

Assessment of Plug-in Electric Vehicles Charging on Distribution Networks

Tsz Kin Au

A thesis

submitted in partial fulfillment of the
requirements for the degree of

Master of Science in Electrical Engineering

University of Washington

2012

Committee:

Miguel Ortega-Vazquez

Mohamed El-Sharkawi

Daniel Kirschen

Program Authorized to Offer Degree:
Electrical Engineering Department

University of Washington

ABSTRACT

Assessment of Plug-in Electric Vehicles Charging on Distribution Networks

Tsz Kin Au

Chair of the Supervisory Committee:

Research Assistant Professor Miguel Ortega-Vazquez

Electrical Engineering Department

The demand for plug-in electric vehicles has grown rapidly in recent years due to lower operation costs and lower emissions in comparison to conventional, gas-powered vehicles. Despite these benefits, it is essential for utilities to investigate the impact of plug-in electric vehicles in order to protect utility system components, especially distribution level networks. Since the operation, plugging timing and energy consumption of these vehicles is subject to uncertainty; we must resort to use probabilistic tools. As a consequence a natural way to investigate the impact of plug-in electric vehicles on distribution networks is by means of Monte Carlo simulations. Since it is of paramount importance to set up scenarios as realistically as possible; therefore in this study, a set of real driving behavior data for 34,000 drivers is used. The investigation considers two different types of distribution loads – commercial area loads, and residential area loads, as well as different types of charging behaviors such as charge-at-home-only and charge-at-work-and-home.

TABLE OF CONTENT

ABSTRACT	i
List of Figures	iv
List of Tables	v
I. INTRODUCTION	1
1. Plug-in Electric Vehicle (PEV) Characteristics	1
2. Plug-in Hybrid Electric Vehicle (PHEV) Characteristics	2
3. Expected Impacts of PEVs	3
3.1 Economic impacts	3
3.2 Technological impacts	4
II. METHODOLOGY	7
1. Data Processing and Initialization	10
2. PEV Penetration and Charging Points	11
3. PEVs' Arrival Time	11
Inverse Transformation for Random Number Generation	12
PEV Charge Station Arrival Time Uncertainty Modeling	12
4. PEVs' Battery State of Charge	14
5. PEVs' Charge Profile	16
6. Customer Load Profile	17
7. Running Power Flow Analysis for the Distribution System	20
III. TEST SYSTEM CHARACTERISTIC AND SCENARIO	22
Charging Method	24
IV. TEST RESULT AND ANALYSIS	26
Voltage Profile	26
Impact on the substation transformer	30

V. CONCLUSION AND RECOMMENDATION.....	32
Voltage drop in different type of networks.....	32
Transformer violations.....	32
Solutions	33
VI. Bibliography	34

List of Figures

Figure 1: Monte Carlo simulation flow chart	9
Figure 2: Number of vehicles arriving to work (top) and to home (bottom) at different hours in a day in the CMAP drivers survey.....	13
Figure 3: Cumulative distribution functions (top two) and the quantile functions (bottom two) of vehicles arriving to work (left two) and to home (right two) times	14
Figure 4: Percentage for different ranges of commute distance	15
Figure 5: Quantile function (blue) and the corresponding fifth-order polynomial function (red).	16
Figure 6: Before (top) and after (bottom) end hours charge profile is handled to the total PEV charge profile	17
Figure 7: Normalized load curve for residential load (in winter weekdays) and commercial load (in weekday though a year)	19
Figure 8: 26-bus-21-load distribution network, four levels of radial feeders with total of nine branches.....	24
Figure 9: Voltage distribution in 0% PEV penetration scenario	27
Figure 10: Voltage distribution in 50% PEV penetration scenario	28
Figure 11: Voltage distribution in 100% PEV penetration scenario.....	28
Figure 12: Voltage profile confidence interval with 0%, 30% and 100% PEV penetration scenario at Bus 16.....	29
Figure 13: Transformer apparent power profile with 0%, 30% and 100% PEV penetration.....	30
Figure 14: Apparent power distribution in different PEV penetration scenario	31

List of Tables

Table 1: Parameters being initialized in the beginning stage	8
Table 2: Locational charging type definitions	11
Table 3: Percentage for different ranges of commute distance	15
Table 4: Charging power and expected charging time for an empty 24kWh battery for each charging method	16
Table 5: Normalized load curve for residential load (in winter weekdays) and commercial load (in weekdays though a year)	18
Table 6: Voltage variables and definations	20
Table 7: Average active power and reactive power at each load bus	22
Table 8: Distances of each line segment	23
Table 9: Percentage of each charging method for each locational type of PEV owners	25
Table 10: Average bus voltage and probability of voltage violation	27

I. INTRODUCTION

There is already some demand for plug-in electric vehicles (PEV) and this is expected to continue to grow rapidly in the following decades because of the issues associated with fossil fuel usage for transportation. While fossil fuels are the dominant source of energy for transportation, issues such as unstable cost, high emissions, and reliance of exports has lead the world to explore alternative energy sources for transportation. In [1], it is suggested that electricity is the most suitable energy carrier for transportation in the next 30 years when considering goods moved, risk, emissions, availability, maintainability, efficiency and reliability. In this sense, PEVs are very attractive because they have low road emissions, they can potentially strengthen the power system by providing ancillary services; they also have a lower operating cost compared to fossil fuels, and they are more energy efficient. However, PEVs could cause undesirable impacts to the power system, especially to distribution networks, because of their high power consumption and uncontrolled charging behavior.

1. Plug-in Electric Vehicle (PEV) Characteristics

PEVs have several characteristics that differ from combustion engine vehicles including the vehicles' operation, economic impacts and technological impacts. Some of these are summarized under the following headings.

Energy efficient and low operating cost

PEVs are more energy efficient than combustion engine vehicles. Nissan Leaf, for instance, consumes 0.34 kWh/mi (1227 kJ/km), while a comparable 30-mpg combustion engine vehicle (e.g. Nissan Micra) consumes 2491 kJ per kilometer. Conventional vehicles and electric vehicles differ in the amount of stored energy they can use to move the vehicles. Conventional gasoline engines can only use 15% of the stored energy in fuel in the tank to move the vehicle and a diesel engine can use 20%. Electric vehicles on the other hand can effectively use up to 80% of the stored energy (electrical energy) [2].

The operating cost of electric vehicles is much lower than the operating cost of conventional vehicles because of the difference in energy efficiency. In the United States, the average residential electricity rate in 2011 was about US\$0.11 per kWh [3]. The Nissan Leaf,

for example, will cost 3.7 cents (USD) per mile to drive, while a 30-MPG combustion engine vehicle will cost 13.3 cents (USD) per mile, using a retail fossil fuel price of US\$ 4 per gallon.

PEV charging power

A PEV battery can be charged at different power levels, typified from level 1 to level 3, [4]. Level 1 and level 2 charging are considered as slow charge and medium charge, and are commonly used in residential households. Level 3 is fast direct current charge which typically is only used in public areas due to the high power and high cost. Using a standard electric cable, a PEV can be plugged in to a standard electric outlet to charge the battery at level 1. However, level 2 and level 3 charging require additional equipment. A level 2 charging station costs roughly US\$1,000 per unit [5], while the cost of a level 3 charging station is at least US\$16,800 [6] [7]. Therefore, level 1 seems to be more attractive since it does not require additional investment.

Connection to the electrical power grid

PEVs are connected to the electrical power grid to be able to charge. Smart Grid technology will allow PEVs to communicate with the grid to control charging process. In addition, Vehicle-to-Grid (V2G) technology will allow power to flow back to the grid from the batteries of the PEV. PEV batteries could potentially be used for storing energy from the grid and to provide ancillary services such as reserve [8]. The PEV owner, aggregator and/or the local utility could make a profit by providing these ancillary services and implementing V2G [9]. In the United States, a vehicle is parked 95% of the time on average [10]. When a PEV is not in use, if the PEV owner, the vehicle manufacture, and the utility agree, the PEV can be used as energy storage when the output from intermittent energy sources (such as wind and solar energy) is high and the demand for energy is low. Then, when demand increases and supply is low, the energy in the PEV batteries can be sent back to the grid. PEVs can also provide reserves to improve system security.

2. Plug-in Hybrid Electric Vehicle (PHEV) Characteristics

Plug-in hybrid electric vehicles (PHEV) have similar characteristics to PEVs mentioned in section 1, however, typically the battery capacity is smaller and as their name suggested, they are also equipped with a small combustion engine. Therefore, PHEVs are multi-energy sourced vehicles, which are commonly powered by fossil fuels and electric energy. The electric motor is

the main power train, and the combustion engine usually acts as a backup. When high power output is desired, or the PHEV battery does not have enough charge, the combustion engine will be triggered [11].

3. Expected Impacts of PEVs

Most studies on PEV and electric grids can be categorized in: 1) economic impacts and 2) technological challenges. The former focuses on cost-benefit analyses related to the introduction of PEVs to the system and the later on specific impacts to the environment, electric grid and PEV technologies.

3.1 Economic impacts

The economic aspects surrounding PEVs will influence the permeation of these in the power systems. Without perceiving any economic benefits, customers would not choose to buy PEVs because these have higher investment cost and reduced convenience due to their long charging times. Policies will also play a key role. In the United States, for instance, PEV owners receive valuable tax credit when buying PEV. This makes them more attractive and as a consequence this result in higher penetrations of PEVs could be expected.

The authors of [12] describe the current status of PEVs in the United States. They report that there were more than 16 million fleet vehicles on the road in 2009. Their sizes vary significantly, from light weight sedans to delivery trucks. These electric fleet vehicles are usually owned by public or private organizations. However, they foresee the electrification of personal-use light-weight vehicles as the most important goal in order to support energy security. In this paper, the authors identify the major challenges to attain this objectives being the cost and range of the PEVs the primary barrier to their full integration to the system.

In [13], the value of different PHEV types and customers is assessed. The authors found that over the lifetime of the vehicle, a PHEV with 30-mile driving capability on a single electric charge can save between \$11,900 and \$13,250 relative on a traditional combustion engine vehicle, and between \$4,425 and \$6,100 relative on a hybrid electric vehicle (without grid connection capability) in operation costs. To commercial building owners, PHEV may potentially lower the electric bill by charging the PHEVs' batteries below peak load, and use the stored energy during peak. The also explore the possibility of using the PHEVs parked at the

specific location to provide storage services to the buildings. These storage services can be effectively used for arbitraging energy resulting in potential savings between \$1,000 and \$2,000 per month for a 1.5 MW peak demand building with up to 50 PHEVs available.

On top of the aforementioned savings attained by deploying PHEVs, these can also provide ancillary services to the system. The authors of [14] propose using the PHEVs to provide primary reserve to the system, creating a new business opportunity for the EVs aggregator.

