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Analysis of EV Charging Load Based on Household Driving Data in California

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Analysis of EV Charging Load Based on Household Driving Data in California

A Thesis submitted in partial satisfaction
of the requirements for the degree of

Master of Science

in

Electrical Engineering

by

Jiarui Liu

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Dr. Hamed Mohsenian-Rad, Chairperson
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ABSTRACT OF THE THESIS

Analysis of EV Charging Load Based on Household Driving Data in California

by

Jiarui Liu

Master of Science, Graduate Program in Electrical Engineering
University of California, Riverside, December 2015
Dr. Hamed Mohsenian-Rad, Chairperson

We analyzed a detailed set of over 1000 daily driving traces of GPS-equipped residential vehicles in South California and combined them with the features of four Plug-in Hybrid Electric Vehicle (PHEV) models in order to develop a test data set for PHEV related studies in the field of smart grid. The four PHEV models that were studied are Chevrolet Volt, Honda Accord Plug-in, Ford Fusion Energi, and Toyota Prius Plug-in. The per-PHEV state-of-charge (SoC) traces, the per-PHEV charging load traces under different charging scenarios, and the distribution of per-PHEV initial SoC information are investigated in our analysis. Furthermore, our analysis addressed the factor of location with respect to six Southern California counties: Ventura County, Los Angeles County, Orange County, San Bernardino County, Riverside County, and Imperial County. Our analysis also separately investigated charging load on weekdays and weekends. Finally, we briefly discussed the various applications of the developed EV charging load models in conducting research related to smart grid and demand side management, incorporating temporal and locational EV charging load diversity.

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Chapter 1

Introduction

With the accelerated pace of economy, people have been increasingly concerned with energy efficiency, energy diversification and environmental protection. Over the past decade, electric vehicles (EVs) have emerged as a potential solution to the growing fossil fuel dependence, as well as a solution of drastically reducing the man-made pollutants in the environment [1]. In particular, there is an increasing attention to Plug-in Hybrid Electric Vehicles (PHEVs), which have internal combustion engine and also on-board battery and are designed to charge the vehicle's battery directly from the power grid.

Just like any other new technology, there are pros and cons of switching to EVs. Some studies have pointed out that, with a high penetration level of EVs, their uncontrolled charging load may have adverse impacts on power grid. Recent studies showed that if EVs, such as all-electric vehicles (BEVs) and PHEVs, replace half of all vehicles on the road by 2050, then they would require only 8% increase in electricity generation and 4% increase capacity [2]. Although EV demand on overall power generation capacity may not be significant, the possible impacts on power delivery systems – both transmission and distribution – can be an issue if the vehicle charging behavior is totally uncontrolled. Hence, nowadays, many smart grid researchers have become interested in studying the challenges and opportunities that EVs may bring to power systems [3].

For smart grid research, a crucial need is to have access to experimental data. However, as the penetration level of EVs is still insignificant, we currently lack detailed EV data sets for smart grid related studies. Thus, for now, one of the best options is to use the existing conventional vehicle data sets and combine them with specific EV features to synthesize EV data sets for related smart grid research [3]-[6].

Following the idea in the previous paragraph, in this thesis, we analyze the driving traces of 1005 daily GPS equipped non-PHEV vehicles from the Southern California Association of Governments (SCAG) 2001-2002 Regional Travel Survey data set. Our analysis includes the following tasks:

- Define parking events for each driving trace.
- Identify home parking location and outside parking locations for each driving trace.
- Process to get the second by second driving speed data trace for driving trace.

Next, we also combine the analyzed data set with features of four PHEV models: Chevrolet Volt [7], Honda Accord Plug-in [8], Ford Fusion Energi [9], and Toyota Prius Plug-in [10] to produce a PHEV data set. This additional step allows us to expand our analysis to the following tasks:

- Calculating the State-of-Charge (SoC) profile for each driving trace for each PHEV type.
- Calculating the charging load profile for each driving trace for each PHEV type.

The rest of this thesis is organized as follow. Section II is a basic literature review. In Section III, we processed the non-PHEV driving traces to create some preliminary data to extract the parking and driving traces for each vehicle. In Section IV, we added the technical features of four PHEV model to create new data set that are specific to different PHEV models, and generated the SoC traces for each sample. In Section V, we analyzed the charging load profiles under different scenarios to get an understanding of PHEV influences in electricity system. In Section VI, locational marginal price data is analyzed for future study of charging cost optimization. The thesis is concluded in Section VII.

Chapter 2

Literature Review

The literature related to this thesis can be classified into four groups. First, the literature on addressing EVs in the context of smart grid is rich and diverse. For example, there are studies that examine the adverse impact of EV charging load on distribution feeders, e.g., with respect to increasing power loss, line overflow, and substation congestion [25, 26, 27, 28]. There are also studies that examine the new opportunities that the EVs may offer to better operating the electric grid. In fact, while PEVs are expected to provide economic and environmental benefits to the transportation sector, they may also have a lot to offer to the electric grid, in particular at the distribution level, whether as a potential source of energy storage or as a means to improve power quality and reliability. The possibility of using PEVs to discharge electricity back to the grid has been studied in vehicle-to-grid (V2G) systems [29, 30, 31, 32, 33, 34]. More recently, it has been shown that PEVs may also offer reactive power compensation, not only in a V2G mode but also during a regular charging cycle, with minimum impact on the EV battery lifetime [35, 36, 37, 38, 39].

Second, driven by the enthusiasm of investigating EV challenges and opportunities in different research fields, there are also studies that have addressed experimental conventional vehicle and EV related data sets. In [4], the authors analyzed a set of 536 GPS-equipped fleet of conventional vehicle taxies in San Francisco area, and developed a PHEV test data set by combined each trip information from the original data set with PHEV features and characteristics. The developed data set then used to analyze the PHEV charging load. Similarly, in [18], the authors converted one day travel trace data of 229 conventional vehicles in Austin area to a PHEV data set to analyze the impact of charger network coverage on PHEV energy consumption and cost. In [6], the authors used a sample of real world driving data from the National Household Travel Survey, and applied the trip profile and drive cycle information to simulate on-road PHEV electricity and gasoline consumption. In [19], the authors converted 830 days of driving traces from Southeast Michigan into a PHEV-resembled data set, and then proposed a statistical model to for generating PHEV daily driving missions. Our study in this thesis is different from the above papers in two aspects. First, we use a different data set that is specific to Southern California, a region that has the highest rate of PHEV sales in the United States. Second, our analysis is particularly tailored on the idea of locational diversity and how the EV charging load patterns may change across different counties, where people have different lifestyles and different driving patterns.

The SCAG Regional Travel Survey data set that we used in this study had once been used for an EV related research project by in [20]. However, the research goal was entirely different from ours. Here, we are concerned with modeling and forecasting the charging load of EVs. However, in [20], the primary concern was to compare the SCAG Regional Travel Survey data set with the Environmental Protection Agency's (EPA) test cycles. In that sense, the study in [20] compliments our work as it may indirectly point out how our results may change if we use the EPA test cycles. We shall point out that the SCAG Regional Travel Survey data set has also previously been used in studies that are not related to EVs, ranging from vehicle movement activity analysis [21] to calculate traffic related air pollution [22].

Finally, the methodology that we used and the type of analysis that we conducted in this thesis can be applied also to other similar data sets, such as the California Department of Transportation (CALTRANS) 2010-2012 Household Travel Survey [12]; the Texas Department of Transportation Household Travel Survey data set that used in [18]; the Crawdad data set in [4], and so on.

Chapter 3

Description and Pre-process of Vehicle Data Traces

3.1. Data Description

The Non-EV vehicle driving traces were obtained from the 2001-2002 Regional Travel Survey, which was commissioned by SCAG [11]. The survey was conducted in June 2001, September through December 2001, and January 2002 through March 2002. In total, there are 464 houses and 623 vehicles involved in this data set [12]; each house has one to three vehicles that were equipped with in-vehicle GPS devices. These houses are located in six different counties in Southern California:

- Ventura County
- Los Angeles County
- Orange County
- San Bernardino County
- Riverside County
- Imperial County

The households involved in the survey are chosen carefully, so that the samples of the SCAG data set are representative to the real conditions of the researching area. For each vehicle, each GPS-enabled data trace record the following quantities:

- Latitude Information
- Longitude Information

- Speed Information
- Time Stamp

The time interval between two data recording was around 1 second. The GPS tracking device was stopped recording every time the vehicle was turned off, and began recording again once the vehicle was turned on.

Some of the data were unusable due to missing values: very short daily use records with missing data or nonsensical values. After eliminated the unusable data, we made a data set with 1060 samples of daily travel traces. The distribution of households, vehicles and samples in each county is shown in Fig. 1.

As we can see in Fig. 1, most of the samples are located in Los Angeles County, Orange County, and Riverside County. Therefore, in our later analysis, we focused our processes on these three main Counties.

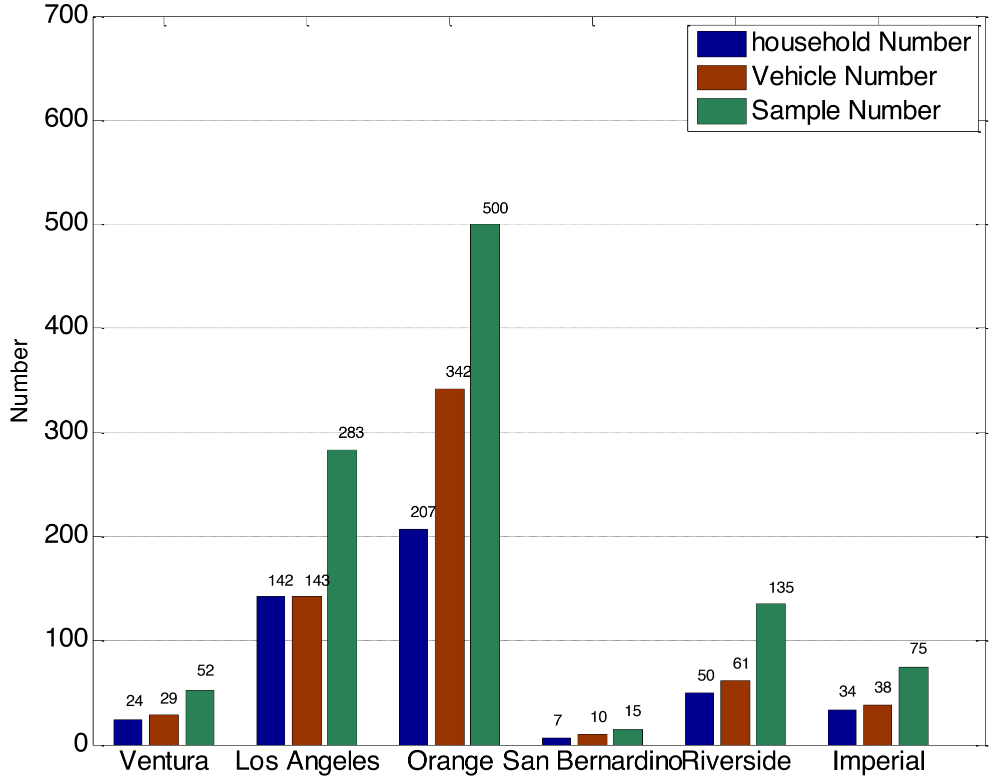


Fig. 1. The Distribution of Household, Vehicle, and Sample Numbers in Each County.

3.2. Data Pre-process

Since we would like to use the constructed data set to do EV-related research, we needed to reasonably translate the vehicle driving traces for the analysis of charging load and charging cost. Therefore, the first step of our analysis was to define parking events. Since we could get timely speed information from the data set, we decided to identify whether a vehicle was moving or parked using the speed data. However, not every stationary behavior should be viewed as parking events. For example, in urban traffic, it is common that vehicles stopped for minutes waiting for the traffic light turn green, and heavy traffic situations can also cause no movement or very slow movements. Also, very short parking behavior has no value for the study of EV charging and smart grid, since it seems meaningless for an EV owner to charge his/her vehicle during a very short parking interval. Therefore, we defined a parking event as any time that a vehicle has a speed equal to 0 or the GPS is switched off for 15 minutes or more.

We assumed that the vehicles in each sample leave home in morning and went back home at night. If the GPS data for a particular sample suggest otherwise, then such sample was not considered. The above assumption was made based on at least two points:

1. The purpose of SCAG survey was *to update regional travel demand models with data on household characteristics and travel behavior* [12], and holiday driving was not recorded. Hence, this data could be viewed as urban commute.

2. By checking the distance between the first and last GPS reading for each sample, we saw that the distance of 85% of all samples are less than 2 miles.

We used the following procedure to identify home parking location for each sample: First, we obtained the latitude, longitude, and speed data of the first and last rows for each sample. Then, we dropped those samples which obviously had very different begin and end locations. Next, for each sample in the cleaned up data set, the speed data of its first and last row is examined. If the speeds are zero or non-zero but equal, then the latitude and longitude of home location was assumed to be the mean of the data-begin row and data-end row GPS readings. If the speeds were non-zero or they were different, then we chose the latitude and longitude of the lower speed row as the home location.

