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Quantifying the Economic Value of Vehicle-Grid Integration: A Case Study of Dynamic Pricing in the Sacramento Municipal Utility District

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Abstract

This study develops a stochastic-systems approach in modeling vehicle-grid integration (VGI), where load management strategies can be compared in terms of their economic value to plug-in electric vehicle (PEV) consumers and their local utility companies. The proposed methodology is demonstrated in an assessment of VGI for the Sacramento Municipal Utility District (SMUD) in California. Monte-Carlo simulations have been performed to randomly assign PEV charging characteristics of the households based on given statistical distributions. Consumer adoption of time-of-use (TOU) rates is modeled as an optimization problem where consumers seek the earliest PEV charge start time among the charge schedules resulting lowest cost and satisfying their transportation needs. The preliminary results show that, considering today's grid system, the deployment of 60,000 PEVs in Sacramento Region will have significant but manageable impacts. These impacts included increasing annual peak demand by 86MWs (%5), and overloading up to 101 neighborhood transformers in the distribution system. On the other hand, adopting proper TOU rates presents a high potential for minimizing these negative impacts of widespread PEV deployment on the grid. The proposed methodology provided several improvements to the VGI modeling literature. These improvements included combining assessments for generation and distribution systems in the same model, and advancing uncertainty analysis for the PEV consumer behavior with considering real-world data sets.

Keywords: Plug-in Electric Vehicles; Vehicle-Grid Integration; Stochastic Systems Modeling; Monte-Carlo Simulations.

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I. INTRODUCTION

Since early 2009, energy planners in California have been considering vehicle-grid integration (VGI) as a potential solution for mitigating negative grid impacts of charging PEVs and integrating intermittent renewables, and improving the economics of PEV adoption. Although these perceived benefits exist, our previous study (Bedir et al., 2015) showed that the PEV-grid stakeholders face difficulties in quantifying potential value from VGI. The complexities related to VGI modeling exist because of the limited available data in the early PEV market, and uncertainties related to consumer behavior, wholesale electricity markets, and utility grid operations. This situation creates a major barrier toward developing a policy framework for VGI.

Several methodologies have been introduced in the scientific literature to evaluate VGI, focusing on the PEV load management mechanisms. These mechanisms included dynamic pricing, demand response, and energy storage (vehicle-to-grid). The proposed methodologies in the literature aimed to address grid impacts of the PEVs considering a particular geographic region, and focusing on a specific grid operation. As discussed by Green et al. (2011), however, these studies did not adequately consider variances and uncertainties in consumer behavior and electricity market conditions. They also usually ignored PEV impacts on the distribution system with a higher interest in wholesale-level grid operations. These two issues remain a gap in the literature that needs to be addressed.

To address the problems mentioned above, this study introduces a stochastic methodology for quantifying technical and economical impacts of VGI. The most basic form of load management, time-of-use (TOU) pricing, is considered in evaluating the impact of the PEV load on various hourly electricity demand curves and distribution networks. The proposed model is demonstrated in the Sacramento Region, where a mid-size utility company currently provides TOU rates for PEV consumers. This study considered a widespread PEV adoption scenario where 60,000 PEVs are deployed in the region, and all of these PEVs are used as commuter vehicles during the weekdays only.

The stochastic variables such as PEV charging levels (kW), commuter daily energy needs (KWh), and daily home arrival and departure hours are randomly assigned to the PEV households based on given statistical distributions. The Monte-Carlo simulations are repeated until the variances among the output data become minimal. For dynamic pricing scenarios, consumer adoption of the load management is presented as an optimization problem. It is assumed that each PEV consumer adopt the most economical charging schedule based on the electricity rates and their individual transportation needs. The major datasets in the model included the following; (1) projected PEV charging levels from Sacramento Municipal Utility District (Berkheimer et al., 2013) varying from 1.4kW to 19.2 kW, (2) commuter daily vehicle-miles traveled (VMT) from US Census (2013), (3) daily home arrival/departure hours (11am to 8pm) from Sacramento Area Council of Government (SACOG, 2012), and (4) SMUD's annual hourly total electricity demand data from Federal Energy Regulatory Commission (FERC, 2013).

The findings are expected to help stakeholders to evaluate grid capacity constraints on handling widespread PEV adoption, and the effectiveness of load management mechanisms. The outputs of the model include PEV impacts on the seasonal load curve, annual peak demand, and distribution system loading. These outputs are chosen as the focus of the model for several reasons. Most importantly, the PEV load impacts on the annual-peak electricity demand have always been a concern for energy planners (see Leo et al. (2011) for the discussion). The maximum capacities for the grid components, including generation, transmission and distribution systems, are being set and, if necessary, upgraded based on the changes in annual-peak electricity demand. This event usually occurs during mid-summer heat waves for the Sacramento Region.

The distribution system has been another concern for widespread PEV deployment, especially in single-unit residential areas. In these areas, the distribution transformers are designed to deliver electricity for a limited number of households. Some studies (e.g. Moghe et al. (2011)) illustrated that if several households located in the same neighborhood charge their PEVs at the same time, this situation might cause reliability problems and require infrastructure upgrades. The proposed method aims to capture such potential PEV clusters in the distribution system through Monte-Carlo simulations.

The following section provides an analysis of the literature related to PEV-grid systems modeling. This analysis focused on a group of 16 selected studies that were conducted within the last ten years. The proposed modeling methodology is discussed in detail in Section-3, including assumptions and data gathering. In Section-4, the simulation results are presented in three topics including PEV load impacts on the seasonal load curves, PEV load impacts on the distribution transformers and, finally, the economic assessment of VGI. The results are compared for different load management scenarios. The findings from the analysis are summarized and discussed in Section-5.

II. LITERATURE REVIEW

The scientific studies related to VGI can be classified as system-level or device-level analysis. As discussed by Sovacool and Hirsh (2009) and Galus et al (2010), improvements to both technology and system are critically important for the successful implementation of VGI. The technological improvements refer to the efficiency and reliability developments in the hardware, including advanced PEV chargers and telemetry systems. On the other hand, system-level improvements are related to addressing economic, behavioral, and infrastructural challenges. The focus of this literature review is to present and compare scientific studies related to system-level assessments on VGI.

The studies on VGI modeling aimed to address the impacts of various numbers of PEVs in a particular grid region, and focused on a specific grid operation. Most of the studies also evaluated how a particular load management mechanism would perform for the chosen PEV-grid system. In this review, the literature is categorized based on their focus of grid operations. These grid operations include (1) wholesale electricity markets, (2) economic dispatch of the generation, and, finally, (3) distribution system overloading. In the following paragraphs, the strength and weaknesses of the relevant studies on VGI will be discussed in detail.

The studies related to wholesale electricity markets focused on estimating market value of PEV demand response and energy storage (V2G). The wholesale markets mostly included frequency regulation and reserve markets. These studies often introduced a direct load control (DLC) algorithm, and modeled their algorithms as complex optimization models. The main focus has been evaluating performance of a DLC algorithm, which could be potentially implemented as a demand response or V2G program in the market. For instance, Kempton et al. (2008), Quinn et al. (2010), Andersson et al. (2010), Pillai-Bak Gensen (2011), and Han et al (2011) evaluated the value of V2G for participating in both regulation and reserve markets for different regions of the US and EU. On the other hand, Sortomme and El-Sharkawi (2011) and Bessa et al (2013) investigated the value of PEV demand response for the reserve markets only. Sortomme and El-Sharkawi (2011) considered a scenario where 10,000 commuter PEVs participate in reserve markets during the daytime from 8am to 5pm. The authors used historical market data from Bonneville Power Administration. Similarly, Bessa et al. (2013) considered a scenario where 3000 PEVs participate in the Iberian electricity market during 2011-2013.

These VGI modeling studies on electricity markets present two common, major weaknesses. First, they use the historical market data and ignore the fact that the market participation of a large fleet of PEVs can greatly reduce the market value of regulation and reserves. For instance, Quinn et al (2010) considered 96,000 PEVs in their analysis. Such an amount of PEVs may saturate the regulation market in a real-world scenario and decrease the market value significantly. The second major weakness that is observed in these studies is the primitive representation of consumer behavior. These studies usually ignored the variances and uncertainties related to consumers' PEV charging hours and charging levels. They considered a "typical" PEV battery and commuter travel hours and presented their results as single-point estimates.

The second group of studies on VGI modeling concern the VGI impacts on the electricity generation dispatch. These studies usually formulate an optimization problem regarding the economic dispatch of resources, considering a particular generation mix. These studies present some major advantages. They have the ability to calculate greenhouse gas (GHG) emissions that would result from PEV charging. For instance, Lund and Kempton (2008), Axsen et al. (2011), Dallinger (2012), Sohnen (2013), and Kim and Rahimi (2014) evaluated GHG impacts of PEV charging in different regions. Additionally, some models (e.g. Lund and Kempton (2008), Dallinger (2012), and Sohnen (2013)) evaluated how PEV charging would coincide with renewable electricity generation. Although these studies present advantages over GHG emission calculations and renewable integration assessments, they usually ignore the complexities involved in demand response and energy storage. These studies present a scenario-based assessment approach, where all, or a certain percentage, of PEV consumers adopt a particular charging schedule at the same time. By assuming the existence of a central control mechanism over the electricity generation, these studies also ignored external impacts on the economic dispatch of the resources (e.g. wholesale market conditions).