3.2 Technological impacts

There are approximately 250 million passenger vehicles in the United States according to a 2010 survey from the Department of Transportation [8]. The current daily average commute distance is roughly 30 miles for each person [15], which is translated in a power consumption of about 12 kWh per PEV. Assuming that 10% of the vehicles will be PEV, they will consume approximately 300 GWh per day. This is a large additional demand to the system that will impact the system in different fronts:

- Grid losses: By integrating PEV to grid, the total demand of the system will increase, which will lead to higher current in the networks and therefore create higher losses. This will have larger impact to the distribution networks due to the lack of interconnections and relatively high current due to the low voltage [16].
- Impact on power quality: Low voltage circuits will have to carry higher currents and these circuits are usually radially configured. When the additional demands from PEVs are connected to these circuits, larger currents will generate larger voltage drops, particularly at the end of the feeders. In addition, integrating PEV to grid will cause congestion on the lines and potential load imbalances at the substation bus [16].
- Impact on generation profile: Generally, the peak load of a system happens during the hours that when people arrive to work or home. As many PEVs are expected to be connected to the grid when they arrive to work and home when there is no control, the PEVs will increase the system's peak load; which in turn will require a more frequent and prolonged deployment of peaking generation. This generation is characterized by higher incremental costs; therefore it is expected to have larger operating costs in the system.

Also the total system capacity might only be able to accommodate a low PEV penetration, since the peak of the system demand is coincident with that of PEVs.

- CO₂ emission: PEVs will decrease the on road emission. For an all-electric vehicle, its emission on road is zero. However, their overall emission depends on the type of resources the PEVs are energized from. If a PEV is located in areas that has much renewable resources, its emission is likely to be lower. In contrast, if a PEV is located in area that is mainly powered by fossil fuels, its emission is likely to be high [11]. For a power system such as the one of the United States, after integrating PEVs, the total greenhouse gases emission from both, the electricity and the transportation sectors, is expected to be lower than those for the same system with fossil fueled transportation sector.
- Vehicle-to-Grid Technology (V2G): Although V2G will provide valuable benefits to both the utilities and customers, there are two aspects blocking its implementation. First, communication between the aggregator and customer is still a challenge. Second, a suitable business model is still under development. In addition, in the current stage of battery technology, they are not suitable for charging to discharging frequently. Third, the cost of providing these services is not yet known with precision.
- Transmission Networks: According to [17], if the charging time of PEVs is controllable, the existing electrical power system resources in the United States should be sufficient to fuel up to about 70% of the light vehicles if the current average commute distance remains the same. However, this will require more maintenance to the power system as the system would be heavily loaded most of the time. Scheduling for maintenance will be difficult. In addition, less spare generation capacity will be available, which would result in the system becoming less reliable. These impacts to the system depend on how close it operates to the total generation capacity. If uncontrolled, PEVs are expected to be plugged in during peak load and if the system is was already operating close to its generation limit, the system may not have sufficient resources to meet the new aggregated demand and reserve requirements with the existing generation assess.
- Distribution Networks: PEVs' effect on distribution networks is expected to be different from the effect on transmission networks. Except for some rare cases, the fact is that distribution networks are weakly meshed. The lack of interconnection forces power to

flow from the substation to a load in certain path [18]. When a PEV is being charged in a distribution network, its power consumption could be up to three times more than a household's average consumption [19]. In addition, the possibility that the PEVs will start charging at system peak load also has to be considered [20]. It is natural to assume that most PEVs will be plugged to the grid once they arrive to home. Therefore, it can often be expected that the time when drivers arrive home coincides the system peak load hours. In this case, the substation transformer may be overloaded and the voltage quality in distribution networks would be compromised.

All of the economic and technological impacts are based on assumptions of energy consumed by PEVs. However, a tool for representing these additional loads is not explained in the open literature. The purpose of this work is to present a tool, that is capable of building a demand curve from PEVs based on the traffic and commute behaviors. This tool is presented in more details in the following sections.

II. METHODOLOGY

Although the PEV owners can only choose between three charging rates, the charging process is subject to uncertainties such as the charging schedule, location preferences and energy requirements, complicating the charging scenario. These effects result in an uncertain total demand that needs to be served by the utility and this further amplified because PEV drivers will use their vehicles differently. The random variables considered in this tool are:

1. Charging time
2. Battery state of charge
3. Charging power (level 1, level 2 and level 3)
4. Base load variation

Monte Carlo simulations are well-suited to calculate probabilities of events of deterministic systems with random inputs. It is especially useful when the system consists of more than one random variable. The Monte Carlo method consists of repeating a system process with random inputs in order to obtain statistical data for the expected outputs. For each trial of the simulation, the output of the system is stored, and the statistical behavior from this stored data can be constructed. The generic algorithm of Monte Carlo simulation is as follows:

1. Determine the variables and random variables
2. Generate random numbers for the random variables
3. Process the deterministic system with all the variables and random variables
4. Store results
5. Repeat steps 2 to 4 if the stopping criteria has not been reached

There is no standard structure for Monte Carlo simulation because it depends on the problem. A flow chart describing the structure in this study is shown in Figure 1. In this study, the first step is to initialize two types of parameters: EV parameters and system network parameters. Table 1 shows that the parameters are initialized before running through the Monte Carlo simulation loop. In addition, the number of simulation trials, number of time segments in a day, the normalized load profile and the drivers survey data must be initialized or loaded in this step. The parameters and data defined in this step will be used in the rest of the steps of the procedure.

The simulation starts by initializing the loop starting with trial 1. For each trial, the arrival time and battery state of charge of each PEV are estimated from realistic probability distributions in a random manner; and this allows computing the charge profile for each PEV for a whole day.

After building the charging profile for all PEVs in the system, these are added up to the customer load profile. The customer load profile is generated based on the average active and reactive power loads at each node, type of load plus a Gaussian white noise; which represents the load's uncertainty.

Table 1: Parameters being initialized in the beginning stage

Electric vehicles	System network
Charging power (e.g. level 1, 2, 3)	Line distance of each segment, ft
Number of EV and their charge preferences and locations	Average active and reactive load of each bus, W and Var respectively
Energy efficiency (kWh/mile)	Line impedance, Ω /mile
Battery capacity (kWh)	Source voltage, V
	Load variation standard deviation, W and Var
	Type of load at each bus, e.g. commercial or residential

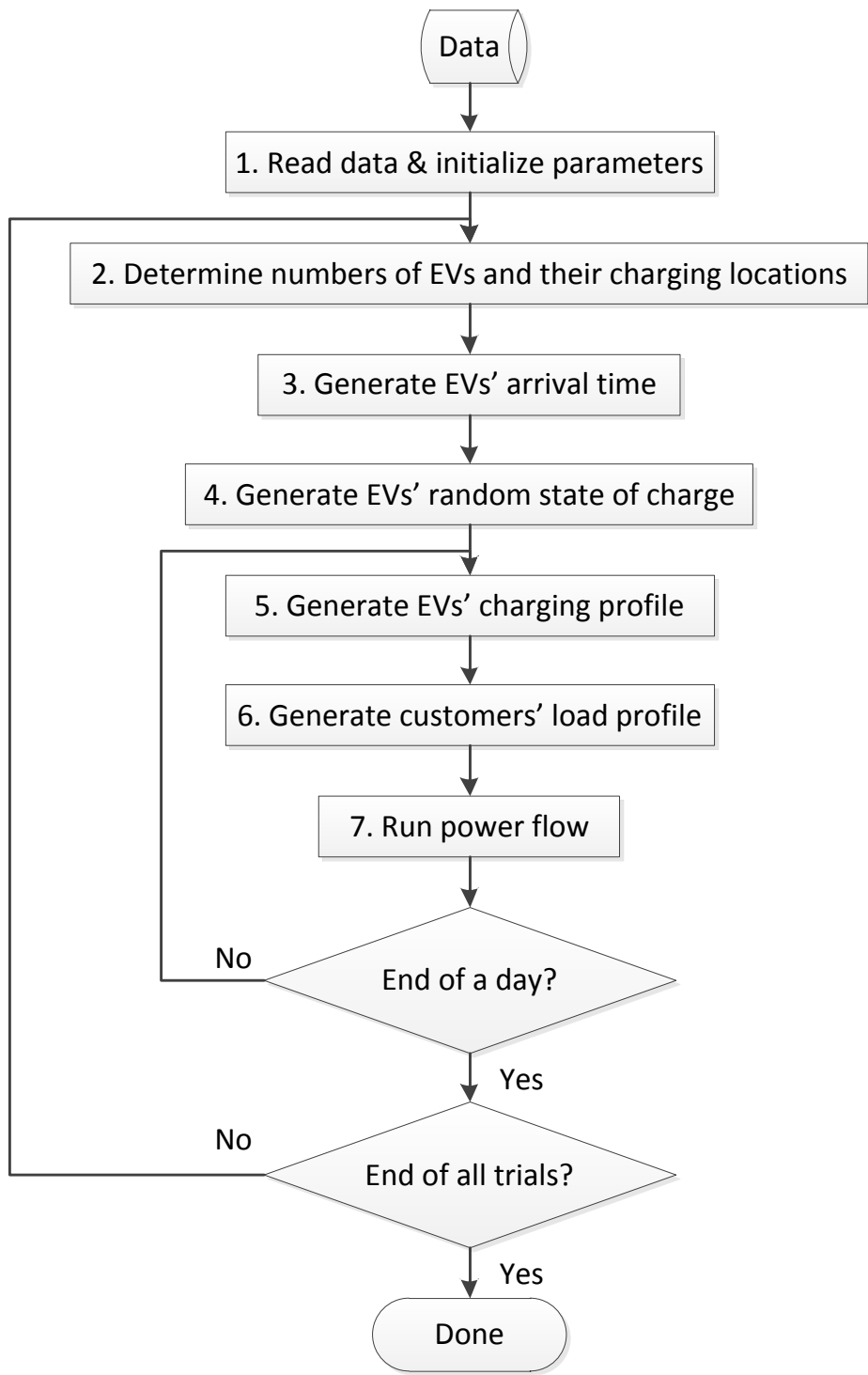


Figure 1: Monte Carlo simulation flow chart

For each trial, a power flow simulation needs to be performed to compute the currents and voltages on each line segment and bus respectively. A conventional power flow method such as Newton-Raphson, decoupled or fast decoupled method is not applicable because the high R/X ratio and weakly meshed characteristics of the distribution networks hinder adequate convergence for these methods. There are many methods to compute the power flow for distribution networks. In this study, the forward-backward sweep method is used because of its simplicity of implementation and robustness [18].

The stopping criterion of the simulation is to reach 1000 trials. This number is selected because it was seen that more simulations does not affect the result significantly after this number of trials is reached. Each trial simulates a whole day (24 hours) which is composed of $n \times 24$ time intervals, where n is the number of time intervals per hour. Figure 1 shows the Monte Carlo simulation flow chart for this study. The function(s) of each block in the flow chart will be explained explicitly in the following sections of this chapter.

