budgets are comprised of fixed and variable terms as follows:

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

where,
C1: the monthly vehicle payment
C2: the monthly fuel cost
C3: the vehicle maintenance cost.

In our agent-based household PHEV ownership distribution 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.

The additional model we added for consumer vehicle choosing model is "neighborhood effect". Recent research (Eppstein et al., 2010; Sullivan et al., 2009) has 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. In bio-inspired computing area, the "neighborhood effect" has been explored for decades and a different term "stigmergy" is used. The stigmergy term was first proposed by Pierre-Paul Grasse in the 1950s in conjunction with his research on termites (Cui et al., 2009). The concept of stigmergy provides a theory for explaining how individual's behavior or contribution causes indirect effects on other adjacent individual behavior. Because of space limitations, please refer to (Cui et al., 2009) for detail. The mathematical equation we used for numerically computing the individual behavior or contribution is described in Equations (3), (4), and (5).

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

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

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

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 Equation (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 Equation (4). Equation (5) describes the vehicle d's probability ρ_d of being chosen. N is the total number of forum threads. The constants F and K are used to tune the consumer's vehicle selection behaviors.

The agent in this ABM represents individual households that have different attributes. 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 to buy what kind of PHEV. If each agent household is geo-located, the global behavior about the community PHEV ownership distribution can be generated from the interaction and independent decision of individual agents in the simulation.

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 first level of guaranty for the simulation to generate useful results. Without some degree of accurate input data, no model can generate predictive results that can be used to support decision making. 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, due to high survey costs, low response rate and privacy concerns, detailed household and personal characteristics and their location are usually unavailable. 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) (ACS, 2010), Census Summary Files 3 (SF3) (U.S.CensusBureau, 2003), Census Transportation Planning Products (CTPP) (U.S.DOT, 2011) and LandScan USA (Bhaduri et al., 2002).

In the next section, we will briefly describe a copula-based household synthesizer and microscopic location process that are designed to preserve the inter-variable dependence structure among survey samples and place the synthetic households in the specific location, respectively. The synthesized households generated from our research results in the same local SF3 statistics at each block group while having similar inter-variable correlations as described in the PUMS and are distributed in the study area.

3. Synthetic household characteristics and locating process

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 will be allocating local household data for the simulation. In this paper, the virtual Knox County households are generated from our unique 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 while having similar inter-variable correlations as observed in the PUMS and distributed throughout the study area by integrating LandScan USA.

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). Therefore, the summary information is deemed the most accurate public demographic statistics. In this paper, the copula-based virtual households are derived from PUMS and then locally fitted to SF3 summaries.

Figure 1 shows the study area (Knox County, TN) with 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:

X_1: Household total income in 1999 (HINC, units in \$).

X_2: Number of household member (PERSONS)

X_3: Number of workers (WIF)

X_4: Number of vehicles (VEHICLE)

X_5: Household highest educational attainment (EDUCmax, unit in Census education attainment index), derived from individual records.

X_6: Household total travel time to work (TRVTIMEsum, unit in munites), derived from individual records.

Since the household is assumed to be the decision-making unit for PHEV 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 found in (Spissu et al., 2009). The marginal distributions $u_j = F_{X_j}(x_j)$, $j = 1,...,6$ are derived by non-parametric kernel density functions, in which the discrete-continuous transformation is considered for PERSON, WIF, VEHICLE, and EDUCmax. The correlation matrix Σ is computed by Spearman's r, and then corrected for formatting issues (tolerance ε set to be 0.002). The Gaussian copulas $C_{U_1,...,U_d}$ are then used to synthesize virtual households.

Figure 1 Illustration of 3 PUMAs and 234 BGs in the Knox County.

At the local level, SF3 summaries for each BGs are collected and treated as constraints. However, it should be noted that not every variable has a corresponding local summary and some variables have different universes (HINC and PERSONS: total households, WIF: total families and VEHICLE: total occupied housing units). In order to avoid making extraneous assumptions, we only take HINC and PERSONS summaries as the two local constraints in this case study. Following the local fitting procedures, virtual households are assigned for each BGs.