Finally, studies on the distribution systems focus on the impacts of PEV charging on the distribution infrastructure such as substation transformers, neighborhood transformers, feeders, and underground cables. For instance, Soares et al. (2010), Moghe et al. (2011), and Shao et al (2012) evaluated impacts of PEV loads over the distribution systems. These studies usually present the highest level of stochastic analysis among the VGI modeling efforts. Because of the limited market data on PEV adoptions, the researchers in this field used Monte-Carlo simulations to randomly assign PEV locations in a chosen distribution system. Each study looked at different levels of the distribution infrastructure for different technical impacts such as system loading patterns, voltage drops, power losses, and aging of the infrastructure. Besides their advantages from stochastic modeling and detail-oriented approach to infrastructure assessment, they only evaluated very small regions compared to the other two groups mentioned previously. The details on the PEV deployment scenarios and focus of the analysis for each study are presented in Table-1.

As seen on Table-1, the studies related to VGI modeling usually focus on either the generation or distribution side of the grid. In contrast to the literature, the proposed methodology aims to evaluate both sides, considering variances and uncertainties in consumer behavior, for each analysis. Additionally, the economic assessment in the proposed model does not focus on the VGI value in wholesale markets (regulation or reserves). It rather focuses on the VGI value in terms of cost-effectiveness measures. These measures include avoided costs of energy procurement, losses, and infrastructure upgrades for the utility company compared to no VGI scenario with the same amount of PEVs. In Table-1, DLC refers to the studies including direct load control programs where a control algorithm is modeled as an optimization problem for the each PEV driver. These studies aim to capture behavioral aspects of the PEV drivers, which differ significantly from the studies with scenario-based load management models where the PEV drivers are represented as one fleet with average PEV driving and charging patterns.

Table-1: Summary of PEV-grid systems modeling literature

VGI Modeling Study	PEV Deployment Rate or Number	Region or Market	Load Management Scenario	Stochastic Inputs
Studies on Electricity Market Value for PEVs				
Sortomme and El-Sharkawi (2011)	10,000 (commuter-only)	Bonneville Power Admin.	Demand response: DLC*	None
Bessa et al. (2013)	3000	Iberian Electricity Market (2009-2011)	Demand response: DLC	PEV locations, battery size
Kempton et al. (2008)	100 and 300	PJM (2004-2006)	V2G: Scenario-based	None
Quinn et al. (2010)	96,000	CAISO (2006-2008)	V2G: DLC	None
Andersson et al. (2010)	500	Sweden & Germany (2008)	V2G: DLC	None
Pillai and Bak-Gensen (2011)	9000 and 18,000	Western Denmark	V2G: Scenario-based	None
Han et al. (2011)	1000	PJM (2004)	V2G: DLC	Charge levels
VGI Studies on Generation Dispatch and GHG Impacts				
Lund and Kempton (2008)	1.9 million	Denmark	V2G: Scenario-based	None
Axsen et al. (2011)	1 million (3.6% of LDV fleet)	CAISO	Demand response: Scenario-based	None
Dallinger (2012)	12 million	Germany (2030)	V2G: DLC	Energy needs
Sohnen (2013)	1 million (4.5% of Households)	CAISO	Demand response: Scenario-based	None
Kim and Rahimi (2014)	1 to 160 million	Los Angeles, CA (2012-2040)	Demand response: Scenario-based	None
VGI Studies on Distribution Systems				
Soares et al. (2010)	25% and 50% of LDVs	Flores Island	Unmanaged charging	PEV locations, charge levels, battery size
Moghe et al. (2011)	10% to 100% of LDVs	Phoenix and Seattle (selected areas)	Demand response: Scenario-based	PEV locations
Shao et al. (2012)	100	Blacksburg, VA (Virginia Tech)	Demand response: DLC	PEV locations, energy needs, charge duration

* "DLC" stands for direct load control where a control algorithm is modeled as an optimization problem for the each PEV driver.

3. SYSTEM DESIGN AND DATA GATHERING

As has been discussed in the previous section, deterministic modeling approaches to VGI requires over-specifying many assumptions in the system, and ignore the variances and uncertainties in real-world conditions and consumer behavior. On the other hand, the stochastic approach acknowledges random patterns of some input parameters in the system, and features a range of outputs considering this randomness (Kulkarni, 2009). In this study, the proposed VGI model is designed based on two major stochastic processes. These processes are PEV-related electricity consumption of households, and PEV locations on neighborhood transformers. The following figure (Figure-1) presents the system inputs, outputs, and scenarios. As seen on Figure-1, the two major outputs resulting from the proposed analysis are (1) total hourly electricity consumption profiles for the region, and (2) numbers of overloaded neighborhood transformers in the grid system related to the additional load from PEV charging.

On the other hand, these outputs are expected to vary depending on the hourly electricity rates. The rates (TOU scenarios) included in this study are; (1) business-as-usual (BAU) scenario where the general fixed price is provided to PEV household, (2) HH-TOU scenario, which is an opt-in TOU rate that is currently being provided to households regardless of owning a PEV, (3) PEV HH-TOU scenario, which is a TOU rate that is being offered for households owning a PEV, and (4) PEV-TOU, which is a TOU rate offered for only PEV charging through a separate utility meter (see Figure-5 for the details). At the time of this study, PEV owner households in SMUD territory were offered these four rate options.

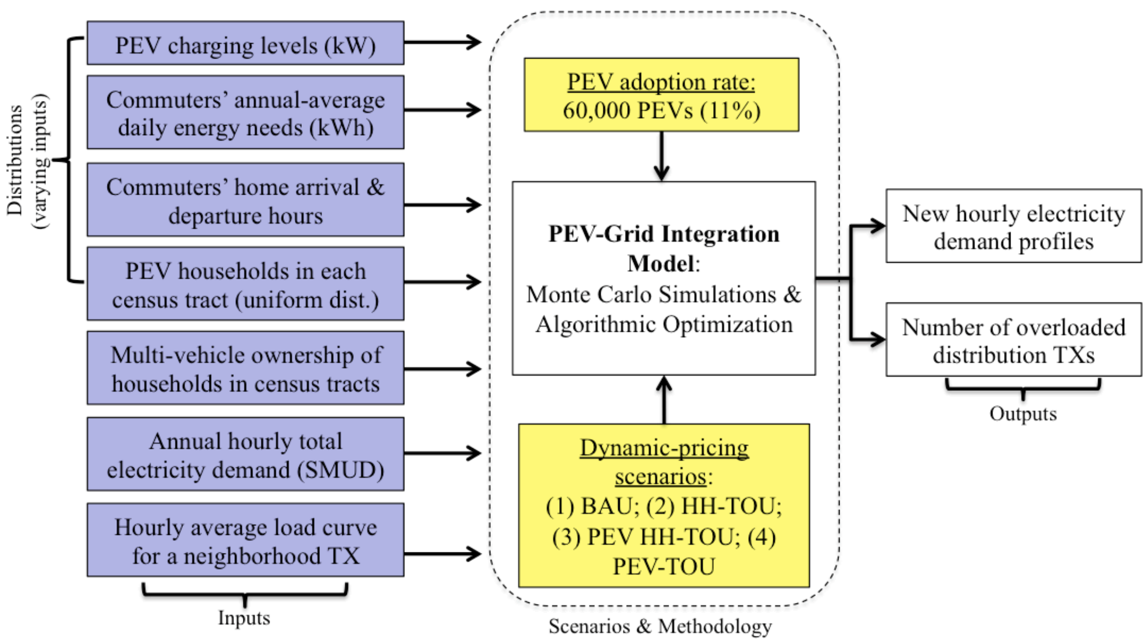

Figure-1: The conceptual design for the proposed PEV-grid systems model (note: "TX" stands for transformer; "HH" stands for households)

The prosed model requires data gathering for seven input parameters from transportation and electricity sectors. These datasets are mostly related to commuters' travel hours, daily vehicle-miles traveled (VMT), power levels of their PEV charging, and regional characteristics of household vehicle ownership. Each of these datasets will be discussed further in the following part (3.1). Collaborating with these inputs, the proposed model calculates household-level electricity consumption for the 60,000 PEV owner households for a 24-hr weekday period. In TOU rate scenarios, the calculations for household-level electricity consumptions are repeated for different electricity prices where individual PEV owners choose the cheapest PEV charging option that does not interfere with their daily transportation needs. The origins of the reference value for PEV deployment and electricity pricing scenarios for PEV load management will be discussed in the following part (3.1) in detail.

As seen in Figure-1, four of the input datasets are clustered as being *distributions*, including commuters' PEV charging levels, home arrival & departure hours, and daily energy needs. These inputs represent probability distributions independently varying for the each household in the system. The values for each varying-input are assigned to individual PEV households randomly based on the given statistical distributions. This task is achieved by a method called inverse transformation (or Smirnov transform) (Kroese et al., 2011). As the first step in this process, the proposed model generated sample numbers for the varying-inputs and assigned these numbers to each household. At the end, the distribution of values for 60,000 households becomes equivalent to the given statistical distribution.

The process of random number generation is repeated 1000 times for the each household in so-called Monte-Carlo simulations. The Monte-Carlo simulations can provide useful insights in evaluating how different combinations of the independently varying-inputs effect the final outcome (Kroese et al., 2011). Besides the varying inputs, Monte-Carlo simulations are also used for the distribution system analysis in the random assignment of PEVs to individual households. The use of the Monte-Carlo simulations will be described further in the following paragraphs.