1. Data Processing and Initialization

The first step of the Monte Carlo simulation is to arrange the data properly and initialize the required parameters. This information includes a data set of 34,000 drivers' behavior from the Chicago Metropolitan Agency for Planning (CMAP), electric vehicles parameters (such as battery capacity, energy consumption among others), distribution network conductor parameters, average load at each node, and load profiles for different types of load.

This study assumes that all the drivers in the system drive to work alone, and thus do not have to make additional trips for “dropping off to work” and “picking up from work”. The drivers' behavior data is loaded and filtered so that the 34,000 drivers' data set only contains drivers who drive alone. This data is used for computing the cumulative distribution function of the arrival time, which will be used in step 3 of the Monte Carlo simulation. The resolution used to build the cumulative distribution function is one minute.

The duration of each time interval is also determined in this step. The number of time segments is then calculated by the following equation:

$$\text{Number of time segment} = \frac{\text{Duration of a interval}}{1440 \text{ minutes}}$$

In this study, a 15-minute interval is chosen in order to have a smooth transition between time intervals of the result and a short computation time.

2. PEV Penetration and Charging Points

This study assumes the electric vehicles are randomly distributed over the network, with different levels of PEV penetration. PEV penetration is the percentage of PEVs to the personal vehicles replaced by PEVs. The PEV penetration can be described by the following equation:

$$PEV \text{ Penetration} = \frac{\text{Total number of passenger PEV}}{\text{Total number of passenger vehicles}}$$

This study considers five cases: 0%, 10%, 30%, 50% and 100% PEV penetrations. According to [21], not many drivers make additional trips after arriving to work until they leave. However, during the evening, roughly one-third of the surveyed drivers make additional trips after work. Moreover, charge station availability in commercial areas is assumed to be small. Therefore, EV drivers who expect their car will have enough energy for the trips of the rest of the day will not charge their EVs in the commercial areas. As a result, this study assumes two third of the EVs will be charged only at home, namely type 1 charging (see table 2), and one third of the EVs will be charged at both home and work locations (residential and commercial areas), namely type 2 (see table 2). The location of the places where the charging process takes place are summarized in Table 2.

Table 2: Locational charging type definitions

Locational charging type	Charging location
Type 1	Only at home (residential areas)
Type 2	Both at home and work (residential and commercial areas)

3. PEVs' Arrival Time

All of the charging preferences for PEVs are assumed to be uncontrolled throughout all simulations, meaning that the PEV drivers will try to charge their vehicles anytime at their convenience. Therefore, for PEVs that will charge both at home and at work, type 2, the PEVs are expected to start charging once they arrive home and work; for home-only charging PEVs, type 1, they will charge only when they arrive home. Knowing the PEVs arrival times to charge stations is important because it will determine the PEV charge profile. Two types of trips

dominate the simulations – to work and to home. Although these two types of trips are expected to be similar for a driver on most of the work days, they most likely will vary from day to day, and from driver to driver. This variation creates uncertainty in the PEV charge profile. To model the uncertainty of vehicles’ arrival time to the charging station, the inverse transformation method is used to generate random electric vehicles arrival times.

Inverse Transformation for Random Number Generation

In this part we need to obtain a set of random number with a given probability distribution (e.g. arrival time or battery state of charge). For this purpose a set of uniform distributed random numbers, U , in a range of zero to one, is generated and then mapped through the desired distribution to obtain a random number with the desired probabilistic characteristic. This process proceeds as follows:

1. Generate a set of uniformly distributed random numbers, $U: \mathbb{R} \rightarrow (0,1)$
2. Compute the cumulative distribution function, F of the subject’s distribution function $f(x)$ as follows (e.g. arrival time):

$$F(x) = \sum_{k=0}^x f(k)$$

3. Compute the quantile function, $Q(x)$ by inverting the cumulative distribution function axes
4. New random variables as $Q(U)$

PEV Charge Station Arrival Time Uncertainty Modeling

A set of real driving behavior data for over 34,000 drivers from the Chicago Metropolitan Agency for Planning (CMAP) is used and processed to generate random to-work and to-home arrival times. Figure 2 shows the numbers of vehicles arriving to work and to home at different times of the day from the CMAP data. As shown, the to-work arrival time peaks during hours 7 and 8; the to-home arrival time peaks at hour 17. In addition, the to-home arrival time variation is much wider than the to-work arrival time. There are more surveyed drivers in the to-home arrival time data set than the to-work arrival time data set. The total number of surveyed drivers for the to-home data set is 25452, whereas the to-work data set has only 8999 surveyed drivers.

The arrival time curves in Figure 2 can be considered probability distribution functions if the numbers on the vertical axes are divided by the total number of vehicles of each type. The vertical axes represent the percentage of all vehicles arriving to work (or to home) at a given time of day.

Applying the methodology described in the previous subsection, we can simulate the arrival time of the PEVs. Figure 3 shows the cumulative distribution function and the quantile function of vehicles arrive-to-work and arrive-to-home time. By applying a set of uniformly distributed random numbers, U , to the quantile function, $Q(U)$, a set of vehicle arrival times can be generated, shown by the black arrows in Figure 3.

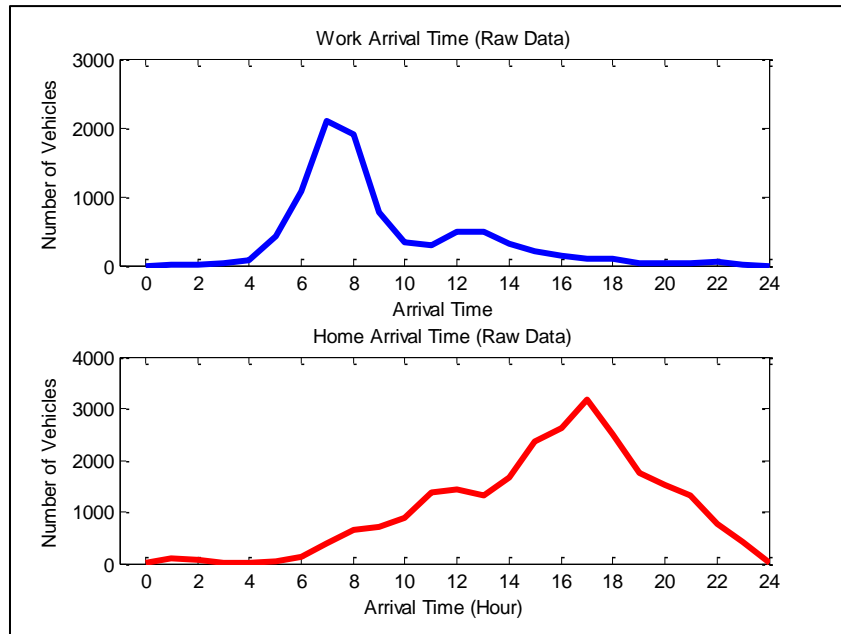


Figure 2: Number of vehicles arriving to work (top) and to home (bottom) at different hours in a day in the CMAP drivers survey

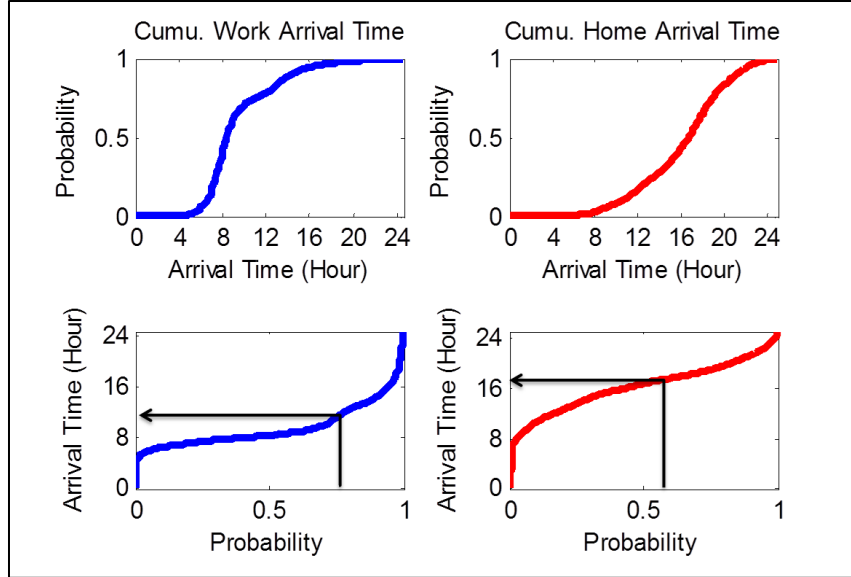


Figure 3: Cumulative distribution functions (top two) and the quantile functions (bottom two) of vehicles arriving to work (left two) and to home (right two) times

4. PEVs' Battery State of Charge

The battery state of charge (SOC) will also have a strong impact on the PEV charge profile. The battery SOC of a PEV can be estimated from the PEV commute distance. Although energy efficiency of a PEV varies with the driver's behavior, traffic conditions, weather and driver's preference such as interior temperature control. This study assumes all PEVs consume on average 0.34 kWh/mi. Although the distance traveled is somewhat predictable, it will vary from day to day, from driver to driver. This introduces uncertainty to the model.

To simulate the battery SOC, it is important to know the distribution of drivers' commute distances. Table 3 and Figure 4 show the percentages of drivers belonging to different ranges of commute distances in Seattle [15]. The data was collected from 7953 interviewees. As shown, the data is given by groups of commute distance ranges. The average commute distance of each group is assumed to be the average value of each group's boundaries. For example, for the group containing drivers commuting 4.1-8 miles, the average commute distance of this group is six miles. This can be easily computed for the rest of the groups except for the group with drivers commuting over 32 miles. This group has a lower boundary, and no upper boundary. Because the quantile function is comparably smooth, it can be fit into a fifth-order polynomial,

with a coefficient of determination (R^2) of 0.9997. Using this fit, the last group of commute distance data is ignored. Figure 5 shows the quantile function of the commute distance distribution function and its fifth-order polynomial function. The random battery SOC of each PEV can then be generated by substituting a set of uniformly distributed random numbers to this polynomial function.