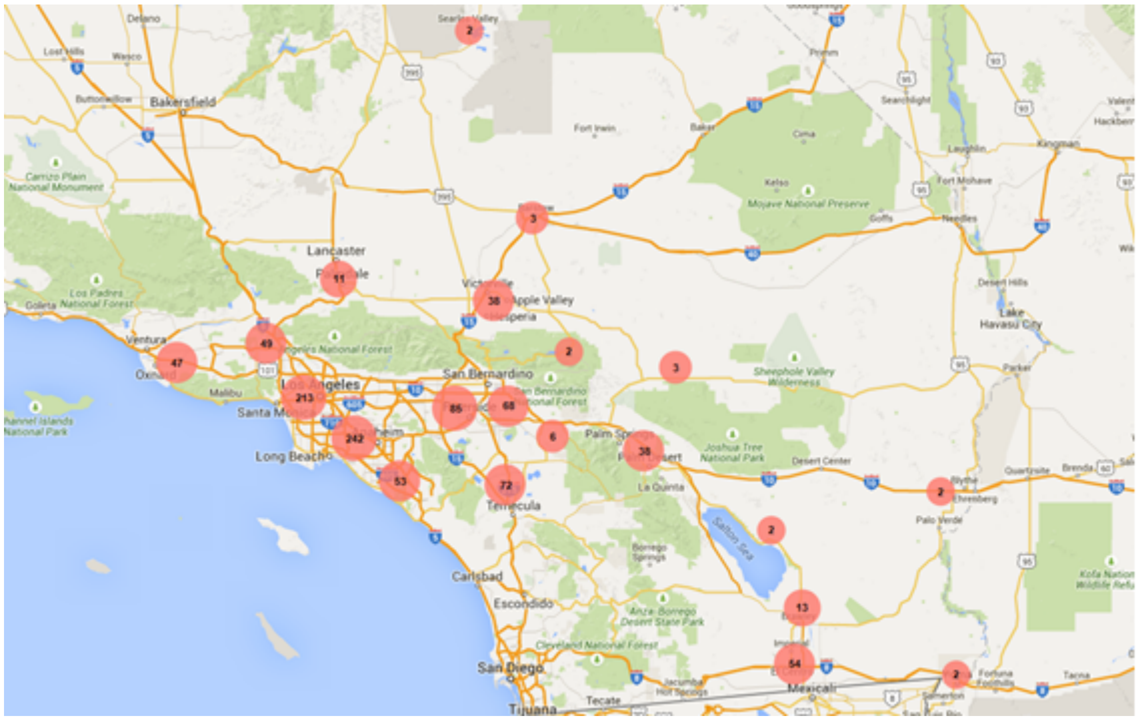


Fig. 2. The geographical distribution of home location for all samples.

After the above procedure, we finalized 1005 samples with reasonable identified home locations. The geographical distribution of home locations of samples is shown in Fig. 2.

For parking event outside home, if the difference of two parking locations is less than 1 mile, then we considered them as two parking events at same parking location, otherwise, they were considered as two parking events at two different parking locations. Note that, this assumption only affects our analysis on the number of parking locations but not the number of parking events.

Following the methodology described above, we analyzed the driving and parking traces for all the 1005 samples. The results are shown in Fig. 3 for three vehicles in Los Angeles County, Orange County and Riverside County, respectively. Here, value 1 on the Y-axis indicates that the vehicle was parked and value 0 means the vehicle was driving. The location of parking event is mentioned above the curve every time the vehicle is parked. Note that, only the outside home parking events are identified by numbers. We can see that different vehicles have generally different driving and parking patterns, and longest parking often happens at home, including the long overnight home parking events.

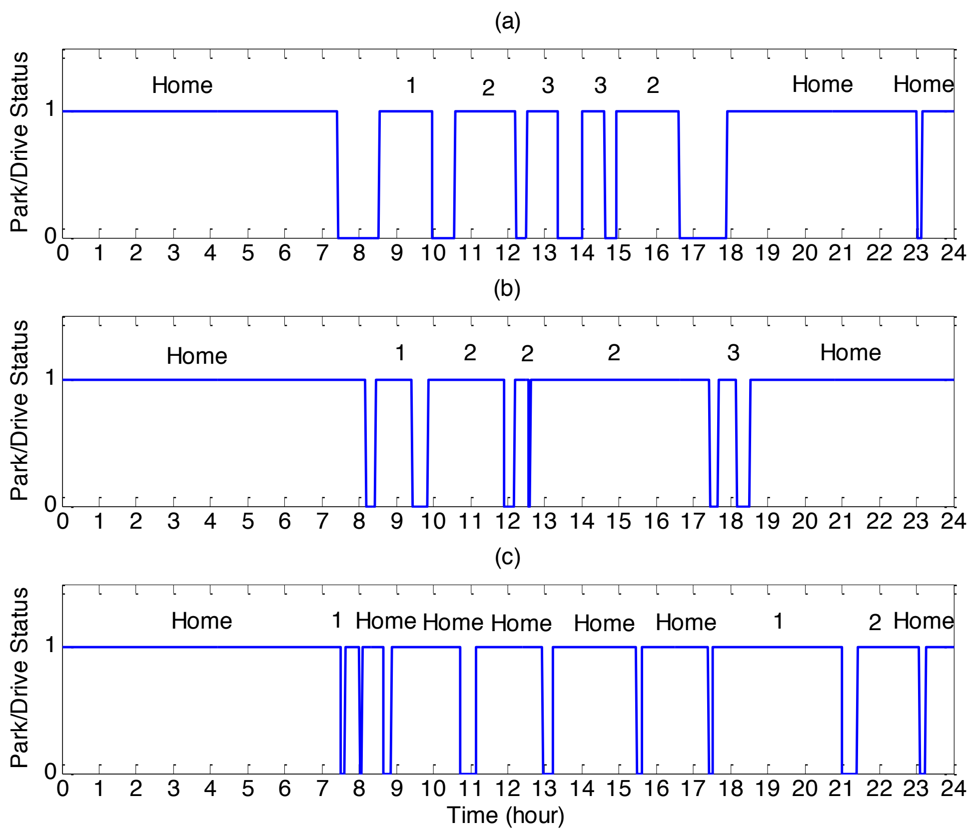


Fig. 3. Three examples for the driving-parking traces for three vehicles in three counties.

Next, after putting together the driving and parking traces of all the samples, we analyzed aggregate characters of all samples from the data set:

- The distribution for the number of parking events.
- The distribution for the duration of parking events.

The distribution of number of parking events is shown in Figs. 4(a) and (b) for home parking and outside parking, respectively. We can see that about 218 samples, comprising 21.7% of all samples, did not have outside parking events during the day. That is why there is a bar for zero parking events in Fig. 4(b).

Note that each overnight parking at home was counted as one home parking event. Therefore, for samples that had only one home parking event, which is about 528 samples comprising 52.54% of all the samples, the vehicle did not drive back home except for overnight parking. This is an important observation, because this observation is related to EV charging location option, as we will discuss later.

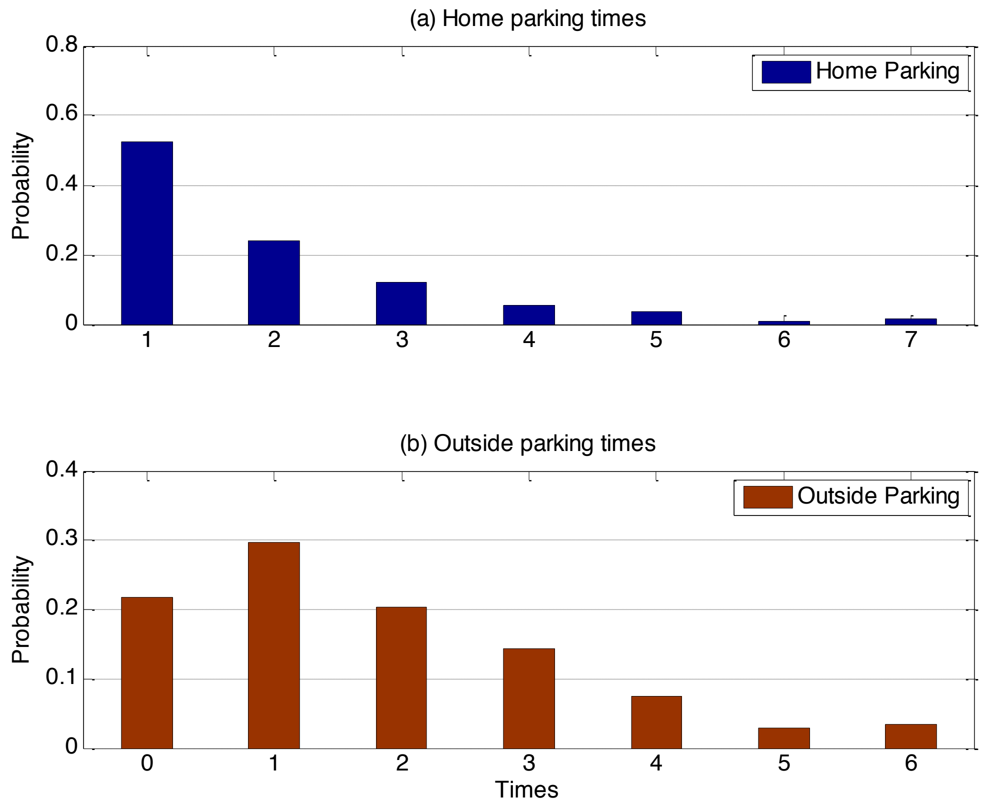


Fig. 4. Distribution of the number of home and outside parking events per sample.

The histogram of the distribution of parking durations is shown in Fig. 5. Based on our observation, there are 1943 home parking events, and 1831 outside parking events in this 1005 days data set.

We can see that, most of the outside parking events are less than 5 hours, this is a reasonable observation, as for daily urban commute, most possible out-of-home parking events would be corresponding to parking during work, and normally each working interval would be less than 5 hours.

About home parking durations, three time intervals occupied the main probability:

- Parking at home for less than 4 hours.
- Parking at home between 9 to 19 hours.
- Parking at home for more than 23 hours.

For those parking durations that are less than 4 hours, it is reasonable to view them as home parking during the day, as they were mostly happened after some driving events.

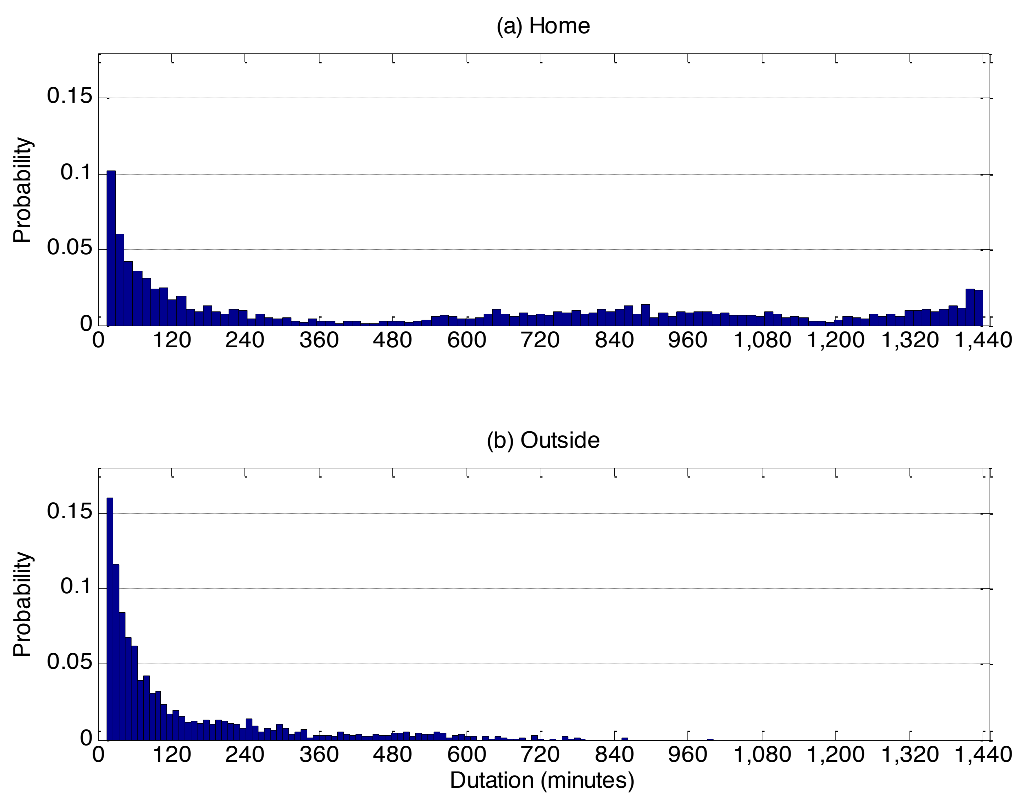
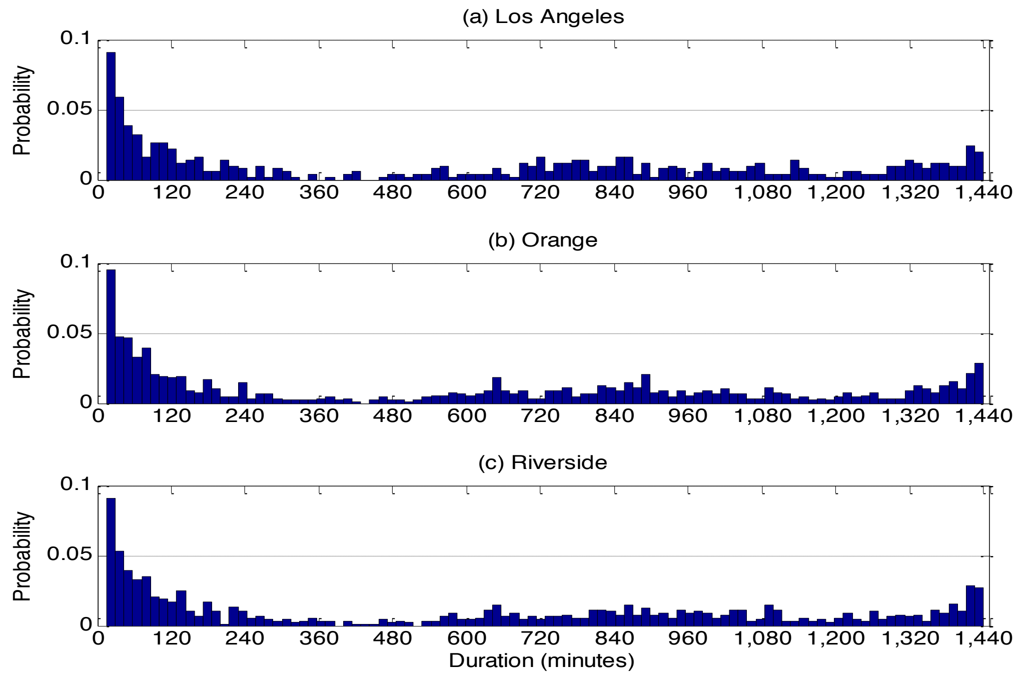


Fig. 5. Distribution of duration of parking events.