3.1 System Inputs

PEV Deployment. In this study, the reference value for PEV deployment is chosen as 60,000 PEVs in the Sacramento County. This amount corresponds to the state of California's 1.5 million PEV deployment goal, and is adjusted based on the ratio of number of households to local utility in Sacramento County (4% of the California households are located in Sacramento County).

The amount of 60,000 PEVs corresponds to 11.5% of the adoption rate (11% of households) considering all households, or 17.9% considering only single-family housing units in the Sacramento County (US Census, 2013). The proposed model considers the use of these PEVs for work-related travel only. This assumption may result in less energy consumption than in reality. However, the other assumption that all vehicles will be used in commuting may balance this decrease because not all vehicle owners drive to their workplace in their own car, but may carpool. For instance, about 80 % of the commuters in Sacramento Region, drive alone to their workplace (US Census, 2013).

PEV Charging Levels. In VGI modeling, the allocation of PEV charging levels is a very important factor that has temporal and spatial impacts on the results. In this study, a probability distribution for PEV charging levels is obtained from the electric transportation department at Sacramento Municipal Utility District. According to SMUD's projections (Berkheimer et al., 2013), the distribution of vehicles charging at Level-2 rates (>1.4 kW) will roughly double in a widespread PEV adoption scenario, relative to the time that SMUD conducted this projection. Such an assumption increases the share of 3.3 kW charging from 12% to 25%, and additionally, the share of 6.6 kW charging from 14% to 33% (Berkheimer et al., 2013). Although, the share of Level-1 charging has decreased compared to today's numbers, it still exists as the dominant charging level at 41% in SMUD's projections. The probability distribution for PEV charging levels are presented as histograms in Figure-2 along with other varying input parameters.

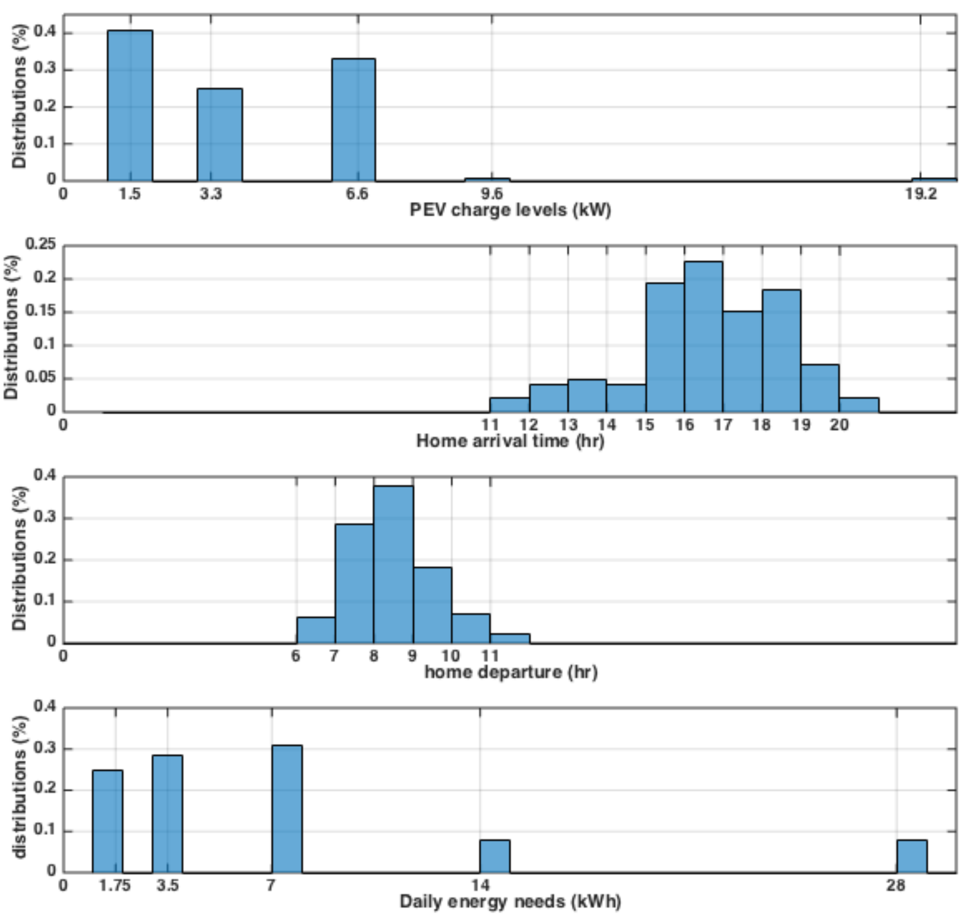

Figure-2: Statistical distributions of the varying inputs for Sacramento County

Home Arrival/Departure Hours. The distribution for commuters' home arrival hours is gathered from the regional air quality management district, Sacramento Council of Governments (SACOG), which conducts transportation-related surveys and planning work as a part of their air pollution assessments in the Sacramento County and surrounding areas. This dataset (SACOG, 2012) considers work-related and school-related travel data for the weekdays, which fits well within the focus of the proposed model. The time frame for commuter home arrivals is chosen between 11am to 8pm, ignoring the hours that correspond to less than 2% of the commuter arrivals in order to simplify calculations. As seen on Figure-2, the peak for home arrival hours rises at 4pm with 22%.

On the other hand, home departure hours are assumed to be directly linked to the home arrival hours in order to prevent any overlaps between home arrival and departure hours, which may exist if both are assigned to individual households randomly. In this regard, the commuters who arrive home early are assumed to be leaving home early. For instance, the commuters who arrive home between 11am and 12pm are assumed to have left home at 6am. The overall calculated distribution of home arrivals correlates to 92% in the actual survey data. The home departure hours are limited between 6am to 11am. Such an assumption ignores only the departure hours that correspond to less than 2% of the commuter departures in the actual survey data. According to this distribution, the peak for home departure hours is 37% and occurs at 8am.

Commuters' Daily Energy Needs. The distribution for daily energy needs is calculated based on the daily commuter vehicle-miles traveled (VMT) data. This data is gathered from the Origin-Destination Employment Statistics under Longitudinal Employer-Household Dynamics (US Census, 2014). The VMT distributions range from 5 miles to 80 miles daily, being most frequent at 20 miles at 31%. Such distribution corresponds to a mean value of 19.2 miles, which is slightly lower than the overall daily VMT average for the Sacramento region. Finally, these VMT values are converted to daily energy needs by using a 35kWh per 100 miles conversion ratio as suggested by Berkheimer et al. (2013) in their VGI study. As seen on Figure-2, according to this conversion the daily energy needs for commuters range between 1.75 kWh and 28 kWh.

The input parameters explained above are all related to the household-level electricity consumption, which only take temporal considerations into account. However, the following two parameters will be related to the distribution system impacts of the PEV load, which have both temporal and spatial dimensions. Among the distribution system components, neighborhood transformers at single-family residential areas have been the focus in this study. Our previous research (Bedir et al., 2015) showed that utilities are mostly concerned with the potential PEV clusters in single-family neighborhoods. In these areas, transformers and related-cabling have much more limited capacity compared to transformers in multi-unit dwelling or commercial areas.

Household Vehicle Ownership. A recent study by Tal and Nicholas (2013) found that the multi-vehicle ownership, high-income levels, detached house ownership, and single vehicle commuting are all very common attributes within growing PEV market. Following this information, it is assumed that the single-family households having two or more vehicles will be most likely to adopt a PEV once PEVs reach a significant market share. A tract-level household vehicle ownership data is gathered from the 2013

American Community Survey. This data on multi-vehicle ownership for each census tract correlates 74% with the number of high-income households, and 91% with the number of households with single driver commuters. These values support the usability of household multi-vehicle ownership data to project future PEV locations in a particular territory.

The census tract-level vehicle ownership data is used for the initial spread of the PEVs in the census tracts. The second spread of PEVs is performed for the households under the same census tracts following a uniform distribution. Therefore, it is assumed that the households within the same census tract have the same likelihood for adopting a PEV. The uniform spread of the PEVs to the households is repeated through Monte-Carlo simulations. The impact on the distribution system can be evaluated for both the average and marginal cases. It is expected that PEV clusters will be observed within some of these random simulations at the high-value side of the results (see Section 4.2 for the details). As seen in Figure-3, for 317 census tracts, the numbers of households having two or more vehicles range between 0 and 2664, with a mean of 875 and a total of 277,283 (σ= 458). When PEVs are spread onto the census tracts based on the rates of multi-vehicle ownership, the numbers of PEV owner households range from 0 to 576, with a mean of 189 and a total of 60,000 (σ= 99).