Table 3: Percentage for different ranges of commute distance

Commute distance (miles)	Percentage (%)
0 – 4.0	19.19
4.1 – 8.0	22.95
8.1 – 12.0	16.67
12.1 – 16.0	13.77
16.1 – 20.6	9.37
20.1 – 24.0	6.07
24.1 – 28.0	4.59
28.1 – 32.0	2.69
32.1 +	4.70

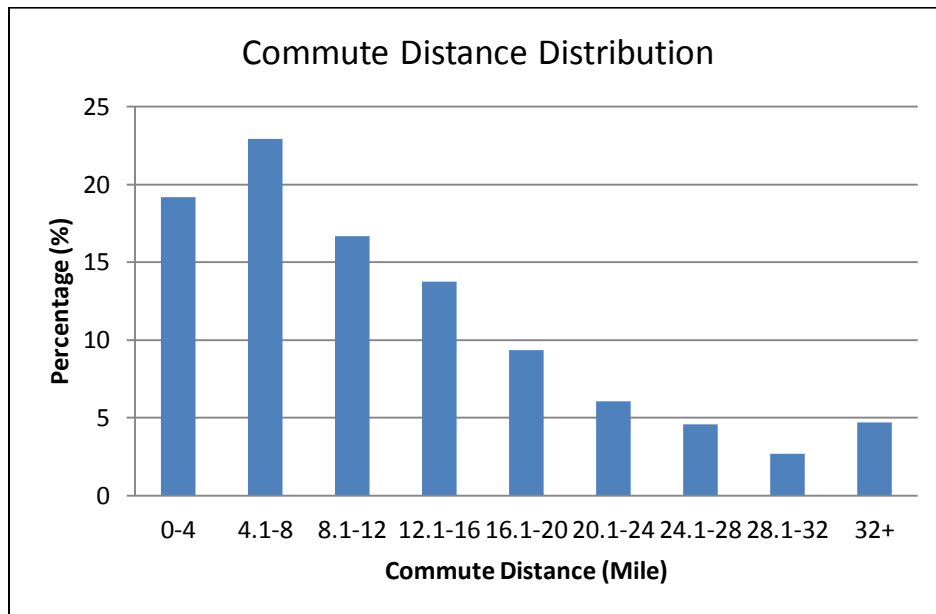


Figure 4: Percentage for different ranges of commute distance

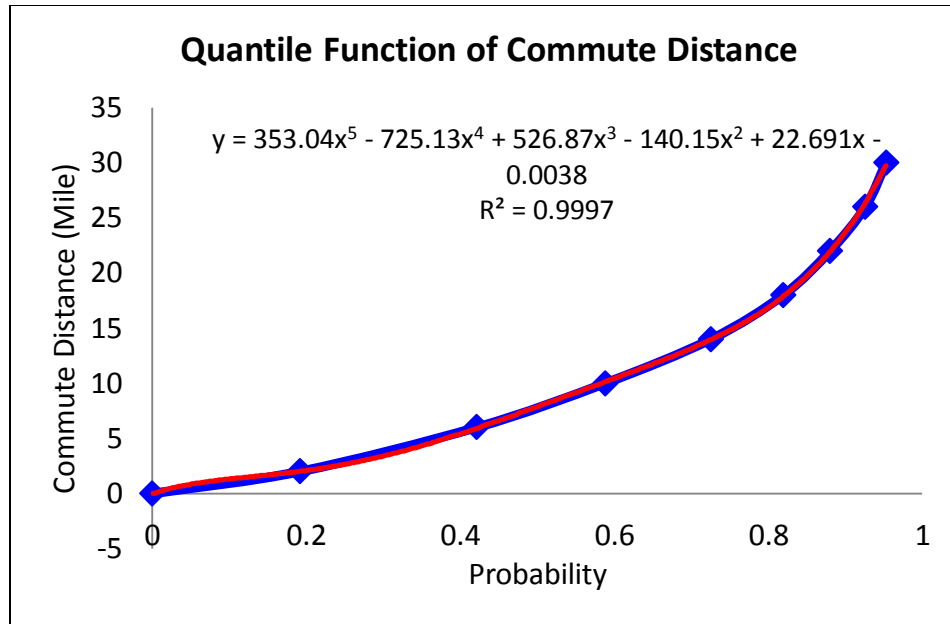


Figure 5: Quantile function (blue) and the corresponding fifth-order polynomial function (red)

5. PEVs' Charge Profile

The total charge profile of each PEV is first computed individually based on the arrival time, energy requirements, and charging method. Table 4 shows the types of charging method considered in this study, as well as the charging power and charging time for an empty 24kWh battery.

Table 4: Charging power and expected charging time for an empty 24kWh battery for each charging method

Charge method	Charging power	Charging time for an empty 24kWh battery
Level 1	1.3 kW	18.5 hours
Level 2	3.3 kW	7.3 hours
Level 3	50 kW	0.5 hours

The total PEV charge profile is the summation of all individual PEV charge profiles. If an PEV starts charging in the last few hours of a day, its end time is likely to exceed hour 24. If this is the case, the exceeding portion of the charge profile will be moved to the initial hours of the day the charge began. For example, if the total PEV charge profile in hours 1 to 3 is 0 kW, in

hours 25 to 26 is 3.9 kW, and 2.6 kW in hour 27, then the charge profile in hours 25 to 27 will be moved to hours 1 to 3. Therefore, the final total PEV charge profile in hours 1 to 2 will become 3.9 kW and hour 3 will become 2.6 kW. Figure 6 shows an example of how the end hours charge profile is handled.

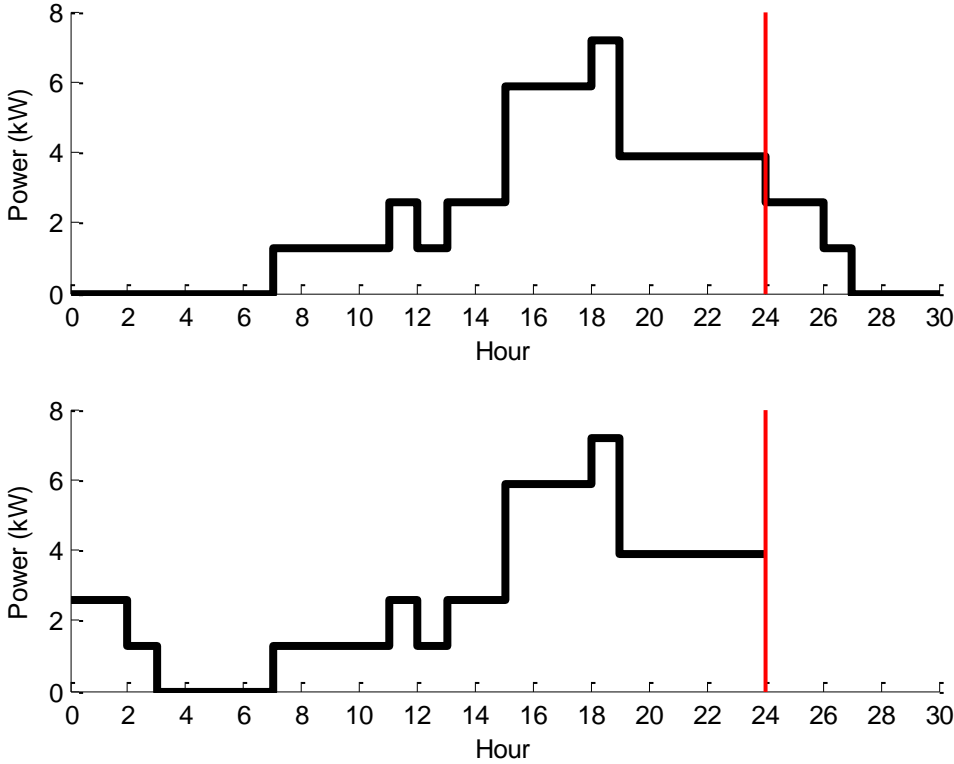


Figure 6: Before (top) and after (bottom) end hours charge profile is handled to the total PEV charge profile

6. Customer Load Profile

The baseline of the load data is from the Institutes of Electrical Engineering of Japan [22]. The data is provided hourly for both weekdays and holidays for residential load, commercial load and industrial load. The residential load data is classified into summer load, winter load and spring/fall load. In contrast, the commercial load and industrial load data is given through a year. In this study, the residential winter weekday loads and commercial

weekday loads is used. Each dataset is normalized by dividing by its average for the 24-hour load. Figure 7 and Table 5 show the normalized datasets.

Table 5: Normalized load curve for residential load (in winter weekdays) and commercial load (in weekdays though a year)

Time	Weekdays Residential Load		Weekdays Commercial Load	
	Power (MW)	Normalized value	Power (MW)	Normalized value
1	70	0.77	26	0.43
2	62	0.69	24	0.39
3	62	0.69	22	0.36
4	60	0.66	22	0.36
5	60	0.66	22	0.36
6	64	0.71	22	0.36
7	80	0.89	24	0.39
8	90	1.00	34	0.56
9	96	1.06	64	1.05
10	98	1.08	90	1.48
11	98	1.08	98	1.61
12	98	1.08	100	1.64
13	98	1.08	100	1.64
14	100	1.11	100	1.64
15	100	1.11	100	1.64
16	102	1.13	98	1.61
17	110	1.22	98	1.61
18	116	1.28	94	1.54
19	116	1.28	82	1.35
20	112	1.24	68	1.12
21	106	1.17	56	0.92
22	100	1.11	46	0.76
23	90	1.00	38	0.62
24	80	0.89	34	0.56

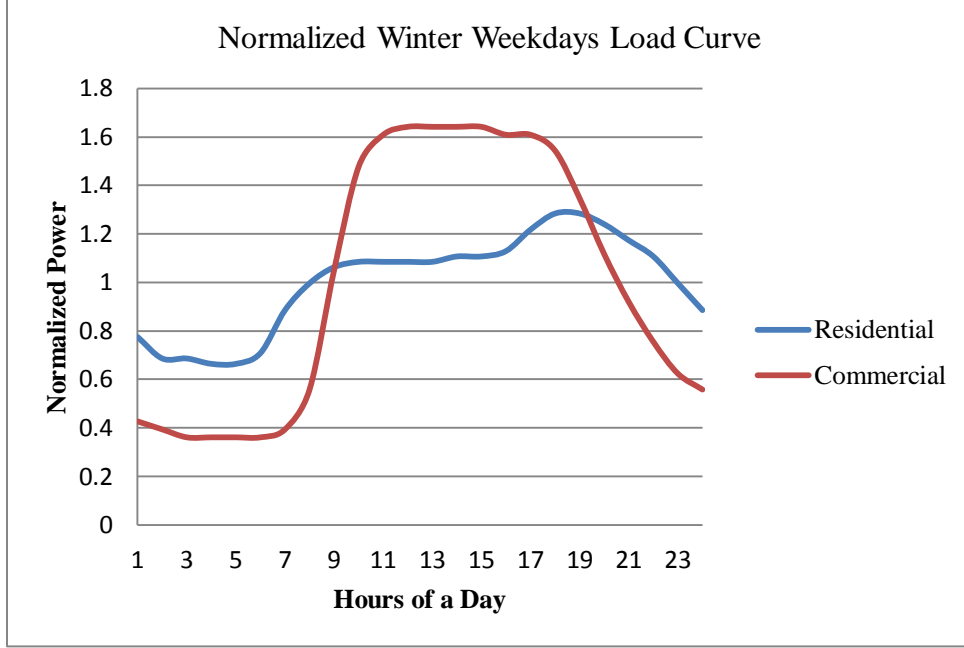


Figure 7: Normalized load curve for residential load (in winter weekdays) and commercial load (in weekday though a year)

The average load of each bus is assigned in the initial state of the Monte Carlo simulation. The load profile of a bus in each trial is modeled by multiplying the average load of the bus with the corresponding normalized load profile, and adding Gaussian white noise. Injecting Gaussian white noise is a common way to model the variation of distribution loads [6]. Thus, the load distribution of a given bus at a specific time interval in the system can be calculated with the following equation:

$$f(P_{bus,ti}) = \frac{1}{\sigma_{bus,ti}\sqrt{2\pi}} e^{-\frac{1}{2} \frac{(P_{bus,ti} - AvgP_{bus,ti})^2}{\sigma_{bus,ti}^2}},$$

$AvgP_{bus,ti}$ is the average load of the bus at time interval ti , which is computed by:

$$AvgP_{bus,ti} = P_{type,ti}^{norm} \times AvgP_{bus},$$

where $P_{type,ti}^{norm}$ is the normalized power at time interval ti corresponding to its type; $AvgP_{bus}$ is the average load of a given bus; $P_{bus,ti}$ is the real power load of a given bus at time interval ti ; $\sigma_{bus,ti}$ is the standard deviation of the load, which is set to 10% of the average load of the bus at a given time - $AvgP_{bus,ti}$.