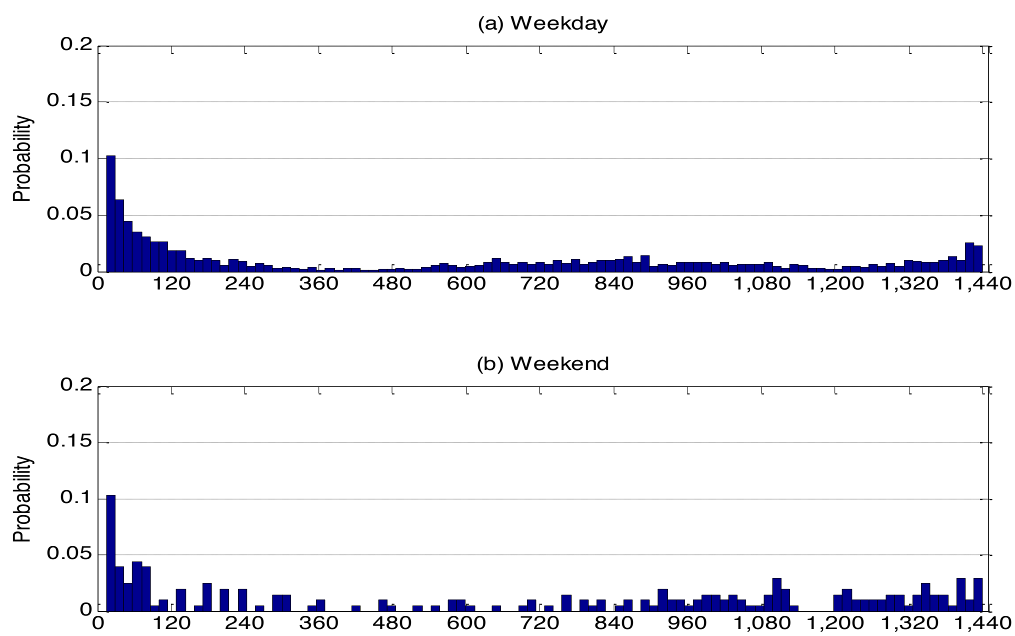
For parking events that took between 9 to 19 hours, they were mostly the night home parking events.

For home parking events with more than 20 hours, they often happened either because the vehicle was parked at home for most of the day or it was because there are some trips missing in that particular sample, so we classified those missed time intervals as a part of home parking durations.

As we can see in Fig. 6(a), the distributions of duration of home parking events in Los Angeles County, Orange County and Riverside County are more or less the same. This observation could be used in our later analysis. In addition, we can also see that, vehicles have higher probability to park longer at home during weekends compared to during weekdays, based on an observation of 1740 weekday home parking events from 890 weekday samples and 203 weekend home parking events from 115 weekends samples, shown in Fig. 6 (b).



(a)



(b)

Fig. 6 Distributions of parking durations by County and by Weekday and Weekend.

Next, recall that the time interval between two consecutive GPS data recordings in the SCAG data set was around 1 second, which means the time interval between two continuous recordings could float from less than 1 second to 2 or 3 seconds randomly, and in addition, we also saw some data missing for short intervals during driving events. As a result, since we needed speed data to calculate EV energy usage in the next section of this thesis, as the last step of our pre-process, we processed the speed and time data traces from the original data set, and yielded second by second speed traces for each sample.

We shall point out a few notes about how we finalized the second-by-second speed traces for our analysis. First, for the situation of two or three records with the same time stamps, we simply added 1 second to the next reading; second, for the situation of having a missing time segment between two non-zero speed driving readings. If the missing interval is less than one minute, then we viewed this segment as a data missing, and we replenish the segment with continuous time and constant speed, where the speed was calculated as the mean of those two non-zero speed readings. Third, for the situation of missing time segments for more than one minute and less than 15 minutes, we assumed that this segment was a short and negligible (for the purpose of our research) parking event.

The distribution of daily driving distance is shown in Fig. 7. We can see that most vehicles drove less than 70 miles per day. Although, there are also quite a few vehicles that drove over 130 miles per day.

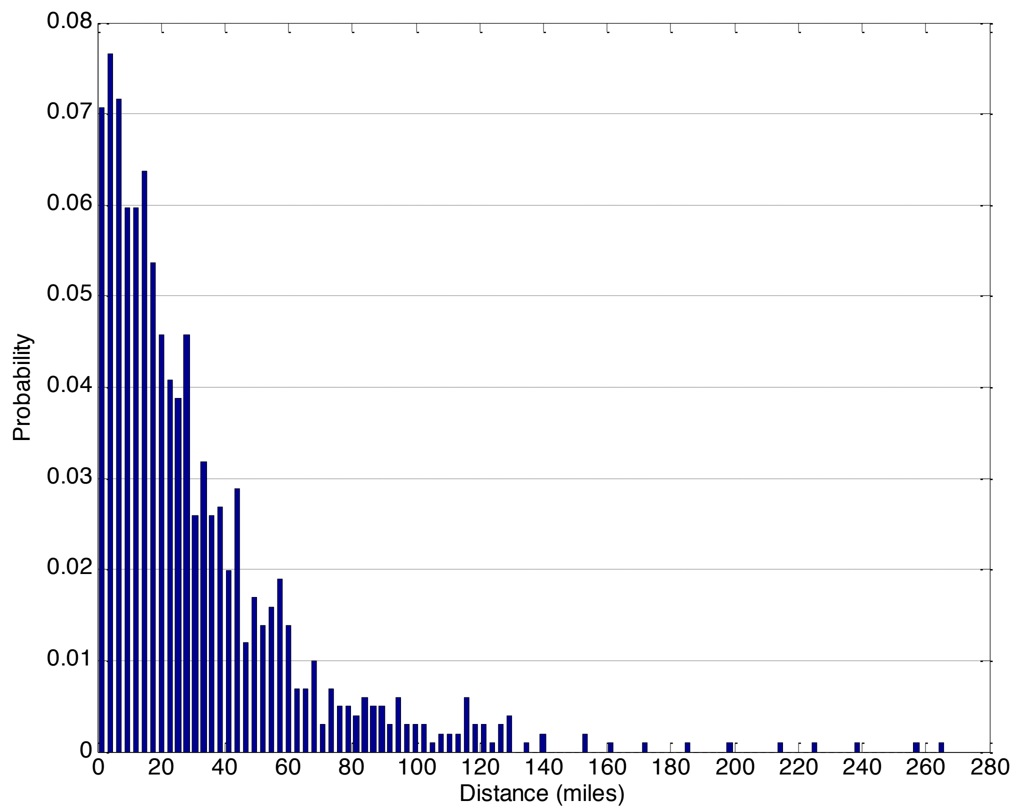


Fig. 7. Distribution of Daily Driving Distance

Chapter 4

Adding Features of PHEVs into Driving Data Sets

4.1 PHEV Selling and Penetration Information in California

As of June 2015, the United States has the largest fleet of plug-in electric vehicles in the world. California is the leading EV regional market in the United States, with a total of 142,886 plug-in electric vehicles registered from December 2010 to March 2015, representing about 46% of all plug-in cars sold in the United States [14]. Among the 142,886 Plug-in electric vehicle registrations, 71,536 units are PHEVs [13]. The market share of PHEV reached 0.72% of new car sales during 2014 in entire U.S., and for California, during 2014, PHEV market share reached 3.2% of the total new car sales in the state [14]. As of December 2014, California had more PHEVs than any other country in the world.

Within all the top selling EV brands in the United States, Nissan Leaf is the best-selling all-electric vehicle, which has sold 82,138 units through June 2015, followed by Tesla Model S, which has sold 49,720 units since June 2012. As for PHEV selling, Chevrolet Volt is the most popular PHEV model, which has sold 78,979 units since it launched in market on December 2010, followed by Toyota Prius PHV – 40992 units, and Ford Fusion Energi – 21929 units, another model which we considered in our later analysis – Honda Accord PHEV, has sold 1034 through 2015 in the entire United States [14].

4.2 Features of Four PHEV Models

In this section, we aim to add features of several PHEV models to the processed second-by-second speed traces data set that we finalized in section III. The purpose is to calculate the State of Charge (SoC) traces and charging load traces of each sample under different PHEV technologies. Four PHEV models are used in this section: Chevrolet Volt, Honda Accord Plug-in, Ford Fusion Energi, and Toyota Prius.

The operational characteristics of these vehicle models are listed in table I.

Table I

OPERATIONAL DATA OF FOUR COMMON PHEVs

Brand	**Chevrolet**	**Honda**	**Ford**	**Toyota**
Model	Volt	Accord	Fusion	Prius
Weight (kg)	1717.3	1576.2	1774.9	1451.5
Frontal Area (square meter)	2.20	2.21	2.21	2.22
Aerodynamic Drag Coefficient	0.28	0.29	0.28	0.26
Battery Capacity (kWh)	16	6.6	7.6	4.4
Available Energy (kWh)	8.8	3.8	7.1	3.2
Average Electric Range (mile)	37	13	21	11
Max Charging Rate (kW)	3.5	6.6	3.5	3.5
Electricity Consumption *	36	29	34	29
Gas Consumption **	2.7	2.2	2.3	2
Power Train Index ***	D	B	D	B

*KW/100 Miles
**Gallons/100 Miles
***D: Charging Depleting. B: Charging Blending

Note that, we classified the four PHEV models into two types based on their power train:

- Charging depleting
- Charging blending

The charging depleting type of PHEVs use electric power stored in their battery at startup, and only switches to gas power after their battery has reached a minimum state of charge threshold. The charging blending type of PHEVs may blend the power sources and use the gas engine to increase the torque in high speed driving even if the battery is not depleted. In our analysis, we assumed that the speed threshold of switching from electric power to gas power is 60 mph. And, based on [4], while Ford Fusion is capable of using the charging blending technology, it typically runs in all-electric power mode. Therefore, it is categorized into the charging depleting mode.

4.3 State of Charge Calculation and Analysis

Next, we used the second-by-second driving and parking traces to calculate SoC for each vehicle.

Instead of using fixed electric power consumption rates (KWh/mile) to calculate PHEV energy usage [4]. We calculated the timely power usage in terms of speed data, according to physical laws.

In general, four different forces affect (impede) vehicle movement [15]:

(1) Rolling resistance.

(2) Aerodynamic drag resistance.

(3) Inertial resistance.

(4) Grade resistance.

For our analysis, since we cannot obtain road grade data for our available data set, we only considered the first three resistances in our energy usage calculation.

Rolling resistance force F_r is related to vehicle tire material, tire construction, and road surfaces, and it can be calculated as a function of vehicle weight. Generally, F_r varies between 20 to 50 lbs. per ton of vehicle weight. We can calculate it based on a rolling resistance coefficient C_r:

$$F_r = C_r \times m \times g. \tag{1}$$

where

m	Vehicle weight (kg).
g	The acceleration of gravity (m/s^2).
C_r	Normally equal to 0.0165.

Aerodynamic drag resistance force F_{air} is a function of weight, speed and air density:

$$F_{air} = \frac{1}{2} \times \rho_{air} \times C_a \times A \times V^2. \tag{2}$$

where

ρ_{air}	Air density (kg/m^2).
C_a	Aerodynamic drag coefficient. Different between each vehicle model.
A	Frontal area (m^2). Different between each vehicle model.
V	Vehicle speed (m/s).

Inertial resistance force (F_a), is the excess effort that is employed for motion. Based on Newton's second principle, inertial resistance can be expressed as:

$$F_a = m \times a \times V. \tag{3}$$

where

m	Vehicle weight (kg).
a	Vehicle acceleration (m/s^2).
V	Vehicle speed (m/s).

The timely total power requirement (P_{total}) can be calculated as the sum of all resistance force multiplied by the vehicle's forward speed V:

$$P_{total} = F_a \times V + F_{air} \times V + F_r \times V$$
$$= m \times a \times V + \frac{1}{2} \times \rho_{air} \times C_a \times A \times V^3 + C_r \times m \times g \times V. \qquad (4)$$

Accordingly, the energy usage (E_{total}) in each second can be calculated as:

$$E_{total} = (F_a \times V + F_{air} \times V + F_r \times V)/C_c$$
$$= (\mathrm{m} \times \mathrm{a} \times \mathrm{V} + \frac{1}{2} \times \rho_{\mathrm{air}} \times \mathrm{C_a} \times \mathrm{A} \times \mathrm{V}^3 + \mathrm{C_r} \times \mathrm{m} \times \mathrm{g} \times \mathrm{V})/\mathrm{C_c} \qquad (5)$$

Where C_c is the *energy converting efficiency ratio*, which represents how much energy that is stored in the battery can be converted into kinetic energy. It is set to be 80% in our analysis [23]. We also considered Regenerative Breaking in power usage calculation, and the energy capture efficiency is 80%.

We assumed that when a vehicle is plugged-in to a charger, the charging rate is 240V-32A [4]; but the actual charging rate for a PHEV model cannot exceed its own maximum charging rate. Accordingly, we calculated the SoC during the charging interval specifically based on the max charging rate listed in table 1.