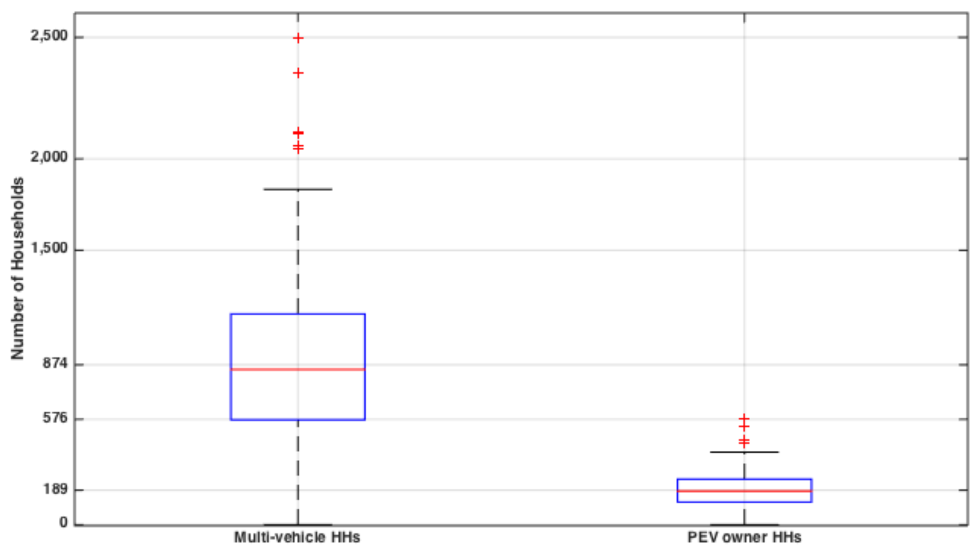

Figure-3 Box and whisker plots for the numbers of multi-vehicle owner households (HHs) and estimated PEV owner households per census tract for 317 census tracts in Sacramento Region

Loading Characteristics of Neighborhood Transformers. It is assumed that the neighborhood transformers reach their maximum utilization rate during the annual peak demand, which happens on July-3 considering the electricity demand data from 2013 in SMUD territory (FERC, 2013). An assessment of PEV impacts on neighborhood transformers requires two major data. These data include (1) the numbers of households that are connected to one neighborhood transformer in the distribution system that is being investigated, and (2) hourly load curve for an average neighborhood transformer during the annual peak day. On average, SMUD prefers to serve power to 10 households through one transformer, in which the typical capacity rating for a single residential transformer is 50 kVA (Berkheimer et al., 2013). Following this information, the single-unit households under each census tract are clustered randomly into groups of 10 to represent a neighborhood transformer. Some census tract does not include any single-unit households. Hence, the numbers of transformers range from 0 to 335 with a total of 33,413 and a mean of 105 (σ= 55).

The estimated load curve for a typical neighborhood transformer on the peak day is provided by SMUD as presented in Figure-4. Here, the hourly load values are calculated by averaging a representative sample of transformers in the system. As seen in the figure, the total power flow on a transformer reaches 27.5 kW between 5pm and 6pm, leaving about 22.5 kW spare capacity for PEV charging. This amount (hourly spare capacity or load tolerance) ranges from 22.5 kW during on-peak hours to 39.8 kW during off-peak hours. Considering the variances in the neighborhood level electricity consumption, the hour load values are assumed to fluctuate up to +/-%10 around the reference value for the each neighborhood transformer. In a given hour period, if the total PEV load on a transformer is higher than the spare capacity, then it is assumed that the transformer is overloaded and needs to be replaced with a higher capacity transformer The cost impacts of transformer replacement for SMUD is provided in Part 4.2.

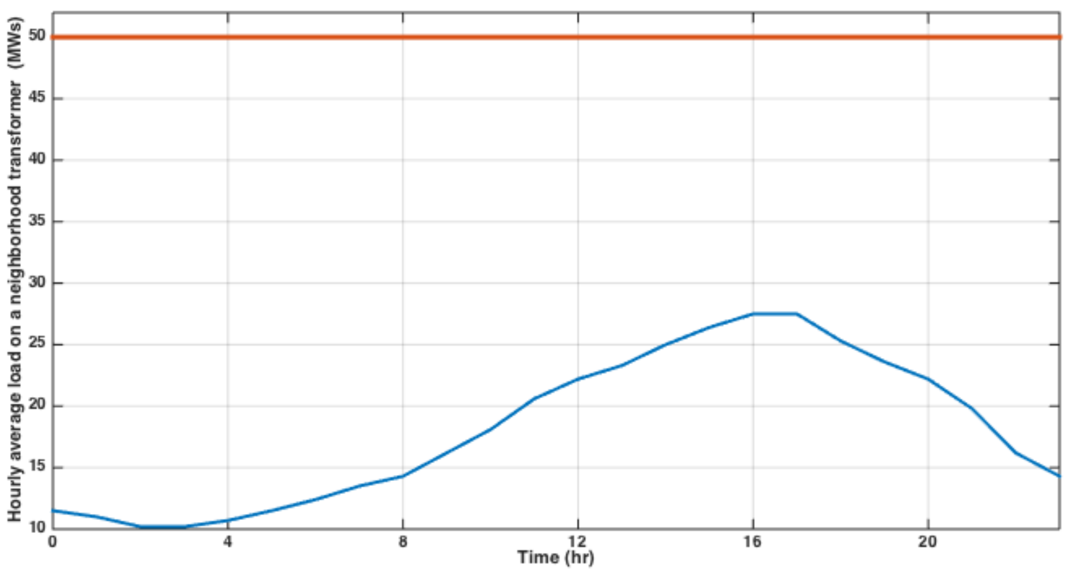

Figure-4 The hourly load curve (blue) and capacity (red) for a typical neighborhood transformer during the annual peak day in SMUD's territory in 2013 (data is gathered from Berkheimer et al. (2013))

3.2 Load Management Scenarios

The load management scenarios in this study include three types of TOU pricing mechanisms for PEV consumers. These mechanisms are all time-of-use (TOU) rates, with different rate schedules. These rates schedules are gathered from the utility company website as offered to PEV consumers within SMUD territory at the time of the study (Berkheimer et al., 2013). The potential PEV impacts on the grid system are investigated by comparing TOU scenarios to the business-as-usual (BAU) scenario where fixed rates were considered only. The three types of TOU rates included; (1) the regular household TOU (HH-TOU) rates which are offered to all customers, (2) PEV owner household TOU (PEV HH-TOU) rates which are offered to the households owning PEVs, and, finally, (3) PEV-only TOU (PEV-TOU) rates where the rates are offered for PEV charging only through a separate utility meter. As the target group is narrowed down, in options (2) and (3), the rates usually have higher on-peak rates and lower off-peak rates, which potentially make them more effective compared to regular HH-TOU rates.

These three TOU rates and the BAU scenario resulted in eight separate pricing scenarios because of the differences between winter and summer pricing for each case. Winter rates range from October 1 to May 31, where summer rates range from June 1 to September 30. On average, SMUD implements higher electricity rates during the summer because of the changes in the electricity consumption. As seen in Figure-5, the electricity demand profiles in the region changes significantly during summers. During winters, there is a slightly higher electricity demand between 6am-9am compared to the average. On the other hand, the electricity consumption increases significantly during summers starting early in the afternoon until 9pm. This increase, which peaks between 5pm and 6pm, happens due to the air conditioner loads during hot and dry summers in the region. These significant changes in electricity demand profiles, and also the wholesale market conditions in summer, result in higher electricity prices accordingly.

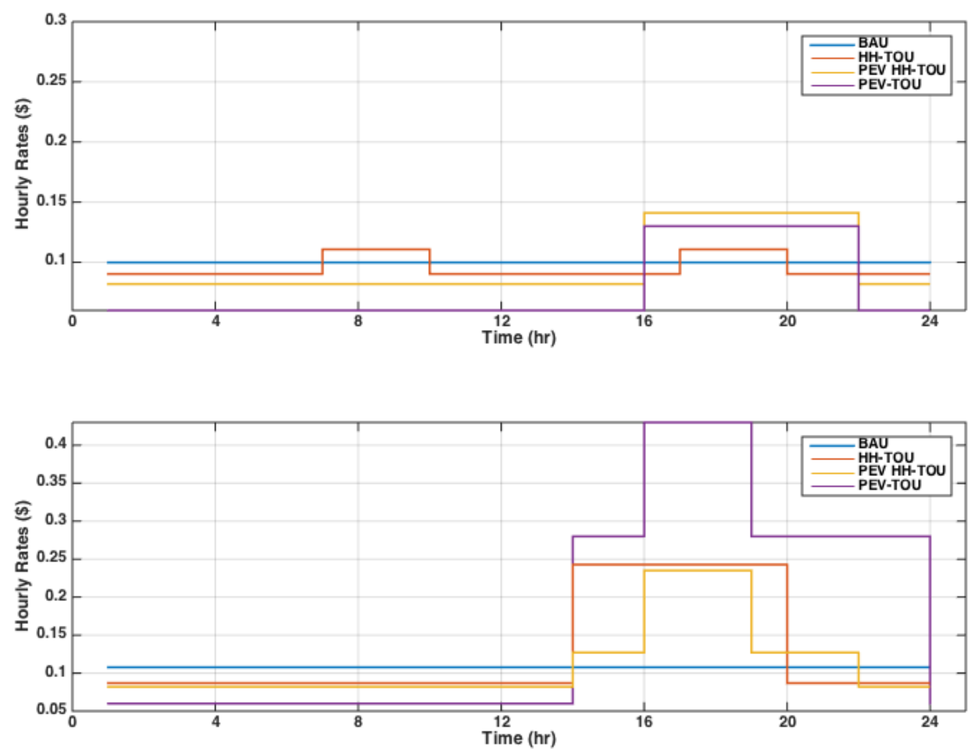

Figure-5 Hourly seasonal electricity rates for winter and summer rate schedules, respectively (source: smud.org)

The seasonal electricity prices for different TOU scenarios are presented in Figure-5. During winters, the HH-TOU rates reflect the morning and evening peaks. On the other hand, the evening peak is extended (4pm-10pm) and morning peak is ignored for simplicity in PEV HH-TOU and PEV-TOU rates. During the summer, the afternoon peak period starts at 2pm for all TOU rates, and in one case (PEV-TOU), the higher prices continue until mid-night.