7. Running Power Flow Analysis for the Distribution System

Since distribution networks have a relatively high R/X ratio as compared to transmission networks, the decoupled and fast decoupled methods are not suitable for finding the distribution network power flow. In addition, some of these iterative methods may have convergence problems because of insufficient reactive power distribution in the network, as reported in [23]. Hence, the forward-backward sweep method is used in this study.

The forward-backward sweep method is implemented by looping through a forward sweep and a backward sweep, then updating parameters on a radial network. On each radial network, the bus located at the substation, which is the closest to the high voltage level network, is called the Substation Bus. The voltage at this bus is called the Set-point Voltage. The End Bus is located at the other end of the radial network; geographically it is the furthest bus away from the substation. The voltage at this bus is called the End Bus Voltage. In each iteration of the forward-backward sweep method, the voltage at the Substation Bus is computed. This voltage is called the Source Voltage. The voltages are presented in Table 6, along with a short explanation of how the sweep works.

Table 6: Voltage variables and definitions

Type of voltage	Comments	Location
Set-point voltage	Set in the beginning, does not change.	Substation Bus
End Bus Voltage	Initialized in the beginning, changes every iteration.	End Bus
Source Voltage	Computed and compared to the Set-point voltage every iteration.	Substation Bus

Initially, the End Bus Voltage is initialized to the Set-point substation voltage. Forward sweeping computes the upstream line segment current and bus voltage, starting from the far end bus of a lateral and toward the substation bus, based on the given active and reactive load of each bus, the line impedance of each segment, Kirchhoff's current law (KCL) and Kirchhoff's voltage law (KVL). If the difference between the computed Source Bus Voltage and the Set-point voltage is not within a given tolerance, the program will set the Source Bus Voltage to the Set-point voltage and perform backward sweeping.

Backward sweeping computes the voltage at each bus, starting from the Substation Bus toward the End Bus, based on the current flows computed from the forward sweeping and KVL, until the new End Bus Voltage is computed. Then the forward sweeping will begin again using the new End Bus Voltage and line impedance of each segment on a radial network. This process will be repeated until the difference between the Source Voltage and the Set-point Voltage is within an acceptable tolerance. The acceptable tolerance in this study is set to 0.1% of the Set-point Voltage. Power flow programs for distribution networks with sub-laterals can use a similar approach.

Note that the transformer impedance is ignored because it is relatively small. The load on each bus is assumed to be in steady state. In addition, all three phases in the system are assumed to be balanced for simplicity.

III. TEST SYSTEM CHARACTERISTIC AND SCENARIO

A 26-bus-21-load distribution network is used in this study. The network is constructed with four levels, with total of nine radial feeders. It is assumed that 4000 residents reside in this network; with a household average of 2.35 people, and 1700 households served in the network. It is also assumed that there are 1.78 passenger vehicles per household, which means 3000 passenger vehicles are parked in this network. With the exception of buses 4 and 5, each load bus in the system represents an 85-house residential area. Buses 4 and 5 are shopping plazas and commercial building loads (commercial area). The power factor in residential loads varies between 0.9 to 1 [24]. Commercial loads usually have a worse power factor because of the inductive loads. These loads include motors and transformer-based lighting, such as air conditioning and fluorescent lights. This study assumes all the residential loads have a power factor of 0.9, where the commercial loads at bus 4 and 5 have a power factor of 0.8. The nominal voltage of the network is 9 kV (phase voltage). The system is assumed to be balanced in three phases. In addition, each line segment conductor has a resistance and a reactance of 0.25 and 0.5 Ω /mi, respectively. Figure 8 shows the network configuration. Each different colored connection represents a lateral.

In the United States in 2010, 29% of residential heating systems were fueled by electricity [25]. According to [26], a household with an electricity-fueled heating system's average power consumption varies between 1200 to 1500 W, otherwise a household's average power consumption varies between 600 to 1000 W. With a power factor of 0.9, each 85-household residential load consumes 81.6 kW active power and 40.8 kVar reactive power on average. The commercial loads consume more power. The average active and reactive power for the commercial loads are 100 kW and 75 kVar, respectively, with a power factor of 0.8. The average active and reactive power of each load bus is shown in Table 7.

Table 8 shows the distances of each line segment in the network.

Table 7: Average active power and reactive power at each load bus

Bus	Average active power (kW)	Average reactive power (kVar)	Power factor	Load type
7-16, 18-26	81.6	40.8	0.9	Residential
4, 5	100	75	0.8	Commercial

Table 8: Distances of each line segment

From	To	Distance (feet)	From	To	Distance (feet)
1	2	1000	12	13	7000
2	3	12000	13	14	7000
2	17	6000	14	15	7000
3	4	6000	15	16	7000
3	6	1800	17	18	5000
4	5	7000	17	24	5000
6	7	7000	18	19	5000
6	12	12000	19	20	5000
7	8	7000	20	21	5000
8	9	7000	21	22	5000
9	10	7000	22	23	5000
10	11	7000	24	25	5000
11	12	7000	25	26	5000

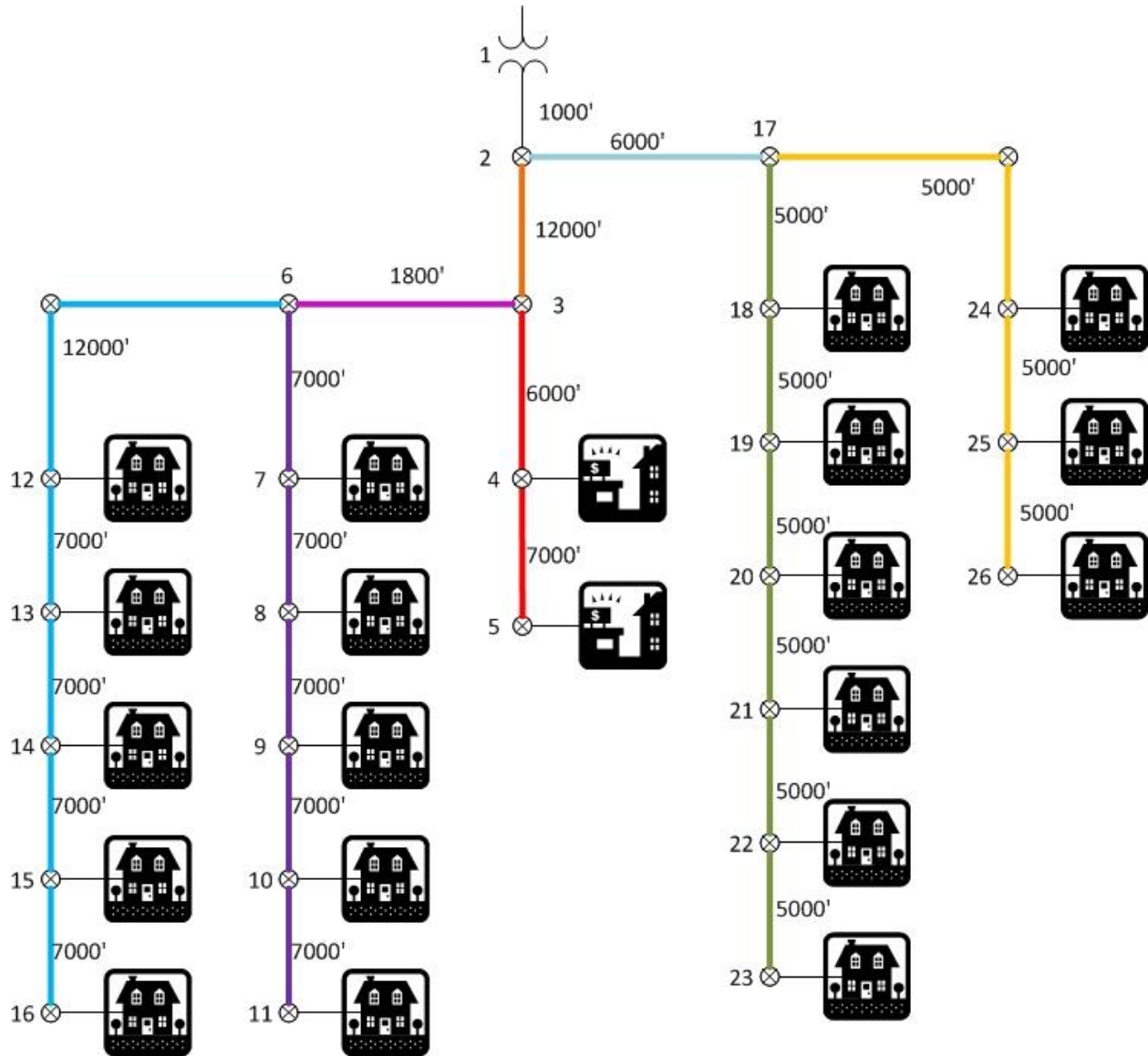


Figure 8: 26-bus-21-load distribution network, four levels of radial feeders with total of nine branches

Charging Method

There are several standards for electric vehicle recharging. This study assumes all PEVs use the same standard, SAE J1772-2009 [4]. In the United States, the standard outlet is rated at 120 V, 12 A maximum allowable current (15 A breaker), 1.3 kW, single-phase. A PEV can be plugged in directly to this type of outlet with the included PEV cable, which is level 1 recharging in this study. A PEV owner who wishes to charge the battery quicker may consider a higher

power recharging method. Level 2 recharging method requires additional equipment but has a power rating of 3.3 kW. This is the on-board charger rating of a Nissan Leaf [27]. A PEV owner who wishes to charge the battery in a very short period of time may consider level 3 recharging, which has a power rating of 50 kW, with multi-phase ac converted to dc, 480 V and 125 A maximum allowable current.