Two charging scenarios are considered in our analysis to help better understand the relationship between SoC traces and the charging strategy:

- **Scenario 1**: EVs only charged during home parking events.
- **Scenario 2**: EVs charged during all home parking events and during the longest outside parking event.

From (5), together based on the second-by-second speed data set we got in section II, we can now develop a new data set that contains the SoC traces for each sample under both scenario 1 and scenario 2 above.

4.3.1 Analysis based on Scenario 1

For scenario 1, three sample SoC trends from three counties are shown in Fig. 8. The SoC traces in this figure are based on Chevrolet Volt data. We can see that, for sample No. 5 and sample No.10, they both had two home parking events, and for sample No. 143, there was only one home parking events.

If the SoC trace goes down, it means the vehicle is moving, powered by its battery energy; if the trace goes up, it means the vehicle is plugged in a charging station, and its battery is being charged. We can also recognize some time intervals where the SoC is flat, i.e., it does not change. These cases are either the time frames where the battery is depleted and no electrical energy is used and the power train is switched to gas, or they indicate that the vehicle is parked without battery being charged.

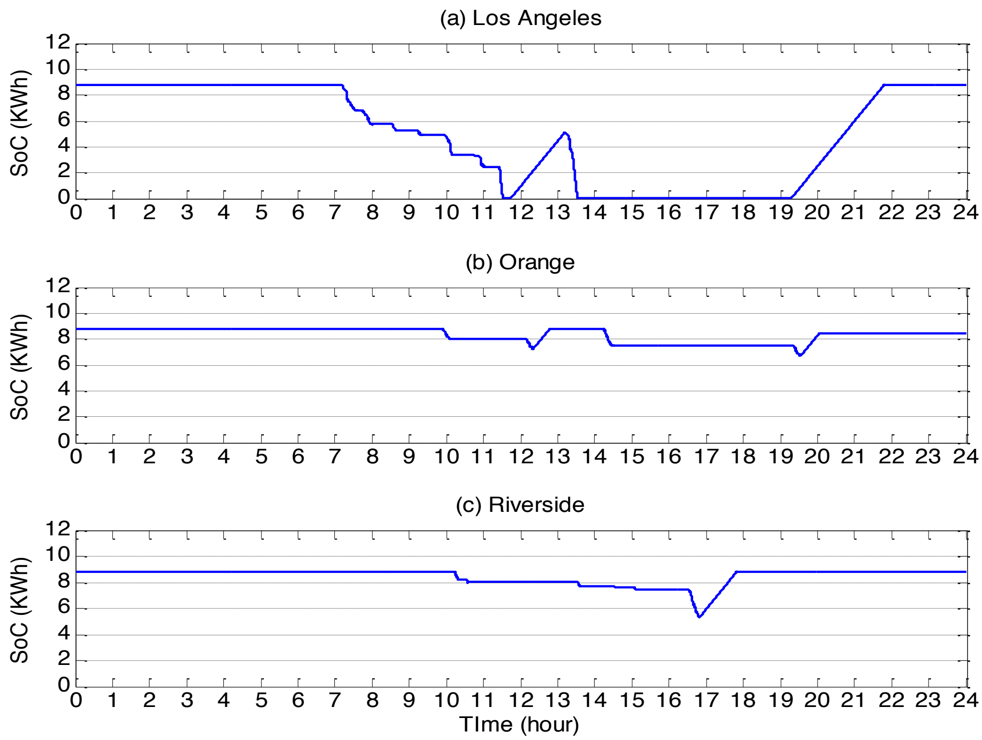


Fig. 8. The State-of-Charge traces under scenario 1 for 3 samples from 3 counties respectively: (a) sample No.5 from Los Angeles County, (b) sample No.10 from Orange County, (c) sample No.143 from Riverside County.

Next, we compare the SoC traces of different PHEV models. Sample No. 5 is used, and four traces based on the features of different PHEV models are generated, as shown in Fig. 9. We can see that, from 7:10 AM to 11:50 AM, for PHEV models Volt and Fusion, they almost run the entire trip in all-electric mode, but for PHEV model Accord and Prius, since their battery capacity is relatively small, they are quickly depleted, and they have to run most of the trip based on their internal combustion engine. In the meantime, because of their smaller battery, Accord and Prius can get fully charged during the noon home parking events, while Volt and Fusion cannot. Also, note the trip from 13:20 PM to 19:20 PM, Volt and Fusion got their battery depleted even faster than Accord and Prius. This is because the vehicle sample No. 5 drove with more than 60 mph during 13:00 PM to 14:00 PM, since Prius and Accord are Charging Blending type of vehicle, they would have switched to gas when the speed is high.

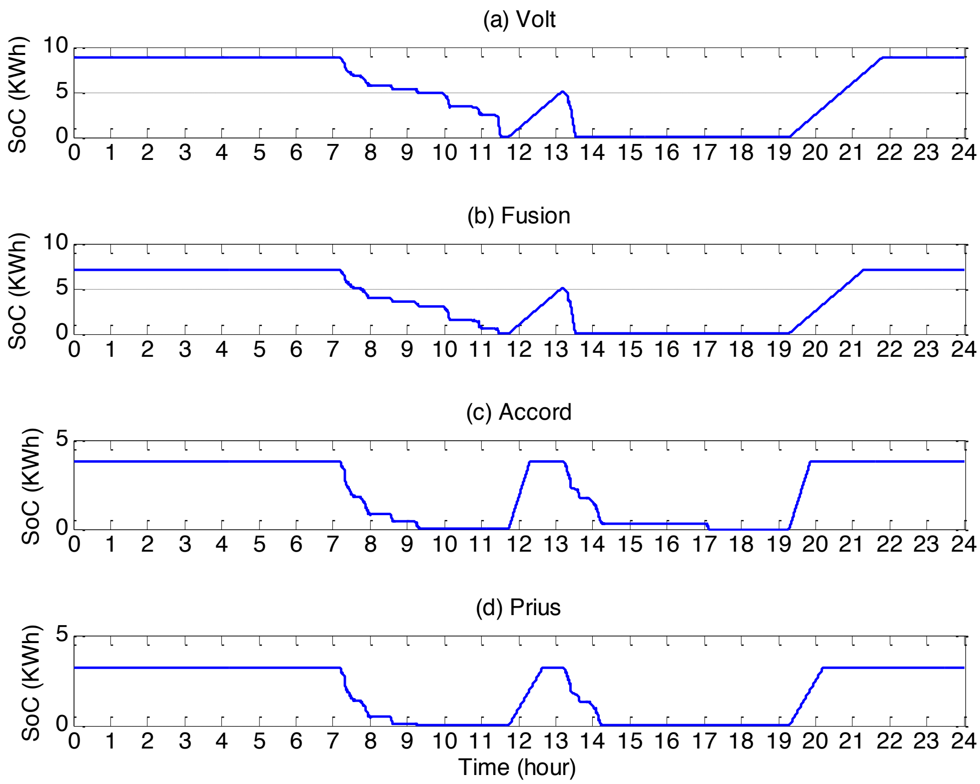


Fig. 9. The State-of-Charge traces of Sample No.5 for Four PHEV models under Scenario 1.

Next, we generate the distribution of all 1943 home parking events in 1005 samples, and compare the results with the distribution of the time that each PHEV model needed to get fully charged during parking. The comparison is shown in Fig. 10. We can see that, around 20% of times, vehicles need relatively longer time to get fully charged, and that time is the time duration to get the vehicles battery charged form depleted to full. This means that, at least 20% of the trips from this data set cannot be completed if only depended on electricity, no matter what PHEV model it is, and also, there are slightly more trips that can be completed by Volt and Fusion, since they have larger battery capacity.

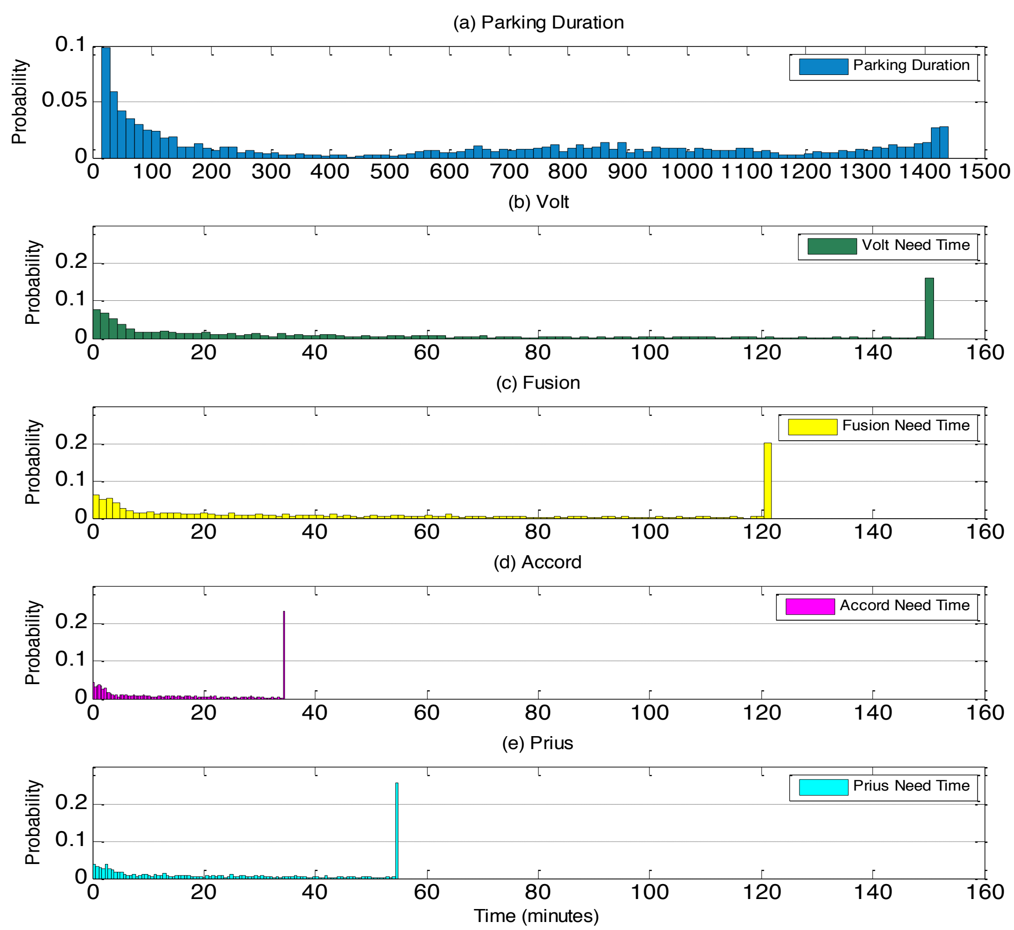


Fig. 10. Distribution of Parking Duration versus Fully Charge Needed Time during Each Parking Events based on Four PHEV models.

As the next step, we generated the distribution of initial SoC before each charging event, as shown in Fig.11. If we compare Fig .11 with Fig.10, there is an interesting observation that the initial SoC profile for each PHEV model in Fig. 11 is symmetrical to the fully charge needed time profile in Fig.10. That is easy to explain, if one vehicle has higher initial SoC at the beginning of a charging event, than it will need less time to get fully charged during that parking event. So Fig. 10 and Fig.11 together shows that the SoC traces we got for each sample in this data set are reasonable and reliable.

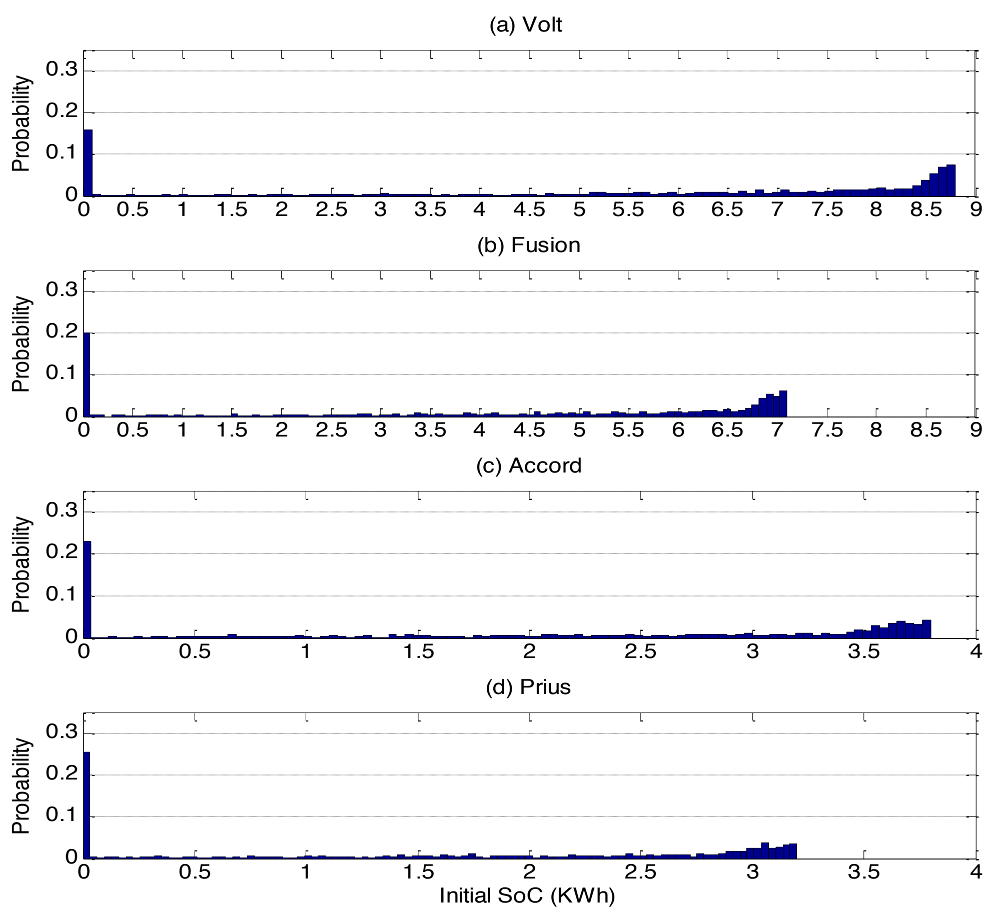


Fig. 11. The Distribution of Initial SoC before Each Charging Event.