3.3 PEV Consumers' Optimization Problem

To evaluate the maximum potential value in VGI, the proposed optimization model represents a case where all PEV consumers "optimally" respond to TOU rates when offered. They choose the earliest PEV charge start time among the options which result in lowest charging costs (the time required for PEV charging does not change). Depending on the energy needs, charging level, and commute hours, some PEV consumers may not have any flexibility in their PEV charge start time while others may have many options. This optimization scenario is chosen to present the maximum potential behavioral change that can be reached in total from a particular load management mechanism. A conceptual representation of the PEV consumers' optimization problem is presented in Figure-6. As seen on the figure, PEV buyers' decide on the "charge start time" considering their individual constraints regarding commute hours and daily energy needs. The individual optimization problems in dynamic pricing scenarios are solved for each of the 60,000 PEV commuters in each of the 1000 Monte-Carlo simulations. The outcomes from these simulations will be discussed in detail in the following section.

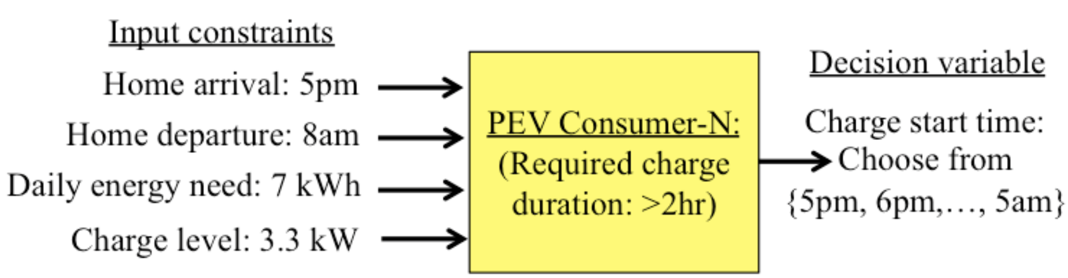

Figure-6: An example of the PEV consumers' optimization problem for the given inputs

4. RESULTS

In this part of the paper, the proposed VGI assessment methodology is applied, and the results are presented for the case of the Sacramento Region. The results are categorized under the PEV load impacts and the economic assessment of VGI. PEV load impacts included the changes in the seasonal electricity demand profiles for the utility region, and the PEV load impacts on the distribution system loading. The changes in the electricity demand profile may have especially important implications for grid operations such as economic dispatch of the generation, and required ancillary grid services. These potential changes will be discussed. The economic assessment has been conducted by using the hourly cost/benefit estimates for potential electricity savings (per MW/hr) provided by the E3 Cost-Effectiveness Calculator. This tool was developed by Energy, Environment, and Economics (E3) to evaluate cost-effectiveness of load management programs. The content and details of the model will be discussed further in part 4.3.

4.1 PEV Impacts on the Electricity Demand

The initial results (shown in Figures 7-8) include the hourly total PEV load for the BAU scenario where PEV consumers start PEV charging as soon as they arrive home. This simulation is repeated 1000 times. The variance among the results has been very low. For instance, the peak PEV demand, which occurs at 6pm, varied between 85 MW to 88 MW, with a mean of 86 MW. A 3MW change would be difficult to notice in SMUD's total load curve, considering its annual average peak in 2013 was 1578 MW. The variance among the simulation results is investigated by the coefficient of variation, which is the ratio of the standard deviation to the mean. In applied statistics, the variance among the datasets is seen as small if the coefficient of variance is smaller than one (<1). Overall, the average coefficient of variation for the 24hr load data is found to be 0.0207. As seen on Figure-7a, variance is very stable after the 25^{th} simulation, approaching 0.015. This low variance can be also observed in the PEV load curves in Figure-7b. Considering this low variance in the hourly PEV load, only the mean values are presented in the following analysis in Part 4.1.

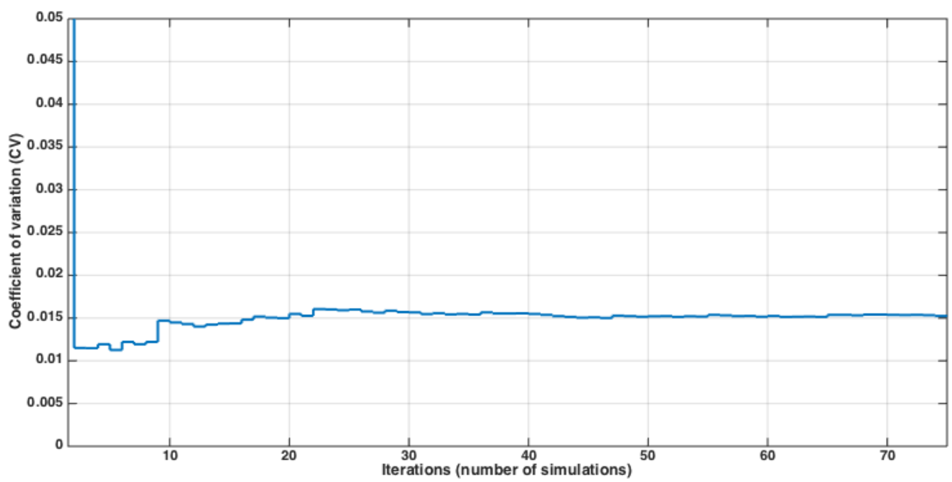

Figure-7a. The changes in coefficient of variation among the results on hourly PEV loads, BAU case.

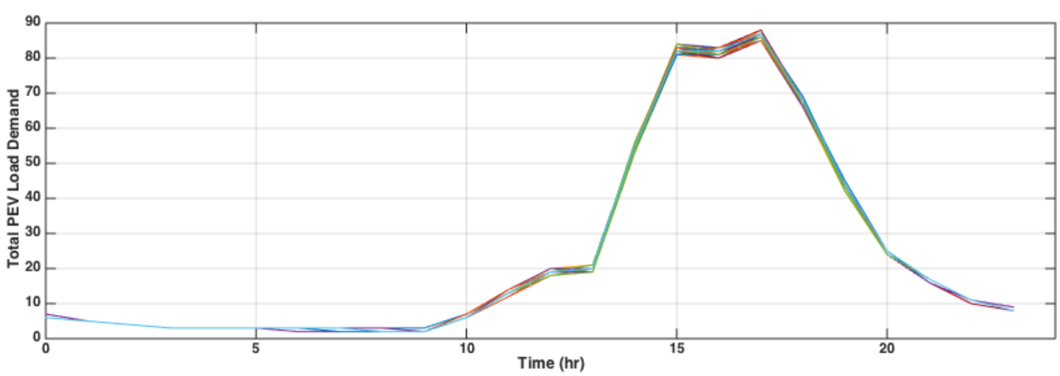

Figure-7b. The total electricity load from 60,000 PEVs repeated 1000 times. BAU case.

The total PEV charging load is added to SMUD's seasonal electricity demand curve in the following chart (Figure-8). As expected, the hourly PEV load pattern has not been changed between summer and winter in the BAU scenario. The PEV impact becomes more significant (above 50MW) between 3pm and 8pm in both seasons. This additional PEV load increased the winter peak by 68 MWs, where summer peak is increased by 86MW. This increase is observed due to summer peak overlaps where the peak for PEV load is at 6pm. As discussed previously, the increase in summer peak has always been a concern for electricity planners. Such peaks risk grid reliability, increase high amount of investments for the capacity increases in generation and distribution systems. Therefore, the peak shaving ability of load management mechanisms is expected to be an important factor in the assessment of their success.

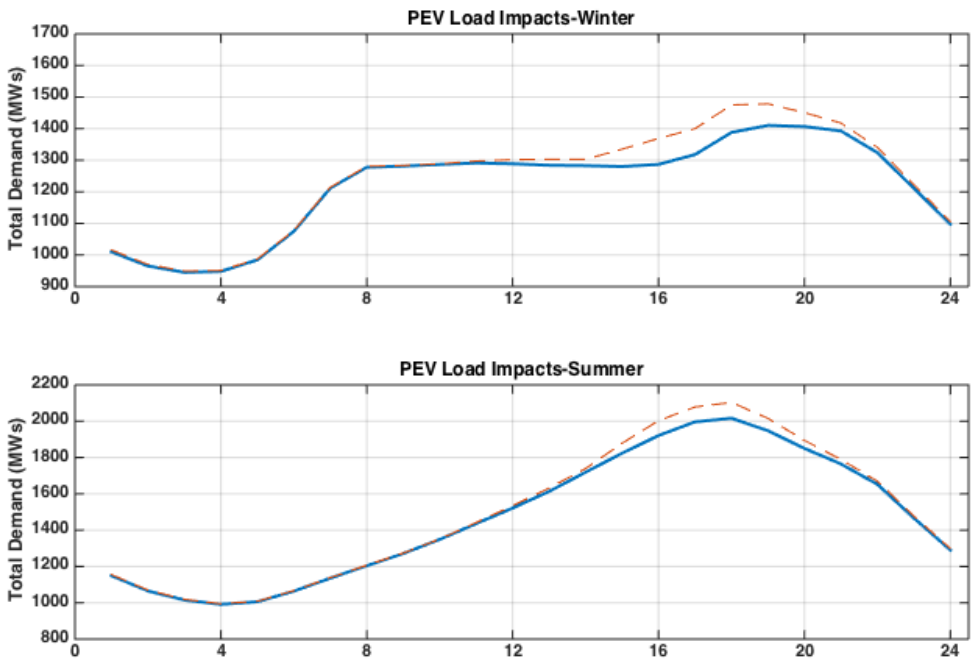

Figure-8. The estimated PEV load added to the SMUD's total electricity demand from 2013, BAU case.