The PEV charge profile of a bus is determined by each PEV charge start time, the SOC of the battery when the PEV begins to charge at the charging station, and the charging method. When a PEV starts charging, it is assumed that it will charge at the set power level until the battery SOC is 100%. Given the additional equipment cost for the levels 2 and 3 recharging methods, this study assumes that most PEV owners use the level 1 charging method (1.3 kW). Since most PEVs will be charged overnight until they are used again for driving to work the next day, it is assumed that the PEV drivers will not care about the long charging time. Assuming that the PEV owners on average will park their PEVs at home for 13 hours, the level 1, 1.3 kW charging method will be able to charge more than 70% of a 24 kWh battery, which will allow the drivers to drive 53.5 mi. This range will easily satisfy most of the commuters according to [15]. In addition, most PEVs' SOC are expected to be greater than zero when they start charging. However, some PEV drivers occasionally need to make a long trip on the next day, or will have unexpected trips, these drivers are more likely to own a level 2 charging station at home. They are assumed to use level 2 charging to prepare for unexpected trips. Level 3 charging stations are very expensive, and are not expected to be present in residential areas. Table 9 shows the percentage of use of each charging method assumed in this study.

Table 9: Percentage of each charging method for each locational type of PEV owners

Locational charging type	Level 1 (1.3 kW)	Level 2 (3.3 kW)	Level 3 (50 kW)
Type 1	75%	25%	0%
Type 2a (charge at residential area)	85%	15%	0%
Type 2b (charge at commercial area)	60%	30%	10%

IV. TEST RESULT AND ANALYSIS

The parameters to determine the impact of the PEVs are mainly two, 1) voltage profile and 2) substation transformer impacts.

Voltage Profile

Current levels on distribution lines will increase because of the extra power demand from PEVs. Voltages on the radial network will drop as moving towards the end of the branch because of the resistance of the conductors. Voltages at the End Bus of each radial branch are expected to have a bigger impact. In addition, End Buses located in long and/or heavily loaded radial branches will have the worst impact on current levels. Since the assumption is that all residential loads in the network are the same, Buses 5, 11, 16 and 23 are considered the worst case buses, and will be investigated in this study.

There are two dominant voltages at each bus. This is because voltage and the power consumption at a bus are highly correlated. Power depends on current squared, and the current causes a voltage drop because of the line resistance. By observing the power profile of the residential load and commercial load in Figure 7, it can be seen that there are two power levels dominating each type of load (residential load: 0.7 and 1.1; commercial load: 0.4 and 1.6). This causes the two peaks on the voltage distribution function.

To maintain good power quality, voltage variations between 0.95 – 1.05 p.u. are usually acceptable. Voltage at a bus operating outside this range is considered a voltage violation. With no PEVs in the system, all the worst case buses operate within 5% of the lower limit of the nominal voltage. Figure 9, Figure 10 and Figure 11 show the voltage distribution of 0%, 50% and 100% PEV penetration cases. As the penetration of PEVs increases, the voltage distribution functions begin to decrease toward the -5% voltage limit. Table 10 shows the probability of voltage violations and average voltages in different PEV penetration scenarios at each worst case bus. As expected, End Buses on long, heavily loaded radial branches (e.g. bus 11 and 16) have a higher chance of voltage violations. As the PEV penetration increases, bus 16 is the first bus that suffers from a voltage violation, and bus 11 is next worse. Buses 5 and 23 do not exhibit voltage violations in this study because they are located on relatively short branches.

Table 10: Average bus voltage and probability of voltage violation

PEV Penetration	Bus 5		Bus 11		Bus 16		Bus 23	
	Voltage violation	Mean Voltage	Voltage violation	Mean Voltage	Voltage violation	Mean Voltage	Voltage violation	Mean Voltage
0%	0%	0.98	0%	0.97	0%	0.97	0%	0.98
10%	0%	0.98	0%	0.97	0.0042%	0.97	0%	0.98
30%	0%	0.98	0%	0.97	1.2%	0.96	0%	0.98
50%	0%	0.98	0.33%	0.97	9.7%	0.96	0%	0.98
100%	0%	0.97	19%	0.96	29%	0.96	0%	0.98