Let us now take a look at the electricity versus gas usage under four PHEV models. The results are shown in Fig. 12. Fig. 12(a) shows the comparison of two charging depleting type of vehicles: Volt and Fusion. Fig. 12(b) shows the comparison of Accord and Prius. Recall that, more than 50% of the 1005 samples have only one home parking event. As a result, they cannot be recharged during the day until they are finally parked at home. This explains the reason why we got the highest probability at the electricity usage equal to battery capacity. We can see from the figure that, as they have relatively smaller battery capacity, Accord and Prius normally need more gas than Volt and Fusion to complete the daily trips.

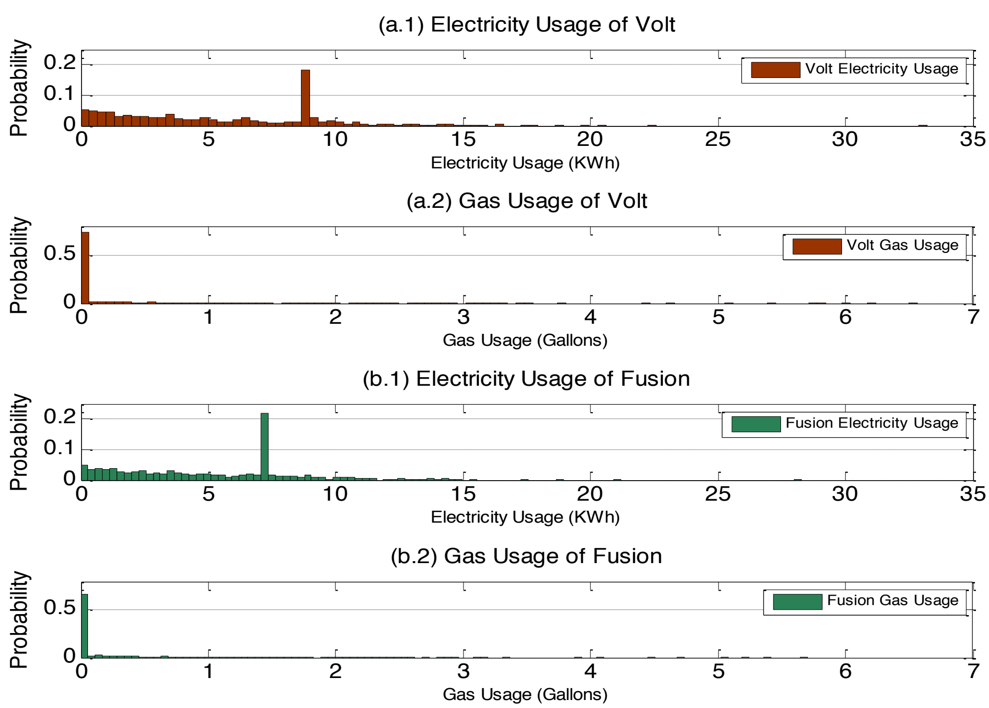


Fig. 12 (a). The Distribution of Electricity versus Gas Usage for Volt and Fusion.

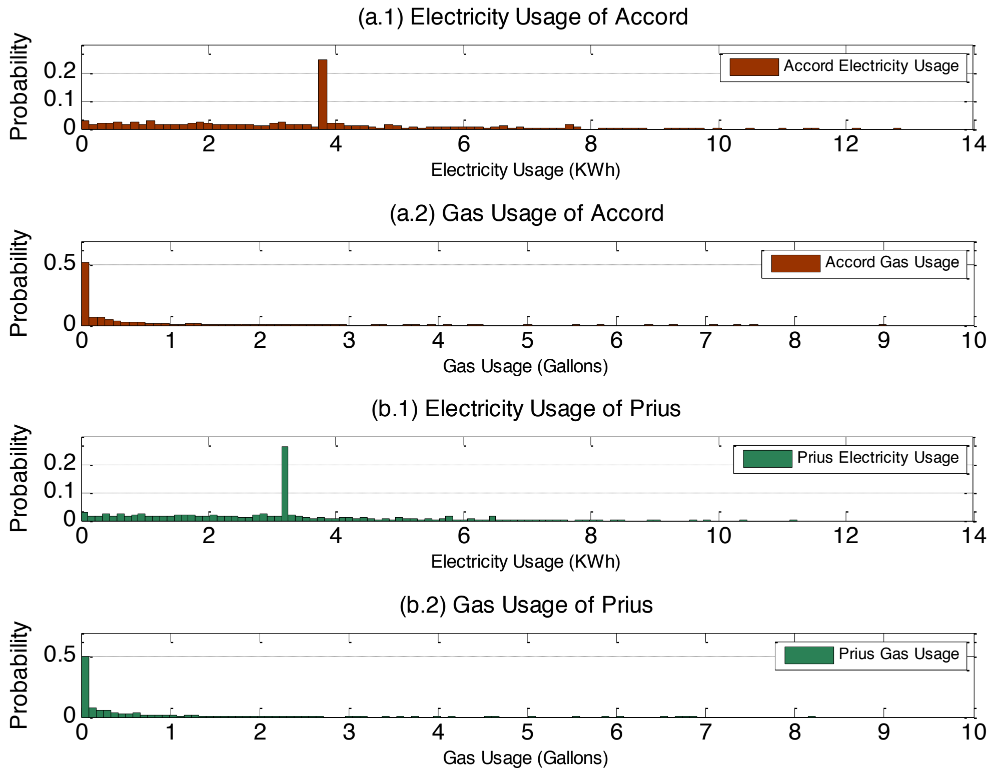


Fig. 12 (b). The Distribution of Electricity versus Gas Usage for Accord and Prius.

4.3.2 Analysis based on Scenario 2

For scenario 2, SoC trends of the same three samples are shown in Fig. 13. All the SoC traces in this figure are based on the Chevrolet Volt data. The SoC traces has changed compare to Fig. 8, as we can see that there appeared one more charging events for all of the three samples, which is the longest outside parking of each sample. Similar changes can also be seen in Fig. 14, compare to Fig. 9. Additionally, because of the additional charging event, we are expected to see some difference in the distribution of parking duration versus fully charge need time, and the distribution of electricity and gas usage, which we will discuss later.

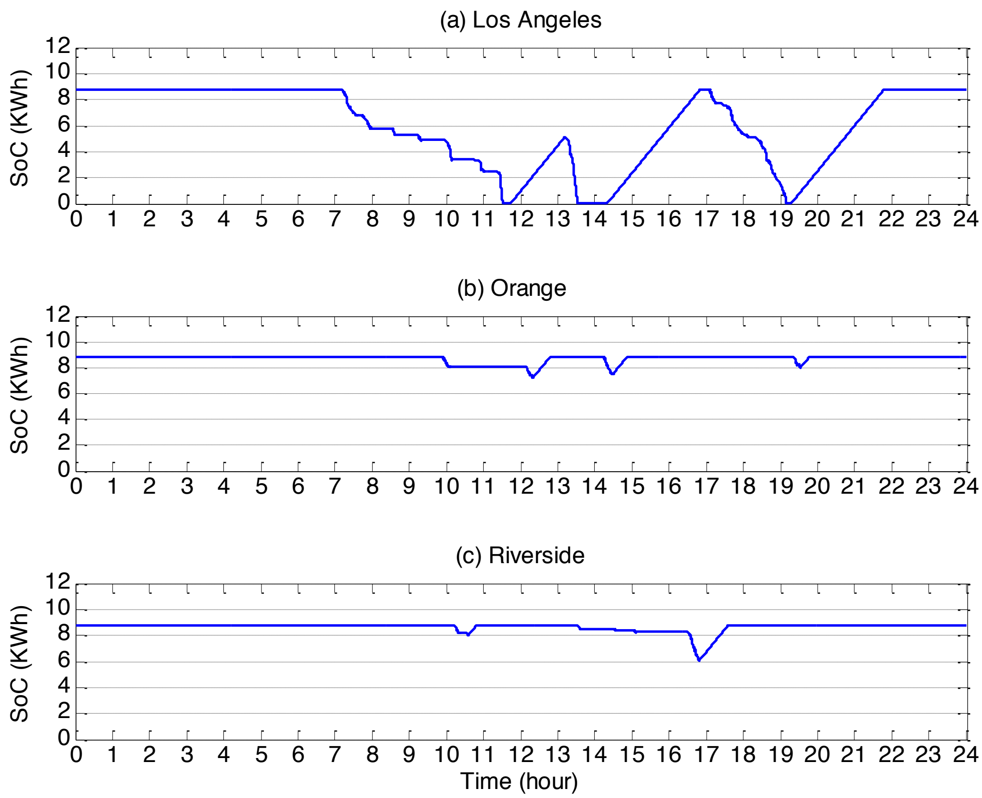


Fig.13. The State-of-Charge traces under scenario 2 for 3 samples form 3 counties respectively: (a) sample No.5 from Los Angeles, (b) sample No.10 from Orange, (c) sample No.143 from Riverside

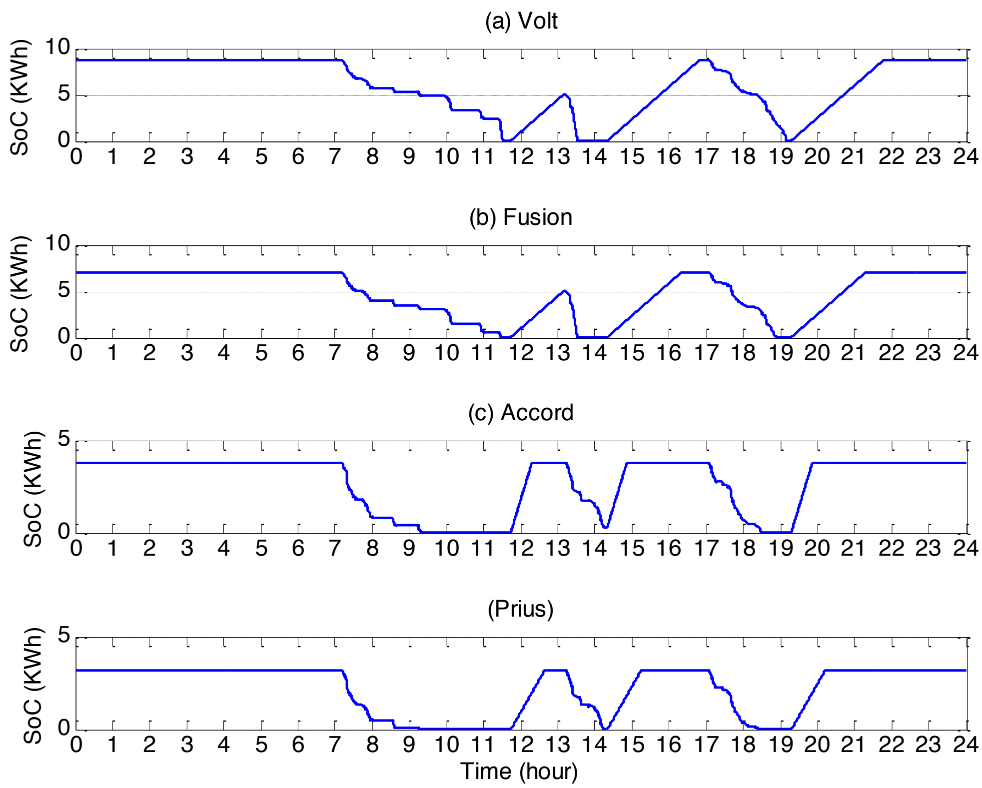


Fig. 14. The State-of-Charge traces of Sample No.5 for Four PHEV models under Scenario 2.

In Fig. 15, we generated the distribution of parking duration versus fully charge needed time comparison, and Fig. 16 shows the distribution of initial SoC before each parking events for four PHEV models, similar to what we have done for Fig. 10 and Fig. 11 in last subsection. But compare Fig. 15 with Fig.10, we can see that, less vehicles needed long time to get fully charged under scenario 2.

Recall that in our analysis under scenario 1, there are 1943 home parking events, but in scenario 2, we allowed vehicles to also get charged during the longest outside parking durations, so that we got additional 776 longest outside parking events under consideration, therefore, there are totally 2719 parking events under this scenario compare to 1943 in scenario 1. Accordingly, as vehicles can charge more times during their daily trip, it is reasonable that some vehicles will not need such a long time to get fully charged any more.

Similar observation can also be seen in Fig. 16 compare to Fig. 11, as there are fewer vehicles had low initial SoC when they began charging.

Bigger change have shown between the two scenarios for Prius and Accord than for Volt and Fusion, since Prius and Accord have smaller battery, so they have higher probability to get fully charged during the additional outside charging events.