The total PEV load for TOU scenarios are calculated for summer and winter seasons. As seen in Figure-9, TOU rates successfully shifted additional load from the peak hour to later hours, relative to the BAU scenario. However, there is 3MW of load that could not be shifted for both winter and summer peaks because of those commuters who do not have any flexibility on their PEV charging time. These results show that only about 3.5% of the peak increase resulting from PEVs cannot be shifted to off-peak hours by the TOU rates. On the other hand, all of these three TOU rates created different smaller peaks on the system. The additional peak in winter season has been around 143 MW at 8pm for HH-TOU rate, and 178 MW at 10pm for PEV HH-TOU and PEV-TOU rates. Although the scenario (3) and (4) resulted higher peak compare to scenario (1), this higher peak occurred after 10pm. Therefore, it is expected to be more manageable for the utility company. The results on the peak PEV loads have been slightly different in the summer.

All of the TOU rates resulted in the same amount of peak (209 MW) occurring at different times of the day. For instance, PEV-TOU created 209 MW peak at 12am, which resulted in most of the PEV charging happening at night, between 12am-5am.

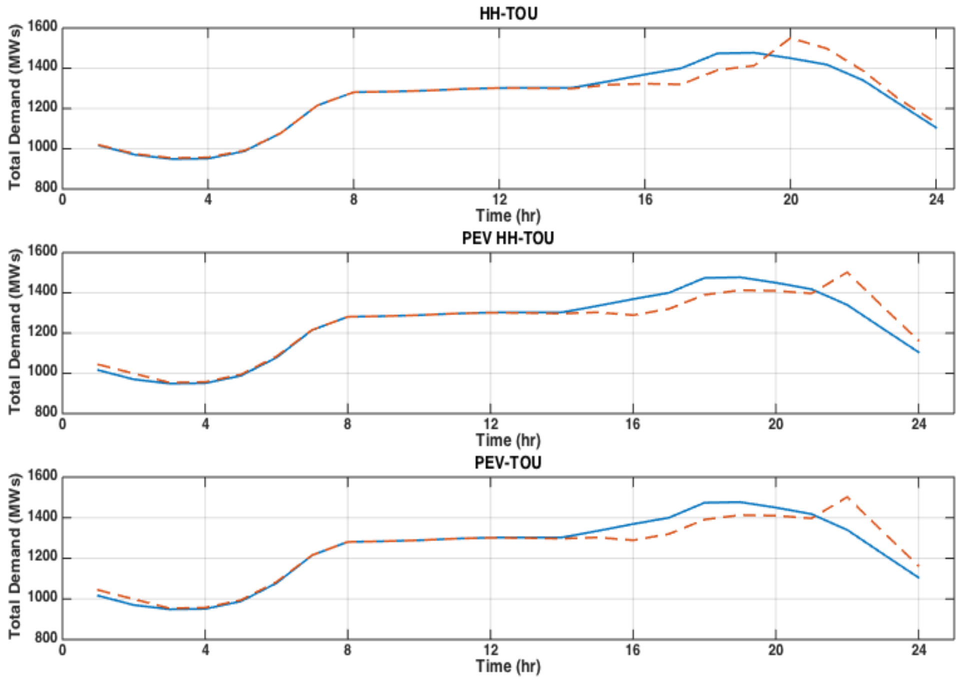

Figure-9a. The impacts of dynamic pricing of PEVs on the SMUD's total electricity demand for Winter-2013. TOU cases (blue: BAU case without TOU rates)

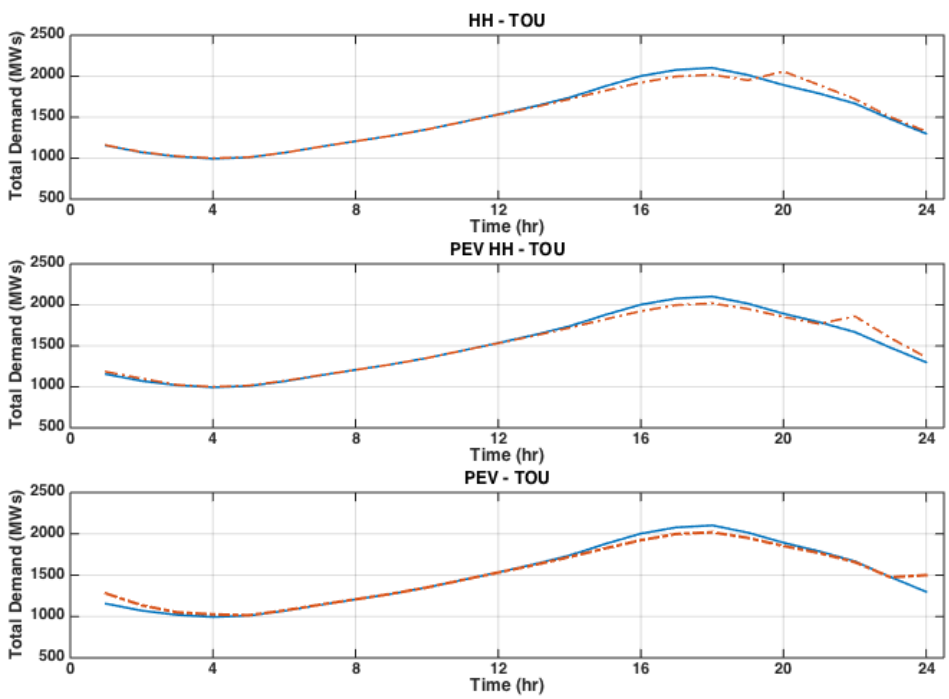

Figure-9b. The impacts of dynamic pricing of PEVs on the SMUD's total electricity demand for Summer-2013, TOU cases (blue: BAU case without TOU rates)

4.2 PEV Impacts on the Distribution System

As discussed previously, PEVs are expected to impact the distribution system loading, especially during the annual peak day. Based on the 2013 data, the annual peak demand occurred in SMUD on July 9th at 6pm. The potential impact of PEVs on the distribution system is evaluated through the random assignment of PEVs to the households for each census tract (see Part 3.1 for the details). To capture the variations among the neighborhood-level electricity consumption, it is assumed that the spare capacity for each neighborhood transformer fluctuates up to +/-10% around the average hourly spare capacity. This assumption is made based on Jardini et al. (2000)'s study, which shows that the hourly electricity consumption levels may vary around %10 among the households.

In contrast to the previous simulations (in Part 4.1), the results for PEV impacts on the distribution system varied significantly. For instance, for the BAU scenario, it is estimated that between 42 to 101 distribution transformers (out of a total of 33,413) will be overloaded due to the PEV charging (σ= 9.3). As the proposed method considered a uniform distribution for the PEV spread, this variance occurred very naturally. The results with higher amounts of transformer overloads represent the cases in which the PEVs clustered in the same neighborhood more frequently compared to the average result. Based on this outcome, we can conclude that at least 42 distribution transformers will be overloaded in BAU cases, where this amount can reach up to 101 transformers if these PEV adoptions tend to cluster within the same neighborhoods. The comparison of results from TOU rate scenarios is provided in Figure-10.

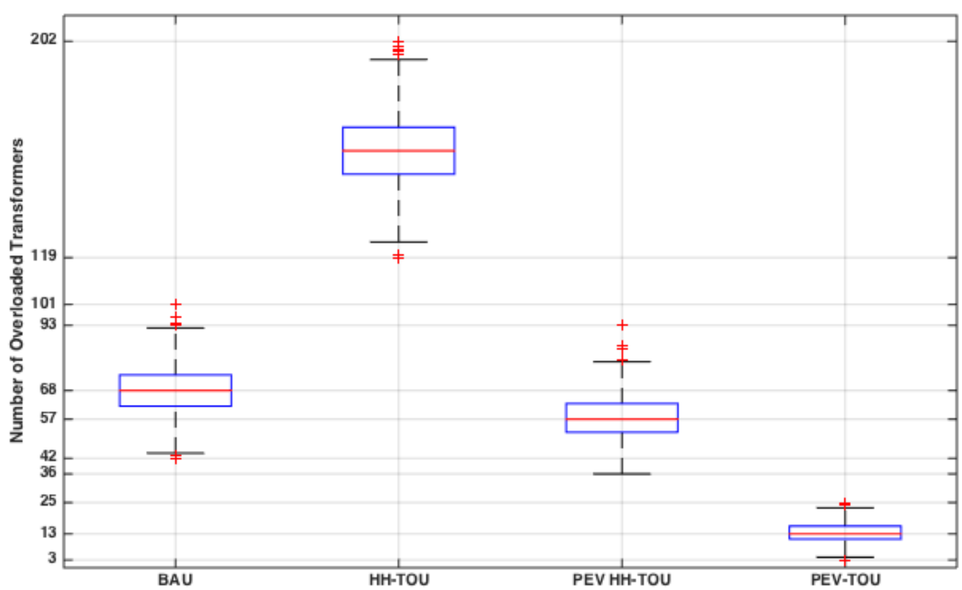

Figure-10 Box and whisker plots for the estimated transformer overloads in 1000 simulations with and without considering TOU rates

The findings above show that the dynamic pricing strategies may not necessarily benefit the distribution system. For instance, HH-TOU rates actually created a worse situation in terms of distribution system loading. The additional PEV load of 209 MW at 8pm increased transformer overloading potential from 101 to 202. On the other hand, PEV-HH-TOU rates resulted slightly lower amounts of overloaded transformers, comparing 93 to 101.