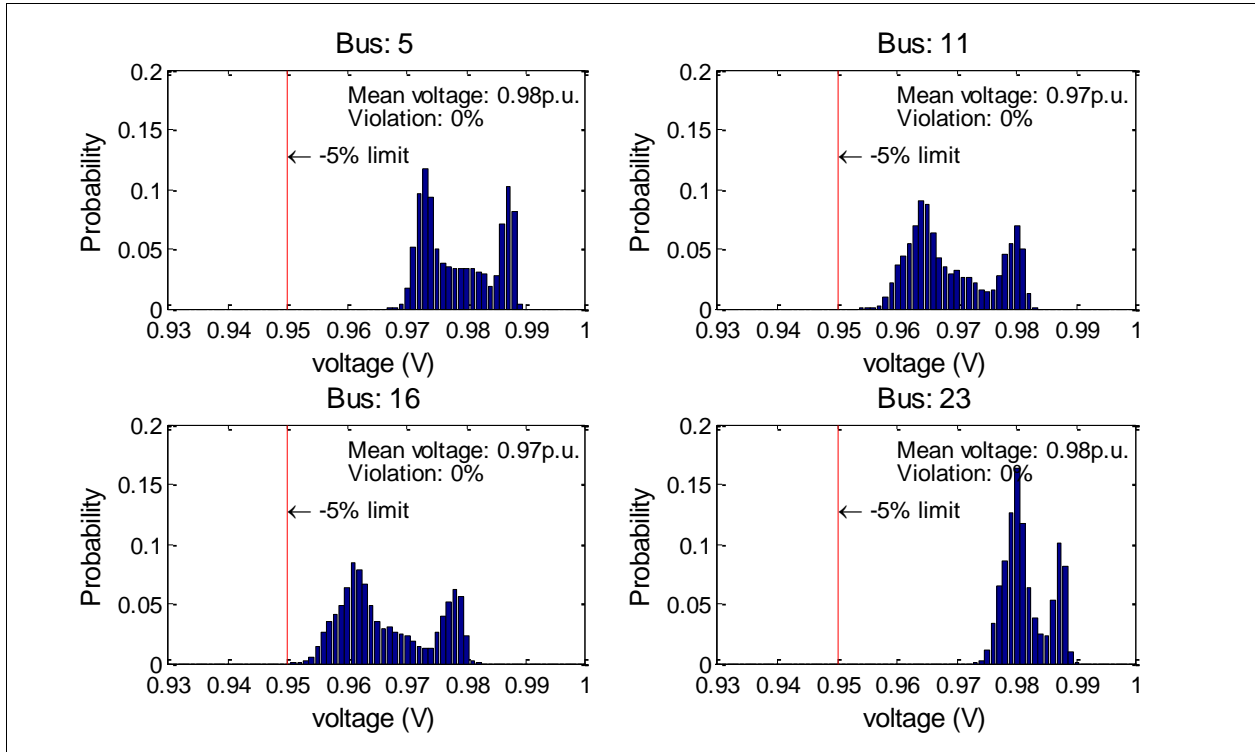


Figure 9: Voltage distribution in 0% PEV penetration scenario

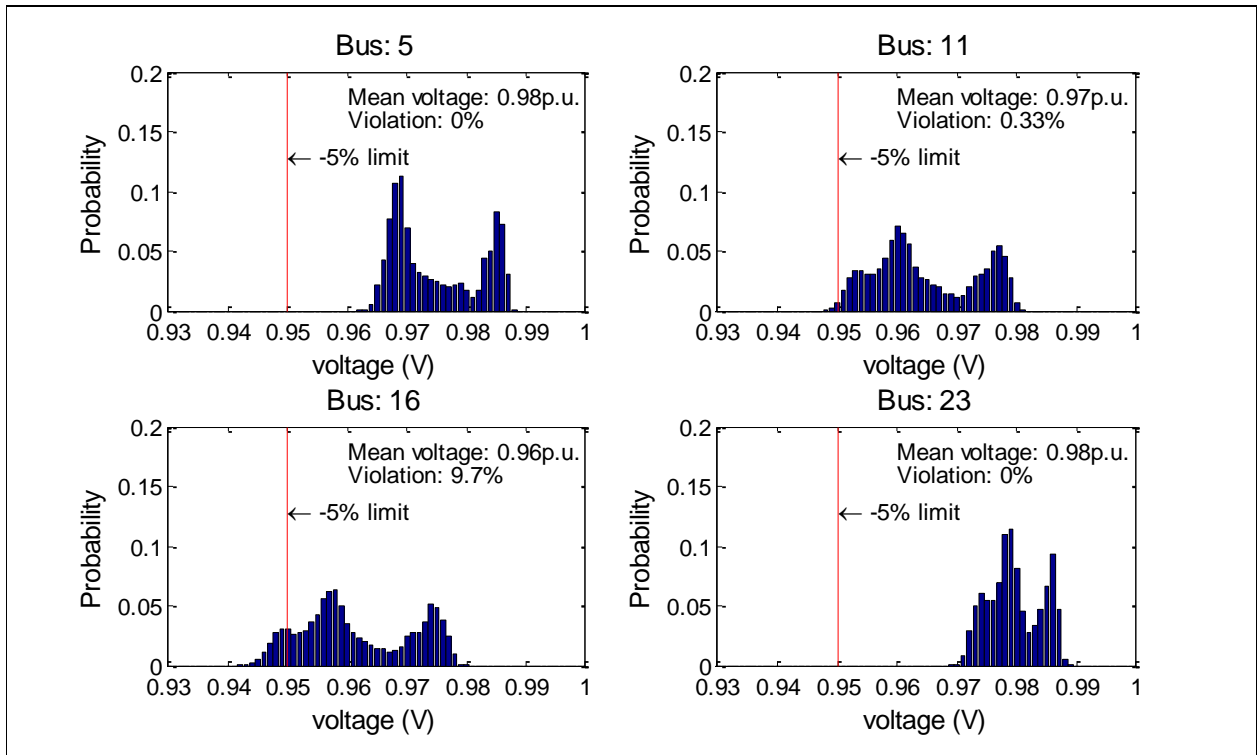


Figure 10: Voltage distribution in 50% PEV penetration scenario

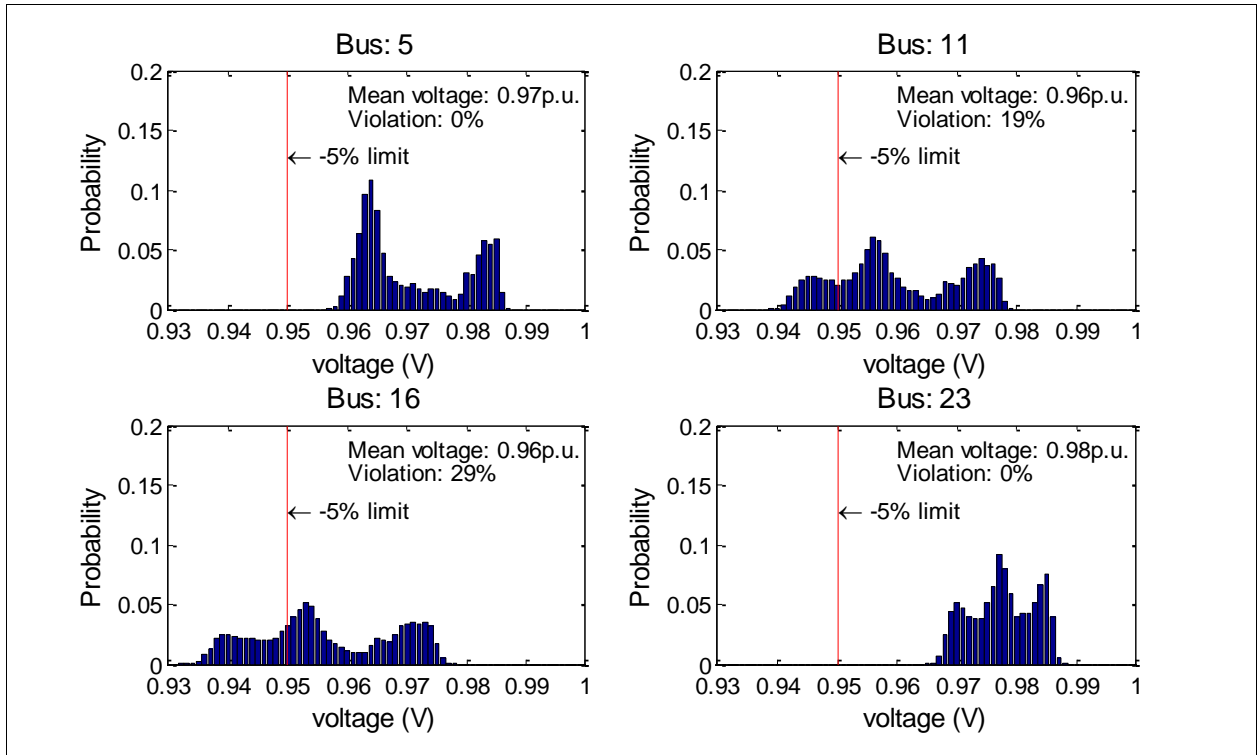


Figure 11: Voltage distribution in 100% PEV penetration scenario

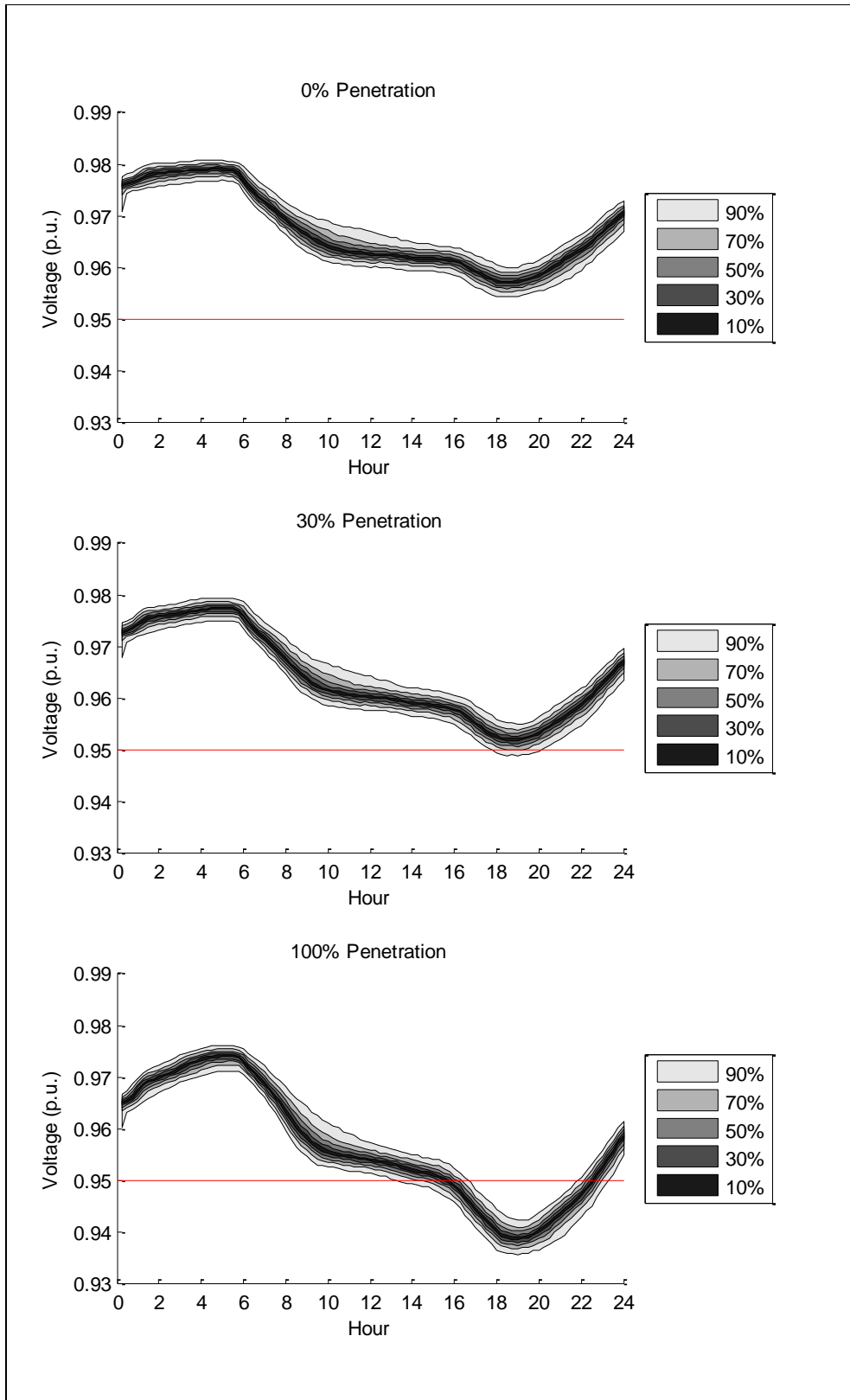


Figure 12: Voltage profile confidence interval with 0%, 30% and 100% PEV penetration scenario at Bus 16

Impact on the substation transformer

Every transformer is designed to handle a certain amount of apparent power. Although most transformers are able to be overloaded for short periods of time with a limited amount of apparent power, exceeding their rated capacities could decrease the transformer's lifetime. In this study, transformer overload means that a transformer is loaded over its rated capacity, and transformer violation means that a transformer is over loaded 20% or above its rated capacity.

The substation transformer at bus 1 is rated at 2.5 MVA in this study. Therefore, 20% above the rated power is 3 MVA. With 0% PEV Penetration, the apparent power varies around 1 MVA to 3 MVA. There are no transformer violation problems. However, as PEV penetration increases in the network, transformer violations become problematic. In the 30% PEV penetration case, there is 9.1% chance that the transformer will be overloaded. In the 50% and 100% PEV penetration cases, the chances of transformer violations are 21% and 60%, respectively.

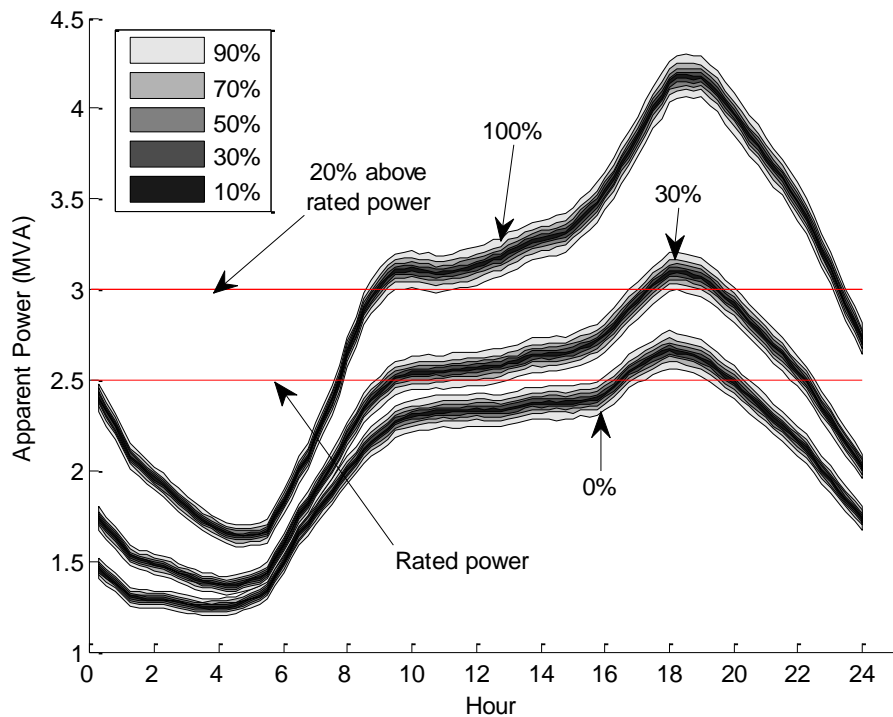


Figure 13: Transformer apparent power profile with 0%, 30% and 100% PEV penetration