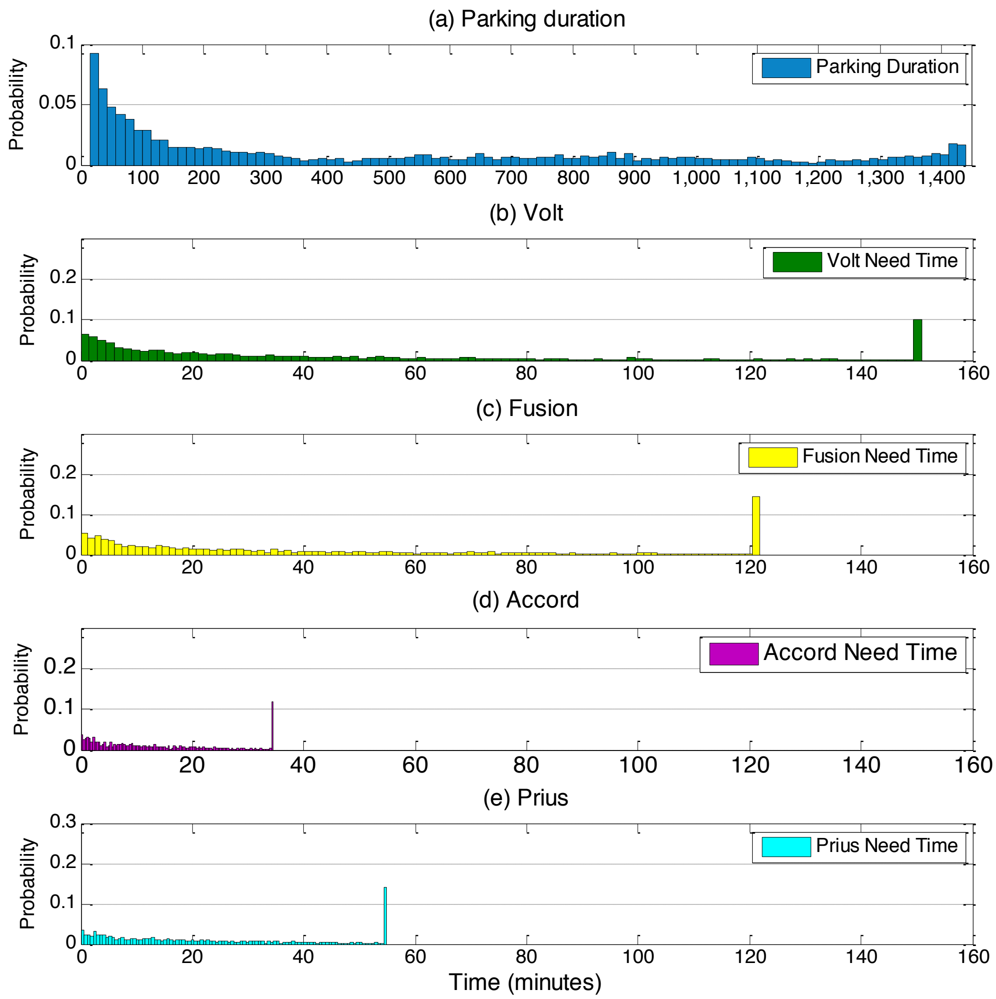


Fig. 15. Distribution of Parking Duration versus Fully Charge Needed Time during Each Parking Events based on Four PHEV models.

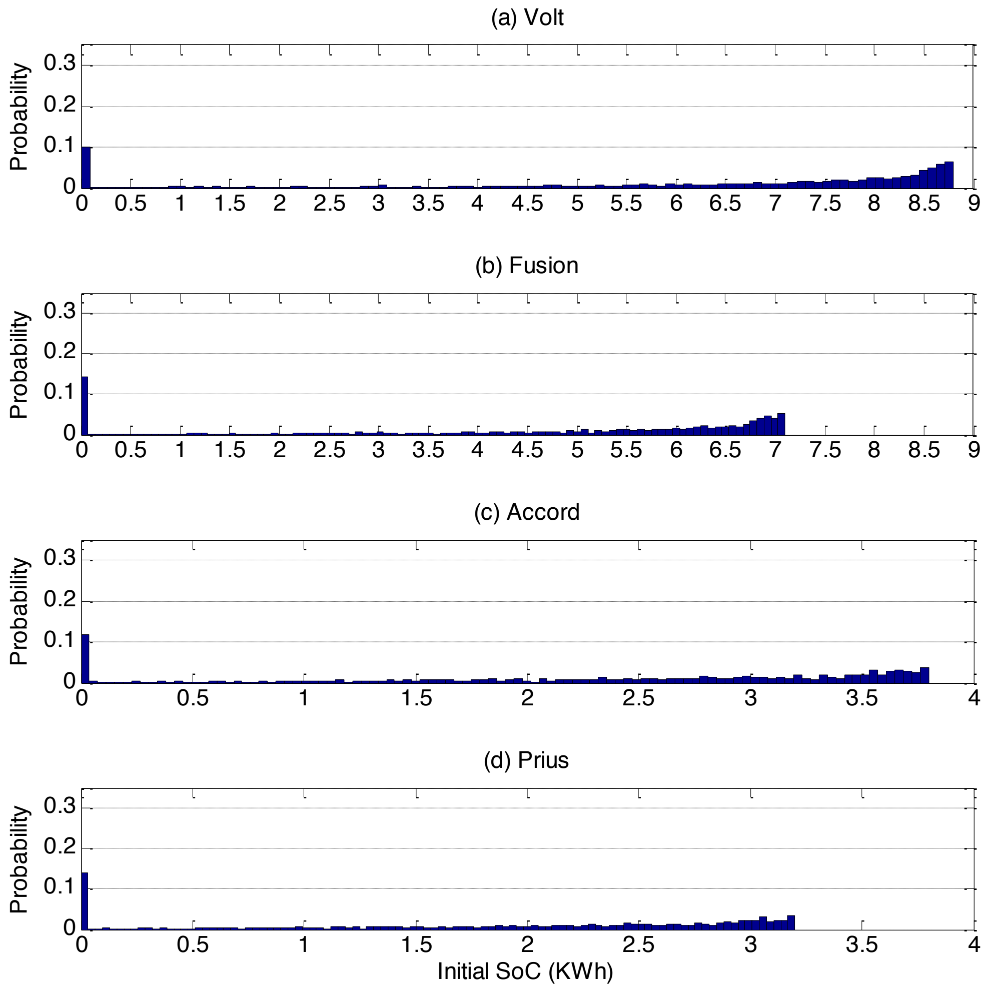


Fig. 16. The Distribution of Initial SoC before Each Charging Event.

Next, we got the distribution of electricity and gas usage for the four PHEV models under scenario 2, which is shown in Fig. 17. Fig. 17(a) shows the comparison of two charging depleting type of vehicle: Volt and Fusion, Fig. 17(b) shows the comparison of Accord and Prius. Compared the distributions shown in Fig.17 with the distributions shown in Fig. 11, we can see a big difference between the two figures. For example, for the electricity usage distribution of PHEV model Volt, in scenario 1, the 8.8KWh electricity usage –as Volt battery capacity – has the highest probability, and we had few samples had electricity usage greater than 8.8KWh. But in Fig. 17, although the probability distribution before 8.8KWh is similar to what we have seen in scenario 1, however, the distribution profile has changed a lot after 8.8KWh usage.

The most reasonable explain for the difference is: For those vehicles in scenario 1, who had their batteries depleted due to no charging chances during the day, now they get an additional outside charging opportunity under scenario 2. Therefore, they can use an additional amount of electricity to cover their trips, and since we are considering about the longest outside parking events, for many samples, that parking duration is long enough for them to get their batteries fully charged again. That is why we have got a higher probability for the electricity usage of twice of battery capacity.

Additionally, we can easily see that, because to the additional outside parking, the gas usage in scenario 2 had deduced compare to scenario 1.

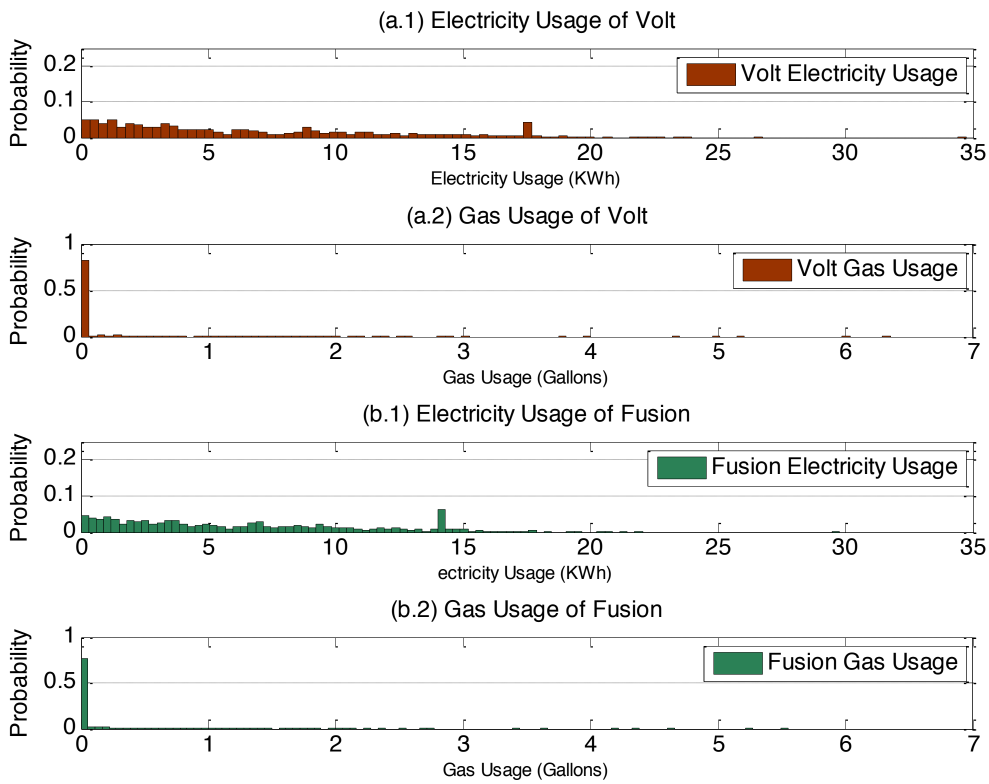


Fig. 17 (a). The Distribution of Electricity versus Gas Usage for Volt and Fusion.

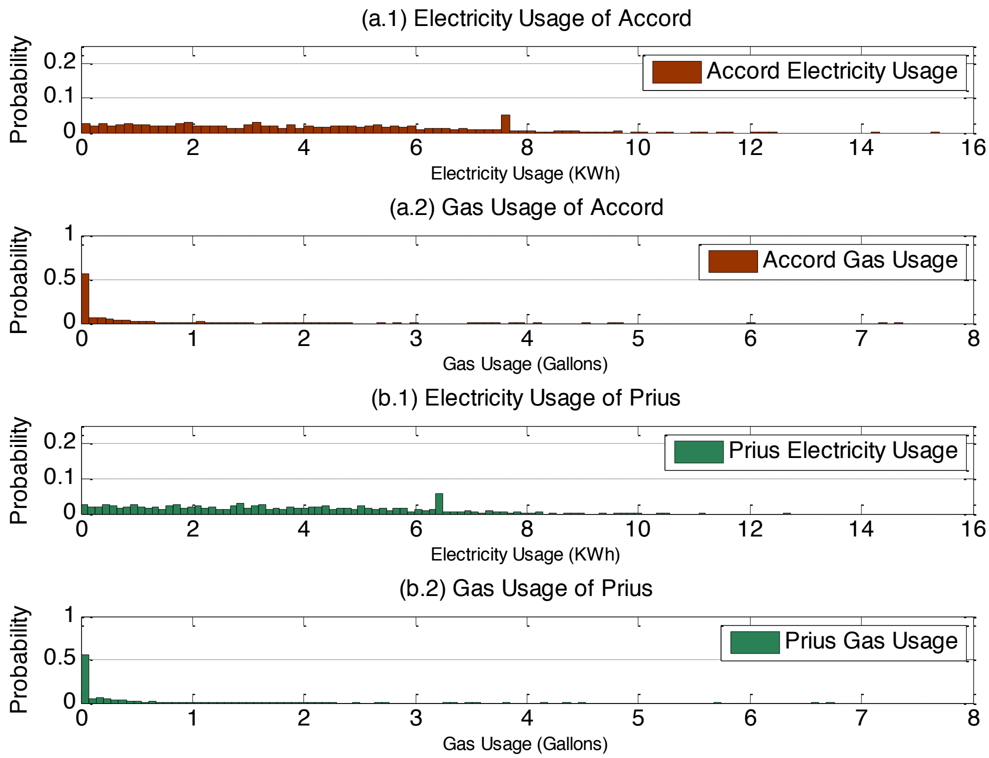


Fig. 17 (b). The Distribution of Electricity versus Gas Usage for Accord and Prius.

Chapter 5

Analysis of Charging Load

In this section, we aggregate the SoC data that we generated in section IV, and then develop a new data set that provides the charging load traces for each sample. Our goals in this section are to

- Calculate the combined charging load of all samples in each County for both charging scenarios.
- Estimating the current actual total PHEV charging load in each County.

5.1. Calculate the Combined Charging Load within Data Set

We start off by first positioning the 1005 samples into the six counties: Ventura County, Los Angeles County, Orange County, San Bernardino County, Riverside County, and Imperial County, by each sample's home location that we identified in section III. Vehicle numbers in each County are list below:

- Ventura County: 50 vehicles.
- Los Angeles County: 265 vehicles.
- Orange County: 472 vehicles.
- San Bernardino County:15 vehicles.
- Riverside County:132 vehicles.
- Imperial County:71 vehicles.

We can see that most of the vehicles were located in Los Angeles County, Orange County, and Riverside County. Therefore, for the rest of this section, we focus our analysis onto these three main Counties.

Recall the sales information of the four PHEV models in Section IV. In order to make our analysis closer to reality, we assume a mixture of all four PHEV models for each county as in Table II.