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 (90m) population distribution data with LandScan USA.

In brief, this study went through empirical cumulative distribution function (ECDF) to synthesize the individual travel times and assigned them to individual block groups based on the proportion of number of workers residing in each block groups of the corresponding census track. After identifying LandScan USA points and night time population associated with individual block groups, workers are given specified map coordinates and combined to form a household in a compliance with the synthetic household demographic information like number of workers in a household with a constraint that the derived number of workers cannot be over the night time population. Figure 2 illustrates the Knox County virtual household distribution. Each dot in the Figure 2 represents virtual synthetic households generated through copula-based synthetic population reconstruction approach and household locating process. Further discussion of the copula-based population synthesizer and locating process will be provided in authors' other papers.

Figure 2 Knox County virtual household distribution.

4. The ABM simulation platform

There are many widely used platforms for ABM simulation: MASON, NetLogo, Repast, and Swarm. We used the NetLogo (Tisue, 2004) multi-agent simulation tool to develop our model primarily because it is freely available on the web, well documented and supported. 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. The NetLogo virtual world consists of a grid of 'patches', each of which can have a state and agents having only local knowledge about their surroundings. Both agents and patches are active agents in the simulation, performing actions and asking other agents to perform other actions. The simulation proceeds by each agent and patch repeating its behavior independently, often by following stochastic functions influenced by the agent's state and local environment. Agents perform their own actions asynchronously and as rapidly as they can. In an agent-based simulation, the overall behavior of the system is an emerging property of the individual, independent interactions of the agents.

Figure 3 depicts the proposed household PHEV distribution simulation platform. 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 PHEV. There are total 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 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, the mileage, etc.) are updated each simulation period (1 calendar month).

Figure 3 Household PHEV distribution simulation.

5. Experimental design and results

5.1 PHEV ownership distribution in census block groups

We used the two scenarios, Base Case and FreedomCARGoals Case defined in (Lin and Greene, 2010), to illustrate the different household PHEV distributions in the Knox County. The same energy prices are used in the two cases. We used the output of (Lin and Greene, 2010) for PHEV distribution model calibration to confirm that the proposed model generates similar total estimated PHEV sales each year from 2011 to 2020. We aggregated the individual household PHEV based on the census block group (i.e., 234 BGs in the Knox County) in which individual households are located. By using PHEV 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 PHEV distribution in the local community and discovering the "PHEV hot zone" (defined as the highest PHEV ownership concentration), we aggregated the individual household PHEV based on the BGs in which individual households are located. The estimated distribution of the PHEV in Knox County for the year of 2020 based on two different scenarios can be shown in Figure 4. Although there are 4 choices each household can make (PHEV-10, PHEV-20, PHEV-40, and Others), since our major concern is how many PHEV ownership in the area, we only display the distribution of the PHEV ownership in Figure 4. The height of the bars in different BGs represents the total number of PHEVs in the corresponding BGs. The longer the bar is, the more PHEVs are in the corresponding BGs. As shown in Figure 4, the FreedomCARGoals scenario will have a higher PHEV market penetration than Base Case. However, both have very similar PHEV 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 noticed that the number of PHEV-40 ownership within Base Scenario is higher than PHEV-40 number within 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 PHEV-10 instead of PHEV-40 which is more expensive than PHEV-10.

(a) Base Scenario
(b) FreedomCARGoals Scenario
Figure 4 PHEV distributions for Basic and FreedomCARGoals scenarios (2020).