Finally, PEV-TOU resulted in the best outcome for reducing distribution system impacts of PEV charging. The maximum amount of transformer overloading is reduced to 25. Although, PEV-TOU provided the best outcome in terms of transformer system loading, it may not be the most cost-effective solution considering the additional infrastructure requirements due to the use of a separate PEV metering system. The economics of the PEV metering systems will be discussed in the following analysis.

4.3 Economic Assessment of VGI

The economic assessment of VGI is performed considering two aspects of PEV impacts: (1) the additional hourly load created by PEV charging and (2) the number of overloaded transformers resulting from this additional load. For utility companies, the hourly cost of the additional electricity delivered to the PEV households has several components. These components may include; (1) the cost of energy (generated by existing power plants only), (2) the cost of increased generation capacity required to supply the additional electricity, (3) the cost of ancillary grid services such as frequency regulation, (4) the cost of additional CO2 emissions, and (5) the cost of energy losses that occurred within the transmission and distribution (T&D) systems (E3, 2014). All of these costs are very much time dependent and change hourly based on the seasonal weather conditions, local climate, and grid system loading conditions.

This study used the annual hourly-avoided cost estimates provided by a model called *E3 Calculator*. The E3 Calculator is a spreadsheet model that provides an estimate on the hourly cost of increased electricity demand considering various components of the electricity delivery described above (Horii and Cutter, 2011). This tool was originally developed to model the avoided costs of energy saved in the energy efficiency programs as requested by CPUC. The three largest utilities in California are required to perform an economic assessment for their energy efficiency related programs, including demand response and energy storage, by using the hourly cost estimates provided by the E3 Calculator (CPUC, 2013). In the proposed analysis, the cost estimates for 2013 data within the Z12 climate zone is gathered from this software. A distribution of monthly average energy generation and delivery costs is presented in Figure-11.

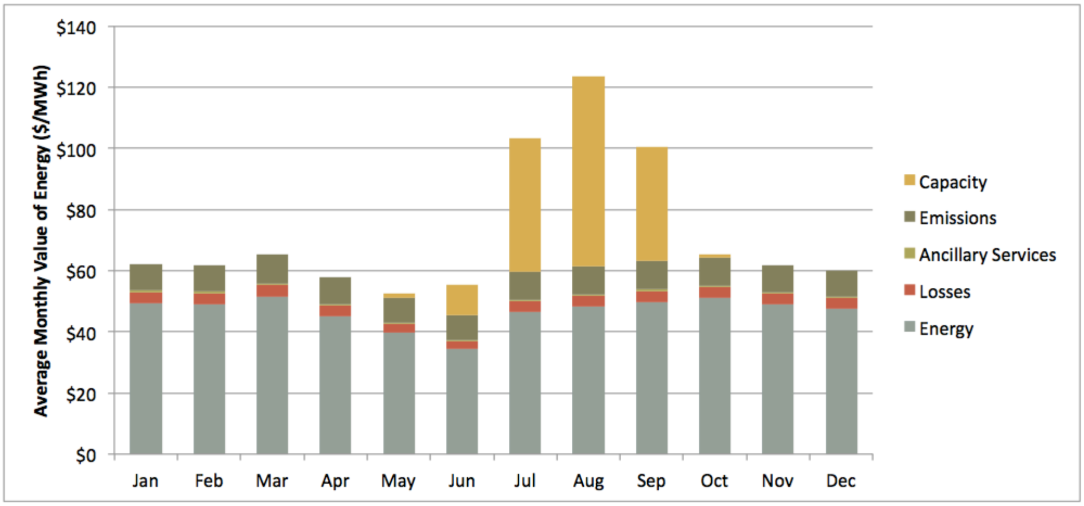

Figure-11. Monthly average estimates of the value of saved electricity (per MWh) to an electricity provider located in Z12 climate zone in 2013 (E3, 2011)

As seen in Figure-11, the majority of the cost of the additional electricity demand occurs due to the cost of energy (generation). The second largest component of this cost is the capacity cost, which is estimated based on the historical data of investment decisions by the electricity providers in California and so-called *resource adequacy values* (see Horii and Cutter (2011) for the details). This cost becomes very significant between July and September. Due to this increase, the cost of delivering additional electricity per MW exceeds $120. This amount stays under $60 during April to June. The third most significant cost is the environmental cost due to CO2 produced by the power stations. This cost seems to be very consistent, and is more dependent on the hour of the day than the month of the year.

The hourly costs of additional electricity load due to PEV charging are calculated based on the hourly cost estimates from the E3 calculator. Only the weekdays are considered due to the assumption that PEVs are used for commute purposes only. The results are provided in Table-2 for BAU and TOU scenarios. The annual cost of $100,000 for the PEV-related program administration is added to PEV HH-TOU and PEV-TOU. According to this assessment, PEV-TOU provided the least cost option. The cost of PEV-related electricity delivery is reduced to about $9 million from $17 million in the BAU scenario. PEV-TOU, however, did not provide the highest value due to the significant decreases in expected revenues from electricity delivery. In this regard, PEV HH-TOU provided the highest value for the utility company, a net profit of $3,838,536. Finally, the BAU scenario resulted in a net loss of $216,658 for the utility company occurring annually.

Table-2 Annual cost and benefit estimates for each TOU rate scenarios

	BAU (reference)	HH-TOU	PEV HH-TOU	PEV-TOU
Total Annual Cost	$17,389,040	$11,409,565	$10,168,485	$9,801,648
Energy	$9,669,550	$8,170,908	$7,111,418	$6,767,068
Losses	$787,993	$562,470	$457,312	$436,300
Ancillary Services	$127,837	$78,402	$43,713	$42,542
Environmental (CO2)	$2,255,451	$1,955,862	$1,814,628	$1,805,501
Capacity Increase	$4,548,210	$641,923	$641,415	$650,237
PEV Program Admin	N/A	N/A	$100,000	$100,000
Total Revenue	$17,172,382	$15,076,355	$14,014,198	$11,158,139
Net Annual Profit (Utility)	-$216,658	$3,666,790	$3,845,713	$1,356,490
Net Annual Savings* (Utility)	N/A	$5,979,475	$7,220,555	$7,587,392
Average Annual Cost of PEV Charging	$286.21	$251.27	$233.57	$185.97
Net Annual Savings (All PEVs)	N/A	$2,096,028	$3,158,184	$6,014,244
Net Annual Savings (per PEV)	N/A	$35	$53	$100

* "Net annual savings" are the savings relative to BAU scenario

The PEV consumers' savings is also provided in Table-2. The BAU scenario resulted in an annual cost of $286 for the commuting-related electricity consumption. This amount is reduced to $233 in PEV HH-TOU and $185 in the PEV-TOU scenario. Although, PEV-TOU provided the lowest-cost electricity option for the PEV consumers, the additional metering system cost is expected to be significant. The current utility practices for separate utility meters require an additional electricity panel in the household, which may cost about $2000 for the PEV buyer. Because of the limited market data on PEV metering systems, this study did not included the cost of PEV metering or telemetry systems in the economic analysis. It is expected that this cost will be impacted significantly by the utility policy developments such as enabling submetering systems for utility billing.

Finally, the cost of distribution upgrades are calculated and provided here as one-time occurring direct costs. The average cost of a transformer replacement is provided by SMUD as $7,691 (E3, 2014). Based on this value, the range in cost of transformer upgrades in the BAU scenario is found to be $334,362 to $804,062. This amount decreased as little as $23,883 in the PEV-TOU scenario. Although a mid-size utility company can easily manage such a one-time occurring cost, the transformer overloading is seen as a serious problem because of the risk factors involved. If a transformer is overloaded unexpectedly, such a situation may result in temporary blackouts for the entire neighborhood, which may impact both the PEV experience and the utility reputation negatively. Therefore, utility notifications of the PEV deployment and the PEV-related load tracking are valued as a critical aspect of VGI.