Next, based on the SoC traces we generated in section IV, we now calculate the aggregate charging load profile of Los Angeles County, Orange County, and Riverside County, for weekday and weekend, under the two scenarios we presented in section IV. Recall that we have 890 weekday samples, and only 115 weekend samples. Thus, for the analysis of charging load, we first generated the normalized charging load profile; then we multiplied it by the number of samples to get the aggregated charging load profiles. Fig. 18 is an example of the normalized per-vehicle charging load profile for analysis of aggregated charging load of all samples. The normalized per-vehicle charging load for each county was also used in our analysis.

Table II

MIXTURE OF FOUR PHEV MODELS IN THE SIX COUNTIES OF CALIFORNIA

County	Ventura	Los Angeles	Orange	San Bernardino	Riverside	Imperial
Chevrolet Volt	27	146	261	8	73	39
Toyota Prius Plug-in	14	76	135	4	38	20
Ford Fusion Energi	8	41	72	2	20	11
Honda Accord Plug-in	1	2	4	1	1	1
Total	50	265	472	15	132	71

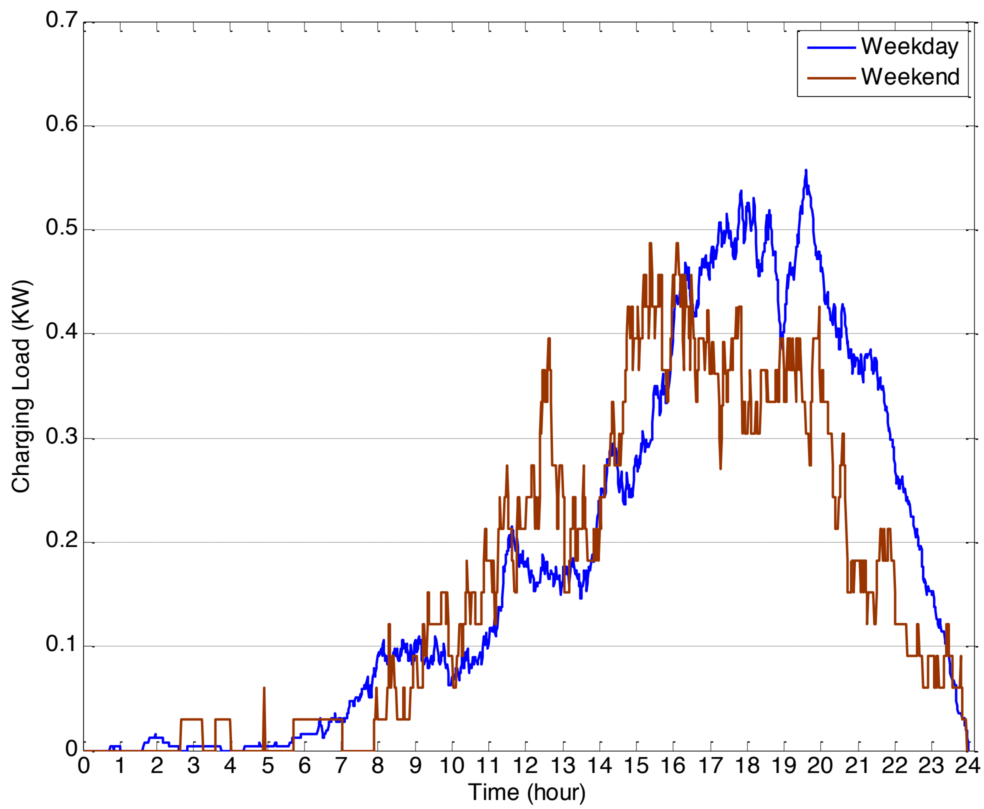


Fig. 18.Example of the Normalized Per-Vehicle Charging Load Profile

5.1.1 Charging Load Analysis based on Scenario 1

The combined charging load of all vehicles is shown in Fig. 19. We can see that the peak load during weekends happened earlier than the peak load during weekdays, since during weekday, people usually went back home around 20:00 PM and plug in their vehicles for charging, but in weekend, there wasn't such a common trend for charging behavior after work. And we can also see that the charging activities have a slightly wider distribution over time during weekdays than during weekends.

- The peak charging load in weekday is 560.77 KW, while the average load is 184.98 KW. Thus, the weekday Peak to Average Ratio (PAR) is 3.0316.
- The peak charging load in weekend is 489.39 KW, while the average load is 161.28 KW. Thus, the weekend Peak to Average Ratio (PAR) is 3.0344.

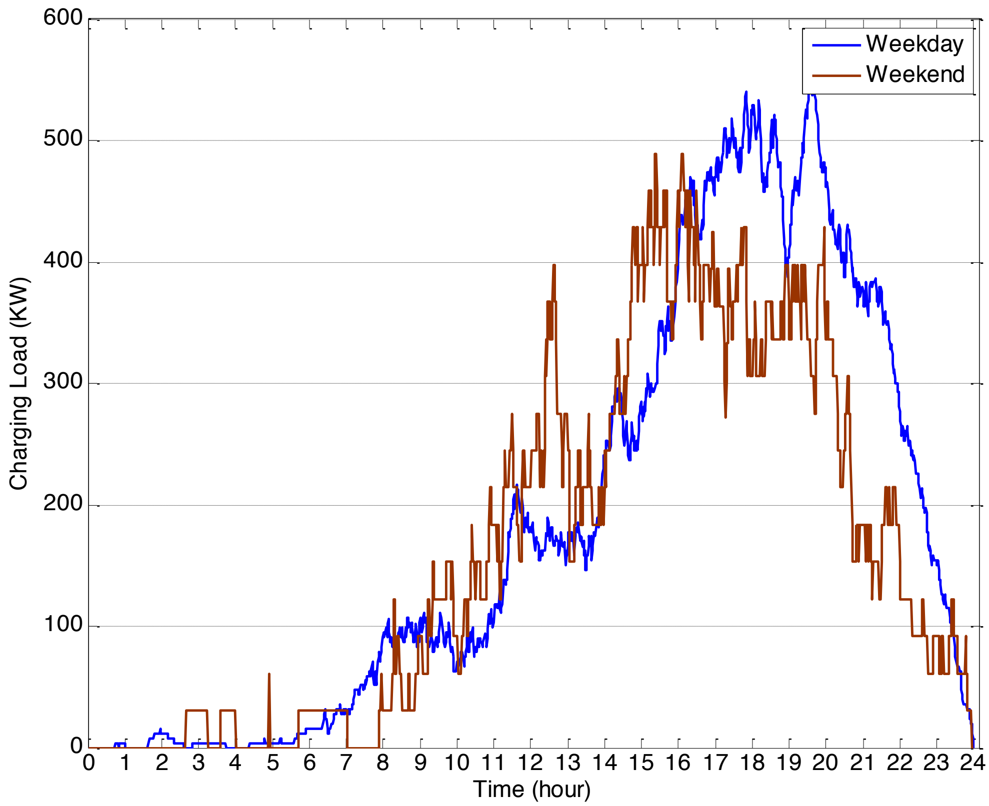


Fig. 19. The Aggregated Charging Load of All Samples under Charging Scenario 1.

In Fig. 20, we have the aggregated charging load profiles for three counties. An interesting observation is that during weekdays, the peak load occurred later in Los Angeles County, than in Orange County and Riverside County. This observation may be explained by the difference between people's daily activity behaviors within the three Counties, which is, people in Los Angeles County most probably went back home every day at around 20:00 PM to 21:00 PM, while that time interval in Orange County becomes 18:00 PM to 20:00 PM, and in Riverside County becomes 16:00 PM to 18:00 PM. The detailed results of charging load in each county are shown in table III.

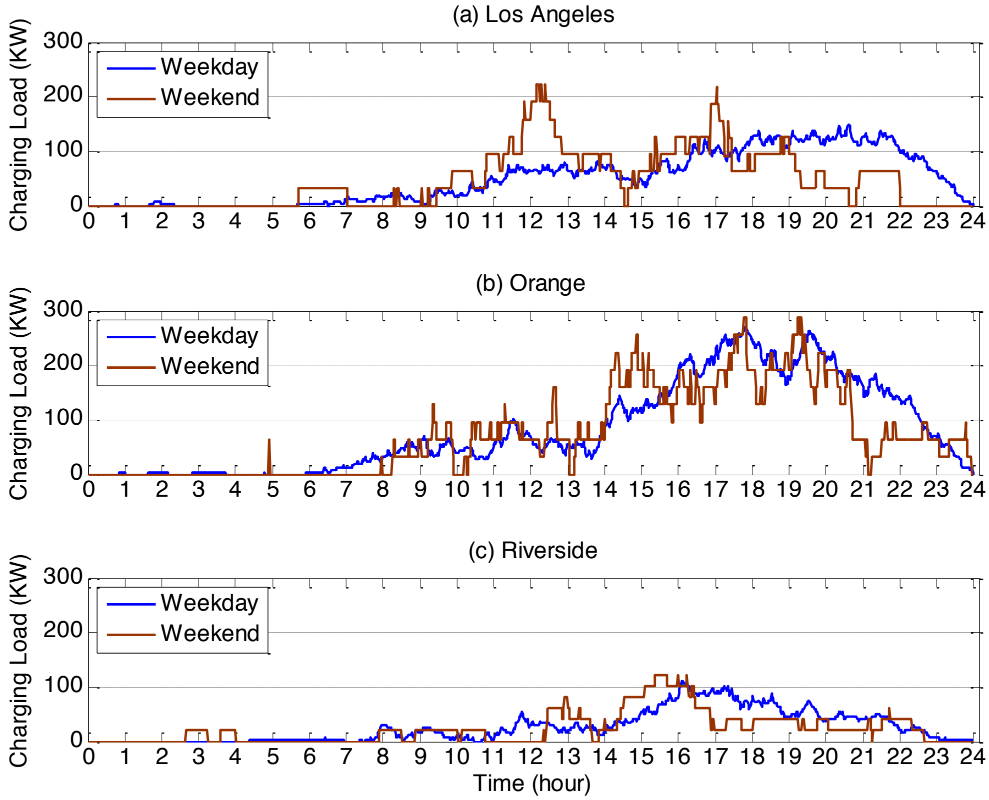


Fig. 20. The Aggregated Charging Load of Three Counties under Charging Scenario 1.

Table III

CHARGING LOAD FEATURES OF THREE COUNTIES UNDER SCENARIO 1

County	**Los Angeles**		**Orange**		**Riverside**	
Weekday/Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Peak Load (KW)	149.4829	222.1897	270.7921	287.2800	109.8868	122.1818
Average Load (KW)	49.9284	46.1132	82.1284	73.6820	26.6528	22.8384
Peak to Average Ratio (PAR)	2.9939	4.8184	3.2973	3.8989	4.1229	5.3498

5.1.2 Charging Load Analysis Based on Scenario 2

The combined charging load of all samples under scenario 2 is shown in Fig. 21, compared to Fig. 19 from scenario 1, we got a quite different charging load profile.

- The peak charging load in weekday is 516.8410 KW, while the average load is 232.1201 KW, the weekday Peak to Average Ratio (PAR) is 2.2266.
- The peak charging load in weekend is 581.1522 KW, while the average load is 197.0680 KW, the weekend Peak to Average Ratio (PAR) is 2.9490.

Compared to the load profile in scenario 1, we can now see a decrease in the peak load on weekdays, since some vehicles got charged during the additional outside parking events, consequently, at around the 8:00 PM peak load interval, fewer charging events occurred and shorter charging duration needed. And because of the additional charging events, the average charging load has increased, lowering PAR.

Another observation is that, the peak load on weekends has increased, which does not appear to be intuitive. However, we might be able to explain this by recalling that we do not have many samples on weekends; thus, the weekend traces may not be able to show the stochastic load traces in real conditions. Similar observations are made in charging load traces of each county in Fig. 22 and table IV.

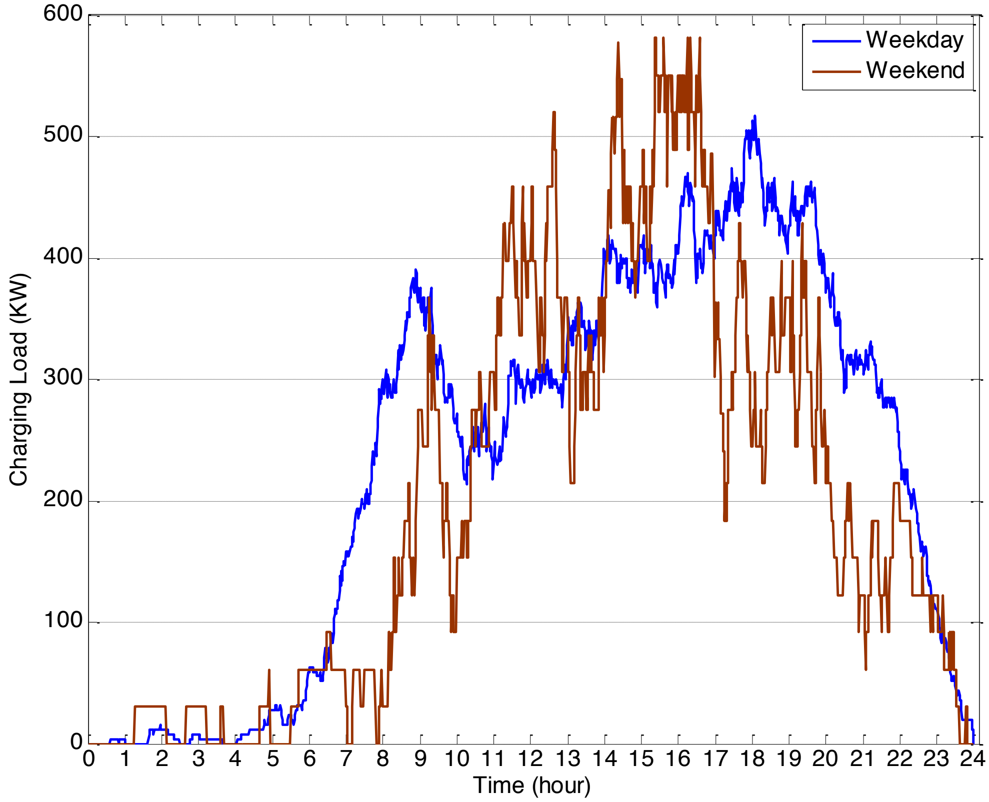


Fig. 21. The Aggregated Charging Load of All Samples under Charging Scenario 2.