5.2 PHEV impact on local electric distribution network

By using the PHEV residence ownership distribution result for the FreedomCARGoals Scenario generated from above experiment, we are able to conduct preliminary analysis of the PHEV battery charge load impact on local electric distribution network. According to our simulation output, the total PHEVs within FreedomCARGoals Scenario will reach 8,192 in 2020 in the Knox County. The most often used method for estimating the impact of the PHEV on the power grid is the worst case scenario, implying that all PHEVs will plug in simultaneously for battery charging during the grid peak time. If each PHEV will consume 1.45Kw during its battery charging, the peak load for all PHEVs in Knox County will be 11,878Kw. However, in most cases, because different PHEV drivers will have different travel patterns and charge time schedules, the maximum possible total load pattern for uncontrolled evening charging will be similar to Figure 5. In 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 total 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. Three different types of PHEV (i.e., PHEV-10, PHEV-20 and PHEV-40) need to be charged from 2 to 6 continuous hours, respectively.

The census block groups 46, 57, 58 and 62, out of total 234 BGs in Knox County, have the highest estimated PHEV ownership distribution in the FreedomCARGoals Scenario. The total PHEVs in these four BGs are 2,670. According to our simulation output, the evening peak charging load for these four BGs can reach 3,625Kw, which is 32.6% of total PHEV charging load generated by the PHEV fleet in the Knox County. These BGs can be considered as the "PHEV hot zones" which could increase peak demand locally and require utilities to upgrade the electric distribution infrastructure in the near future.

Figure 5 The charging load for uncontrolled PHEV charging system.

6. Model validation discussion

This paper proposed an agent-based framework for simulating local community household PHEV distribution and electric network impact. Several models are used in this framework. All models need to be validated before it can be accepted and used to support decision making. Because of the heterogeneity of the agents and the possibility of new patterns of macro behavior emerging as a result of agent interactions at the micro level, model validation in agent-based complex social systems is different from the traditional validation (Axtell et al., 1996; Fagiolo et al., 2007; IEEE, 1998; Midgley et al., 2007; Moss, 2008; Moss and Edmonds, 2005). For this research, we are conducting two additional stages of model validation, corresponding to the two levels at which agent-based models exhibit behavior: the micro level and the macro level. The first stage is the micro-validation of the behavior of the individual agents in the proposed model. In the simulation, agents are simplified and general representations, not replications of specific human individuals. The simplicity and generality reduces the ambiguity of any analysis of their behavior and social interaction at the cost of losing expressiveness relative to qualitative studies of observed actors. The only behavior we implemented in the agent is vehicle choice behavior model adopted from existing publication which has been partially validated. The synthetic household data employed by the proposed simulation framework to generate estimated results has proven to have the same local SF3 statistics at each block group while having similar inter-variable correlations as described in the PUMS.

The second stage is macro-validation of the model's aggregate or emerging behavior when individual agents interact. We will compare the macro results of our agent-based model results with mathematical model results by using method addressed in (Bankes, 1993; Macal and North, 2005; Sargent, 2005). There already exist many mathematical models for estimating the PHEV market penetration at the national level. These provide for comparison of the result from our model with the result from these mathematical models. However, our framework mainly focuses on estimating the probability of a local community's PHEV penetration rate instead of national level. Our next research goal will be applying our agent-based framework to every county in the country and simulating the household PHEV distribution of these counties. Aggregation of the results will be the national level PHEV penetration and can be used for direct comparison with the results of mathematical models (Moss and Edmonds, 2005).

7. Conclusions

In this paper, we have presented an agent-based simulation framework for modeling the spatial distribution of PHEV ownership in a local residential area and evaluating 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 different residential areas may generate different PHEV 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.

Estimating the future PHEV ownership distribution in the residential area can help us understand the impact of a PHEV fleet on electric line congestions, transformer overloads and other unforeseen problems at the local residential distribution network level. It can also help utilities manage the timing of recharging demand to maximize load factors and utilization of existing distribution resources. The current simulation is purely based on statistical data for estimating the adoption rate of the PHEV. Our next step will integrate this simulation with power systems simulations and a transportation simulation to study the impacts.

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