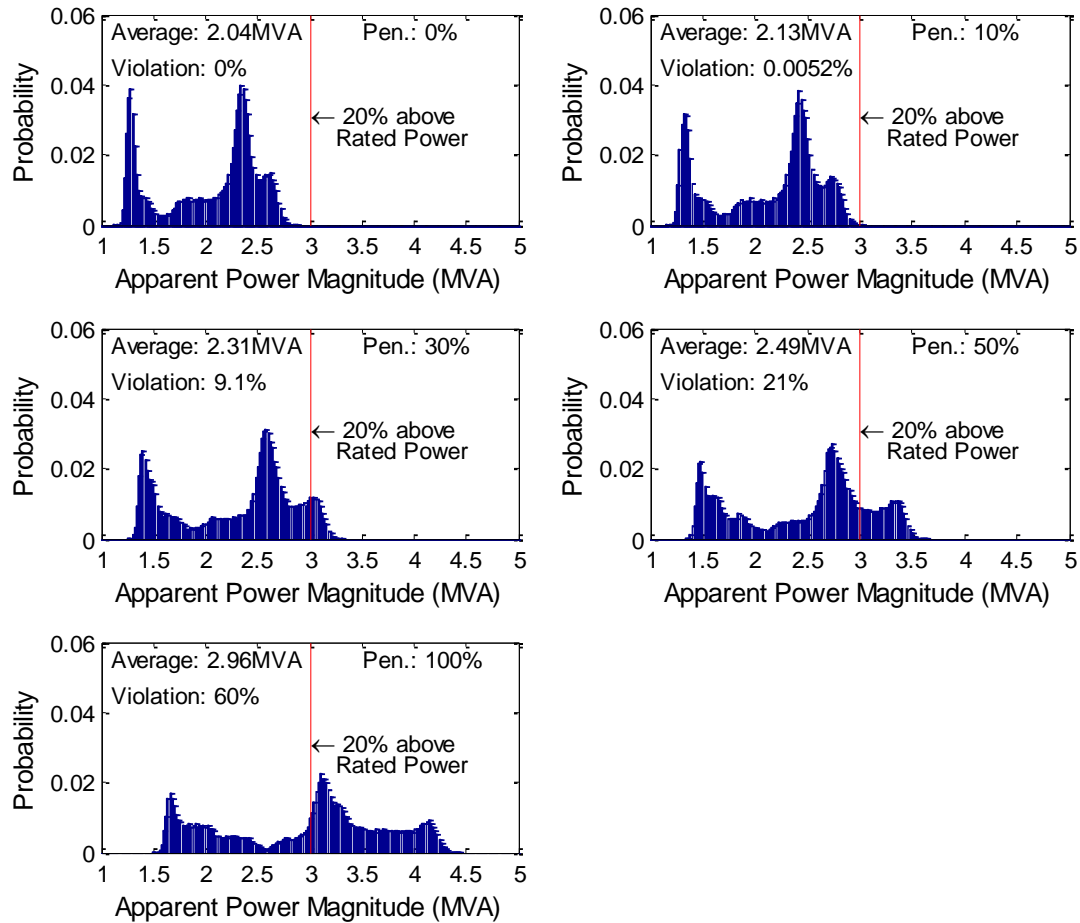


Figure 14: Apparent power distribution in different PEV penetration scenario

A transformer is more likely to be exceeding its overloading capabilities during peak hours. Figure 13 shows the confidence interval of the transformer’s load profile for the 0%, 30% and 100% PEV penetration cases. The lower and upper horizontal red lines are the apparent power levels of the transformer’s capacity and 20% above it respectively. It shows that when there is a 30% PEV penetration in the network, a transformer will likely to be overloaded between 0900 – 2200 hrs, and violated between 1700 – 2000 hrs; and when there is 100% PEV penetration, the overload period will begin around at 0700 until midnight, and violate begin at around 0900 hrs and last until 2300 hrs. Figure 14 shows the transformer load distribution for all studied PEV penetration cases.

V. CONCLUSION AND RECOMMENDATION

Although plug-in electric vehicles create opportunities to reduce reliance on fossil fuels and lower operating costs, the impact to the electrical power system must be carefully considered and addressed in order to avoid damaging equipment and assure that a utility maintains good power quality. Due to the similarity of most drivers' driving patterns and their electricity usage behavior after arriving at a location, uncontrolled PEV charging behavior could cause voltage and transformer violations. Chapter IV shows PEVs' impacts on the voltage profile and substation transformer violations. However, the purpose of this study is to demonstrate how plug-in electric vehicles will affect the electrical distribution system operations. A conclusion for each type's impact to distribution network cannot be generalized from these results because the impacts depend on the specific network structure. This section begins with discussing how these impacts may vary in different type of networks.

Voltage drop in different type of networks

Power demand is proportional to the square of the current. Increases in power demand could result in significant increases in current on radial distribution lines. In addition, because voltage is a function of current and resistance, voltage on a long line will drop. As the power demand increases on a long line, the voltage will drop significantly. Therefore, distribution networks in rural areas are expected to have higher impacts on the voltage than in urban and suburban areas.

The test system in this study shows that buses 11 and 16, which are located at the end of two long radial lines, have greater impacts on voltage than other end buses. Bus 5, although it is heavily loaded, its connection to the network is short in comparison to the line lengths of other buses and thus there is not much impact on voltage at bus 5.

Transformer violations

Transformer violations could be a bigger problem if a transformer frequently operates close to 20% above the rated capacity in the 0% PEV penetration situation. When PEVs are integrated in the network, the transformer is very likely to exceed its nominal capacity during peak hours, even for small penetrations of PEVs. Transformers are an expensive component in the power system. When system planners consider upgrading a transformer, they should not

only take into account the probability of transformer having insufficient capacity, but also how large are these requirements expected to be and for how long.

Solutions

There are several solutions to address the impacts of PEVs to distribution networks. Some traditional ways to reinforce the distribution network are to upgrade the equipment of the system, such as utilizing higher admittance conductors, or using transformers with higher capacities, among other things. However, these solutions are cost prohibitive and some of them take a long time to implement. A more modern approach, and possibly the trend of the future, is to manage the demand side of the network.

Demand side management is a method to control the customers' consumption behavior based on a control signal. This could be effectively used to shave the peak demand by shifting some of the energy consumed during these hours to off-peak load hours. A natural way to achieve this could be by means of introducing financial incentives and/or rules to control customers. For example, since most PEV drivers are expected to park their car at home until they drive it to work the next day, the time at which the vehicles are actually charged does not matter to the end user, as long as the PEV is charged to a certain level, at an hour designated by the end user. Without any control, most PEVs will start charging when they arrive to home from work and are connected to mains; which coincides with residential peak load. A network with demand side management can increase the energy prices during the peak load period, and decrease during off-peak load period so that the PEV owners have an incentive to shift their charging preference.

VI. Bibliography

- [1] M. Irdmoussa, P. Singh, M. Seraj and Z. Abideen, "Analysis of Alternative Energy Sources for the United States Roadway Transportation System.," *Systems and Information Engineering Design Symposium (SIEDS), 2010 IEEE*, pp. 46 - 50, 2010.
- [2] D. Sandalow, *Plug-in Electric Vehicles: What Role for Washington?*, Brookings Institution Press, 2009.
- [3] "Electricity," U.S. Energy Information, May 2012. [Online]. Available: <http://www.eia.gov/electricity/monthly/index.cfm>.
- [4] "SAE J1772-2009 Electric Vehicle Chargers," Electric Car Stations, 2011. [Online]. Available: <http://carstations.com/types/j09>.
- [5] "Leviton EVB22-3PM Evr-Green 160 Home Charging Station, 3.8kW output, Level 2," Amazon.com, [Online]. Available: <http://www.amazon.com/Leviton-EVB22-3PM-Evr-Green-Charging-Station/dp/B004G6ZSZG>.
- [6] "Nissan Introduces Quick EV Charger," Nissan, 04 - 06 2010. [Online]. Available: http://www.nissan-global.com/EN/NEWS/2010/_STORY/100521-01-e.html.
- [7] S. Abuelsamid, "Nissan announces 49 kW quick charger for EVs," *autobloggreen.com*, 21 May 2010. [Online]. Available: <http://green.autoblog.com/2010/05/21/nissan-announces-49-kw-quick-charger-for-evs/>.
- [8] "Table 1-11: Number of U.S. Aircraft, Vehicles, Vessels, and Other Conveyances," Research and Innovative Technology Administration (RITA), [Online]. Available: http://www.bts.gov/publications/national_transportation_statistics/html/table_01_11.html.
- [9] E. Sortomme and M. El-Sharkawi, "Optimal Scheduling of Vehicle-to-Grid Energy and," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 353 - 359, 2012.

- [10] A. Suutari, "USA - Oregon (Portland) - Flexcar: A Model of For-Profit Carsharing," The EcoTipping Points Project, [Online]. Available: <http://www.ecotippingpoints.org/our-stories/indepth/usa-portland-flexcar-carsharing.html>.
- [11] "Plug-in hybrid," Wikipedea, [Online]. Available: http://en.wikipedia.org/wiki/Plug-in_hybrid.
- [12] "Electrification Roadmap: Revolutionizing transportation and achieving energy security," Electrification Coalition, 2009.
- [13] K. Sikes, T. Gross, Z. Lin, T. Sullivan, T. Cleary and J. Ward, "Plug-in Hybrid Electric Vehicle Value Proposition Study: Final report U.S.," U.S. Department of Energy, 2010.
- [14] E. Sortomme and M. El-Sharkawi, "Optimal Combined Bidding of Vehicle-to-Grid Ancillary Services," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 70 - 79, 2012.
- [15] W. Clark, Y. Huang and S. Withers, "Does commuting distance matter? Commuting tolerance and residential change," *Regional Science and Urban Economics*, vol. 33, pp. 199 - 221, 2003.
- [16] J. Peças Lopes, F. Soares, P. Almeida and M. Moreira da Silva, "Smart Charging Strategies for Electric Vehicles: Enhancing Grid Performance and Maximizing the Use of Variable Renewable Energy Resources," in *EVS24*, Stavanger, Norway, 2009.
- [17] M. Kintner-Meyer, K. Schneider and R. Pratt, "Impacts assessment of plug-in hybrid electric vehicles on electric utilities and regional U.S. power grids, Part 1: Technical Analysis," *Online Journal of EUEC 1*, p. paper #4, 2007.
- [18] W. Kersting, *Distribution System Modeling and Analysis*, Boca Raton: CRC, 2002.
- [19] C. Weiller, "Plug-in Hybrid Electric Vehicle Impacts on Hourly Electricity Demand in the United States," *Energy Policy*, vol. 39, no. 6, pp. 3766 - 3778, 2011.
- [20] L. Kelly, *Probabilistic Modelling of Plug-in Hybrid Electric Vehicle Impacts on*

Distribution Networks in British Columbia, University of Waterloo, 2005.

- [21] C. Bhat and S. Singh, "A comprehensive daily activity-travel generation model system for workers," *Transportation Research Part A: Policy and Practice*, vol. 34, no. 1, pp. 1-22, 2000.
- [22] W. Kempton and J. Tomic, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *Journal of Power Sources*, 2004.
- [23] J. Veleba, "Stability Algorithms for Newton-Raphson Method in Load Flow Analysis," *Intensive Programme "Renewable Energy Sources"*, 2010.
- [24] J. Dickert and P. Schegner, "Residential Load Models for Network Planning Purposes," in *Modern Electric Power Systems*, Wroclaw, Poland, 2010.
- [25] S. Zweig, "What are the Most Popular Fuels for Home Heating Systems in the United States?," *Heat USA*, 28 January 2011. [Online]. Available: http://www.heatusa.com/heating-oil/what-are-the-most-popular-fuels-for-home-heating-systems-in-the-united-states_0128/.
- [26] I. NAHB Research Center, "Review of Residential Electrical Energy Use Data," Partnership for Advancing Technology in Housing, 2001.
- [27] "Nissan LEAF Q&A," Nissan, [Online]. Available: <http://www.nissanusa.com/leaf-electric-car/faq/list/charging>.