Table-3. Estimated costs for the distribution infrastructure upgrades related to PEV charging under various TOU rate scenarios

	BAU (reference)	HH-TOU	PEV HH-TOU	PEV-TOU
Estimated Cost Range	\$ 334,362-\$804,061	\$ 947,359-\$1,608,122	\$ 286,596-\$740,373	\$ 23,883-\$199,025
Average Cost	\$541,348	\$1,273,760	\$453,777	\$103,493
Cost Savings (Relative to BAU)	N/A	-\$732,412	\$87,571	\$437,855

The economic assessment above provided several cost and revenue estimates for the utility company and cost estimates for PEV consumers. This assessment can be expanded into a time-series analysis, where a comprehensive net-present value (NPV) analysis is performed considering several policy and market developments in the field. Additionally, the integration of residential solar panels into the model would provide more accurate values for both the consumers and the utility. These potential improvements on the model are left for future work.

5. CONCLUSIONS

This study introduces a stochastic methodology for quantifying technical and economical impacts of VGI. The most basic form of load management, dynamic pricing, is considered in evaluating the impact of the PEV load on various hourly electricity demand curves and distribution networks. The proposed model is demonstrated in the Sacramento Region, where a mid-size utility company currently provides dynamic pricing programs for PEV consumers. The findings bring contributions on both, the methods for PEV-grid systems modeling, and the case study of evaluating PEV deployment for the Sacramento Region.

In terms of the methodological improvements, the proposed model provided an assessment for both generation and distribution systems, which is different than the studies mentioned in the literature review. Expanding the focus of the VGI analysis to both systems provided a more comprehensive picture on understanding PEV impacts. Additionally, the proposed methodology considered variances and uncertainties related to consumer behavior in higher detail. The varying-inputs related to consumer behavior included PEV charging levels, daily energy needs, home arrival/departure hours, and PEV locations (households).

The preliminary results show that, considering today's grid system, the deployment of 60,000 PEVs in Sacramento Region will have a significant but manageable impact on the utility grid operations. These impacts include increasing annual peak demand, and overloading distribution transformers, while having a very small impact on the total annual energy use. Providing dynamic-pricing signals to PEV drivers, however, may minimize these impacts depending on the rate schedules. Although, all TOU rates minimized the increases in peak demand, they did not necessarily mitigate negative impacts of PEV charging on the distribution system. This issue is highly dependent on the details of the rate schedule. Among the three TOU scenarios, the special TOU rate for

PEV owner households (PEV HH-TOU) resulted in the highest economic value for the utility company.

The economic assessment in this study provided several cost and revenue estimates for the utility company and the PEV consumers. This assessment can be expanded into a time-series analysis, where a comprehensive net-present value (NPV) analysis is performed considering several policy and market developments in the field. Additionally, the integration of residential solar PV can be considered. These potential improvements on the model are left for future work.

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REFERENCES

Andersson, S. L., Elofsson, A. K., Galus, M. D., Goransson, L., Karlsson, S., Johnsson, F., & Andersson, G. (2010). Plug-in hybrid electric vehicles as regulating power providers: Case studies of Sweden and Germany. Energy Policy, 38, 2751-2762.

Axsen, J., Kurani, K. S., McCarthy, R., and Yang, C., “Plug-in hybrid vehicle GHG impacts in California: Integrating consumer-informed recharge profiles with an electricity-dispatch model,” Energy Policy, vol. 39, pp. 1617-1629, 2011

Bedir, Abdulkadir, Mark Lubell, Joan M. Ogden, Thomas S. Turrentine (2015) Integrating Plug-in Electric Vehicles into the Grid: Policy Entrepreneurship in California. Institute of Transportation Studies, University of California, Davis, Research Report UCD-ITS-RR-15-23.

Berkheimer, J., Tang, J., Boyce, B., and Aswani, D., "Electric Grid Integration Costs for Plug-In Electric Vehicles," SAE Int. J. Alt. Power. 3(1):1-11, 2014, doi:10.4271/2014-01-0344.

Bessa, R. J., & Matos, M. A. (2013). Optimization models for EV aggregator participation in a manual reserve market. IEEE Transactions on Power Systems, 28(3), 3085-3095.

CPUC (2013). Energy Efficiency Policy Manual. From http://www.cpuc.ca.gov/NR/rdonlyres/E17D21C5-6A8B-4101-83B3-9AE4EC117D84/0/EEPolicyManualV5forPDF.pdf

Dallinger, D., (2012) Plug-in Electric Vehicles Integrating Fluctuating Renewable Electricity. Kassel University Press

E3 (2011) Cost-Effectiveness Calculator. From https://ethree.com/public_projects/cpuc4.php

E3 (2014). Transportation Electrification Assessment: Phase-2. From http://www.caletc.com/wp-content/uploads/2014/10/CalETC_TEA_Phase_2_Final_10-23-14.pdf

FERC (2013). Annual Electric Balancing Authority Area and Planning Area Report. From: http://www.ferc.gov/docs-filing/forms/form-714/overview.asp

Galus et al. (2010). On integration of plug-in hybrid electric vehicles into existing power system structures. From: http://www.sciencedirect.com/science/article/pii/S0301421510005070

Green et al. (2011). The impact of plug-in hybrid electric vehicles on distribution networks: A review and outlook. From: http://www.sciencedirect.com/science/article/pii/S1364032110002674

Han, S., Han, S., & Sezaki, K. (2011). Estimation of achievable power capacity from plug-in electric vehicles for V2G frequency regulation: Case studies for market participation. IEEE transactions on smart grid, 2(4), 632-641.

Horii and Cutter (2011). Energy Efficiency Avoided Cost 2011 Update. From: http://www.cpuc.ca.gov/NR/rdonlyres/18579E92-07BD-4F24-A9B4-04975E0E98F5/0/E3AvoidedCostBackground.pdf

Jardini, J.A.; Tahan, Carlos M.V.; Gouvea, M.R.; Se Un Ahn; Figueiredo, F.M., "Daily load profiles for residential, commercial and industrial low voltage consumers," in *Power Delivery, IEEE Transactions on* , vol.15, no.1, pp.375-380, Jan 2000
doi: 10.1109/61.847276

Kempton, W., Udo, V., Huber, K., Komara, K., Letendre, S., Baker, S., Pearre, N. (2008). A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system. Newark, DE: University of Delaware.

Kroese D. P., T. Taimre, Z.I. Botev (2011). Handbook of Monte Carlo Methods, Wiley Series in Probability and Statistics, John Wiley and Sons, New York.

Kulkarni (2009). Modeling and Analysis of Stochastic Systems, Second Edition, Chapman & Hall/CRC Texts in Statistical Science

Kim, J., & Rahimi, M. (2014). Future energy loads for a large-scale adoption of electric vehicles in the city of Los Angeles: Impacts on greenhouse gas (GHG) emissions. Energy Policy, 73, 620-630.

Leo, M., Kavi, K., Anders, H., & Moss, B. (2011, April). Ancillary service revenue opportunities from electric vehicles via demand response. Ann Arbor, MI: School of Natural Resources and Environment, University of Michigan.

Lund, H., & Kempton, W. (2008). Integration of renewable energy into the transport and electricity sectors through V2G. Energy Policy, 36, 3578-3587.

Moghe, R., Kreikebaum, F., Hernandez, J. E., Kandula, R. P., & Divan, D. (2011). Mitigating distribution transformer lifetime degradation caused by grid-enabled vehicle (GEV) charging. IEEE Energy Conversion Congr. Expo., 45, pp. 835-842.

Pillai and Bak-Jensen (2011). ntegration of Vehicle-to-Grid in the Western Danish Power System . From:
http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5560848&tag=1

Quinn, C., Zimmerle, D., & Bradley, T. (2010). The effect of communication architecture on the availability, reliability, and economics of plug-in hybrid electric vehicle-to-grid ancillary services. Journal of Power Sources, 195, 1500-1509.

SACOG (2011). Metropolitan Transportation Planning Report. From:
http://sacog.org/mtpscs/files/MTP-SCS/5B-VMT%20Final.pdf

Shao, S., Pipattanasomporn, M., & Rahman, S. (2012). Grid integration of electric vehicles and demand response with customer choice. IEEE Transactions on Smart Grid, 3(1), 543-550.

Soares, F. J., “Impact of the deployment of electric vehicles in grid operation and expansion,” Ph.D. dissertation, Univ. Porto, Porto, Portugal, 2012.

Sohnen, Julia (2013) Electric Vehicle Charging and the California Power Sector: Evaluating the Effect of Location and Time on Greenhouse Gas Emissions. Institute of Transportation Studies, University of California, Davis, Research Report UCD-ITS-RR-13-21

Sortomme, E., & El-Sharkawi, M. (2011). Optimal charging strategies for unidirectional vehicle-to-grid. IEEE transactions on smart grid, 2(1), 131-138.

Sovacool and Hirsh (2009). Beyond batteries: An examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition. From: http://www.sciencedirect.com/science/article/pii/S0301421508005934

Tal, G., and Nicholas, M. A., "Studying the PEV Market in California: Comparing the PEV, PHEV and Hybrid Markets," presented in EVS 27, Barcelona, Spain, November 2013

US DOE. (2012). Benefits and consideration of electricity as a vehicle fuel. Retrieved January 2, 2013, from U.S. Department of Energy: http://www.afdc.energy.gov/fuels/electricity_benefits.html

US Census (2013). American Community Survey 5-Year Estimates. From: https://www.census.gov/programs-surveys/acs/

US Census (2014). Longitudinal Employer-Household Dynamics : Origin-Destination Employment Statistics. From: http://lehd.ces.census.gov/data/lodes/