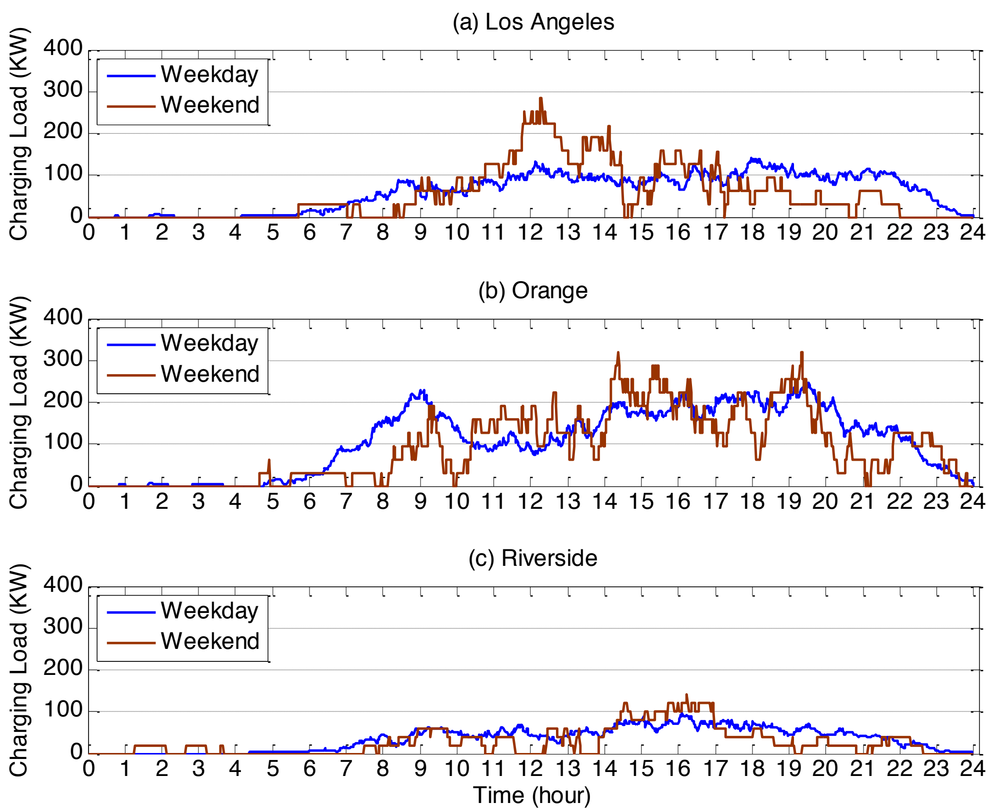


Fig. 22. The Aggregated Charging Load of Three counties under Charging Scenario 2.

Table IV

CHARGING LOAD FEATURES OF THREE COUNTIES UNDER SCENARIO 2

County	Los Angeles		Orange		Riverside	
Weekday/ Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Peak Load (KW)	141.1658	285.6724	247.6552	319.2000	97.2075	142.5455
Average Load (KW)	60.2979	54.1310	106.4194	92.4350	34.6086	28.3535
Peak to Average Ratio (PAR)	2.3411	5.2774	2.3272	3.4532	2.8088	5.0274

Once comparing the aggregate charging load profiles in scenario 1 and scenario 2, we can get a common conclusion that, relatively speaking, having more charging events may increase the charging load on the distribution system, but may have positive influence on helping smooth aggregated EV load profiles. This could potentially be advantages as it can help with making the EV charging loads more predictable.

5.2 Estimating the Current Charging Load of EVs

Although we can get EV sales data of entire United States from [14], but we could not find dependable official data resources about PHEV numbers and penetration levels within California. This will be a holdback for our research, since we want to calculate the actual aggregated charging load in each county of California in this section.

Fortunately, there are two ways to get the close-to-real PHEV numbers that can be used in our study.

The first access is to calculate the rough PHEV numbers based on the data set from the California Clean Vehicle Rebate Project (CVRP) [16], which is hosted by The Center of Sustainable Energy. Within the data set of CVRP, we can get the number of issued rebate events from March 18, 2010 to July 7, 2015 in each County of California, along with the total PHEV number in California we got in section 4.1, we can calculate the rough PHEV numbers in each county based on a simple equation:

$$P_x = R_x \div R_C \times P_C. \tag{6}$$

where

P_x Vehicle number in County x.

P_C Vehicle number in Entire California.

R_x Rebate events in County x.

R_C Rebate events in Entire California.

Results are shown in table V.

Table V

ESTIMATED PHEV NUMBERS IN SIX COUNTIES OF CALIFORNIA

County	California	Ventura	Los Angeles	Orange	San Bernardino	Riverside	Imperial
Rebate Events	47,023	1093	14,579	6856	1224	1528	11
PHEV Number	71,536	1663	22,179	10,430	1862	2325	17

The second data resource is an article from *PACIFIC STANDARD* [17], where the precise PHEV numbers and PHEV penetration level are given. Details are listed in table VI.

Table VI

PHEV NUMBERS AND PENETRATION LEVELS IN SIX COUNTIES OF CALIFORNIA

County	Ventura	Los Angeles	Orange	San Bernardino	Riverside	Imperial
Number of EVs per 1000 People	2.16	2.38	3.41	0.82	0.95	0.11
PHEV number	1810	23845	10623	1712	2186	19

Compared the result we calculated in table V with the number provided by the article in table VI, we can see that the numbers do not have big difference. So in our later analysis, we used the PHEV numbers from table VI for our calculation, and the results are shown in Fig. 23 and Fig. 24. As we can see, the peak aggregated charging load of all 71536 PHEVs in California can be up to 40,000 KW during a weekday, which is a huge number, and for each county, for example, in Los Angeles County, the daily peak aggregated charging load can also be up to 20,000 KW, detailed results are shown in table VII.

Accordingly, we can get the numerical evidence of how much PHEVs can have influences on the local power system, which is the reason why we will do charging load optimization in our future study.

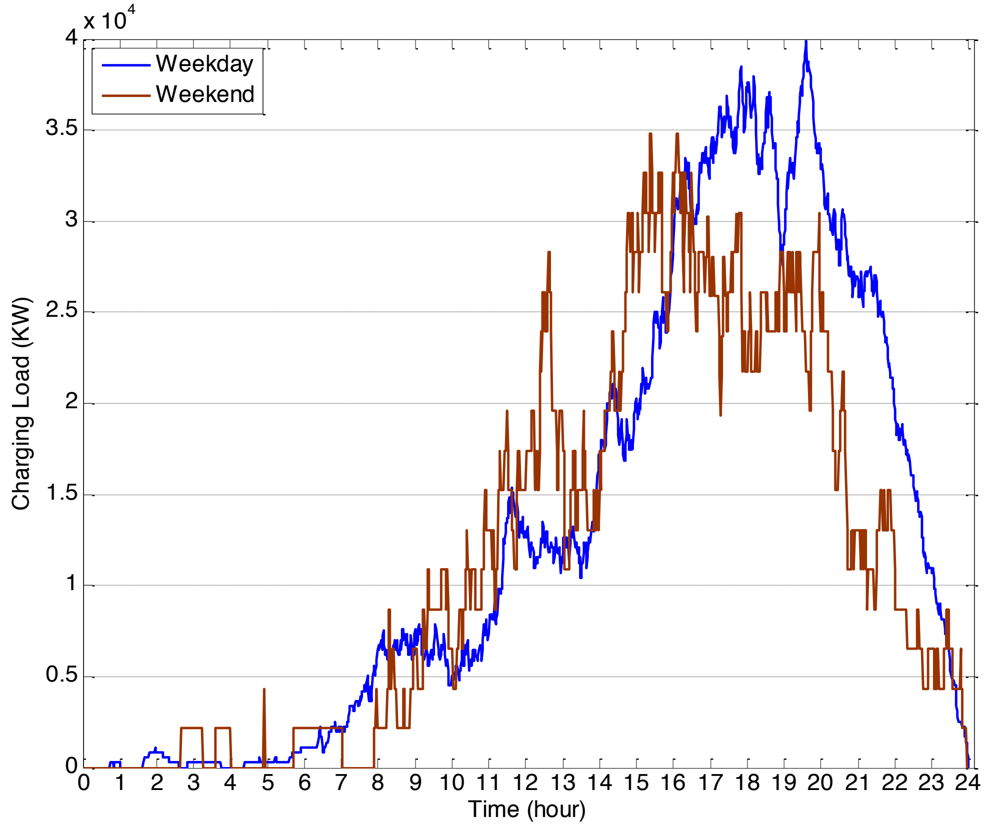


Fig. 23. The estimated current aggregated charging load in California based on our modeling approach.

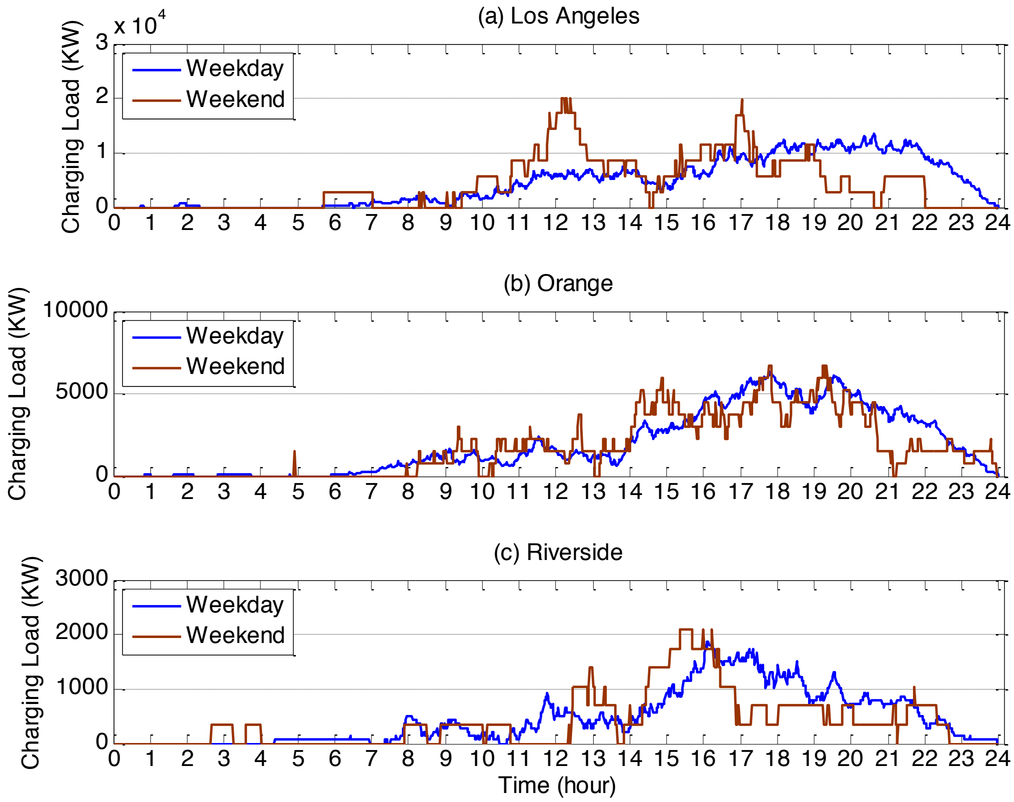


Fig. 24. The Aggregated Charging Load of Three Counties.

Table VII

CHARGING LOAD OF THREE COUNTIES

County	Los Angeles		Orange		Riverside	
Weekday/Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Peak Load (KW)	13,553	20,145	6,308.4	6,692.5	1,876.7	2,086.6
Average Load (KW)	4,526.8	4,180.9	1,913.2	1,716.5	455.1804	390.0368
Peak to Average Ratio (PAR)	2.9939	4.8184	3.2973	3.8989	4.1229	5.3498

Recall that as the first step of our pre-process, we defined parking events as any time that a vehicle has a speed equal to 0 or the GPS is switched off for 15 minutes or more, so as the last part of charging load analysis, we made a sensitivity analysis of the chosen minimum time duration to define parking event, in order to that, we compared the estimated current aggregated charging load profiles in California based on two other parking event definitions:

- Parking events as any time that a vehicle has a speed equal to 0 or the GPS is switched off for 5 minutes or more.
- Parking events as any time that a vehicle has a speed equal to 0 or the GPS is switched off for 30 minutes or more.

Then we processed the data set with the same procedure as we mentioned in the above sections, and got the estimated current aggregated charging load profiles in California under this two parking event definitions, the results are shown in Fig. 25 and Fig. 26.

By comparing Fig.23, which is the charging load profile under 15 minutes parking event definition, to Fig. 25 and Fig. 26. We can see that there are no conspicuous differences between them. That is mainly because of two reasons: first, most of the parking durations within this data set are relatively longer time intervals, so changing the time duration of parking events don't affect the number of parking events a lot. Second, since 5, 15, or 30 minutes are relatively short time intervals for vehicle-charging activities, so different time durations don't affect aggregate charging load profiles a lot.

Since we care most in our study about the charging load traces, we can say that the 15 minutes parking event definition is appropriate and acceptable for our study.

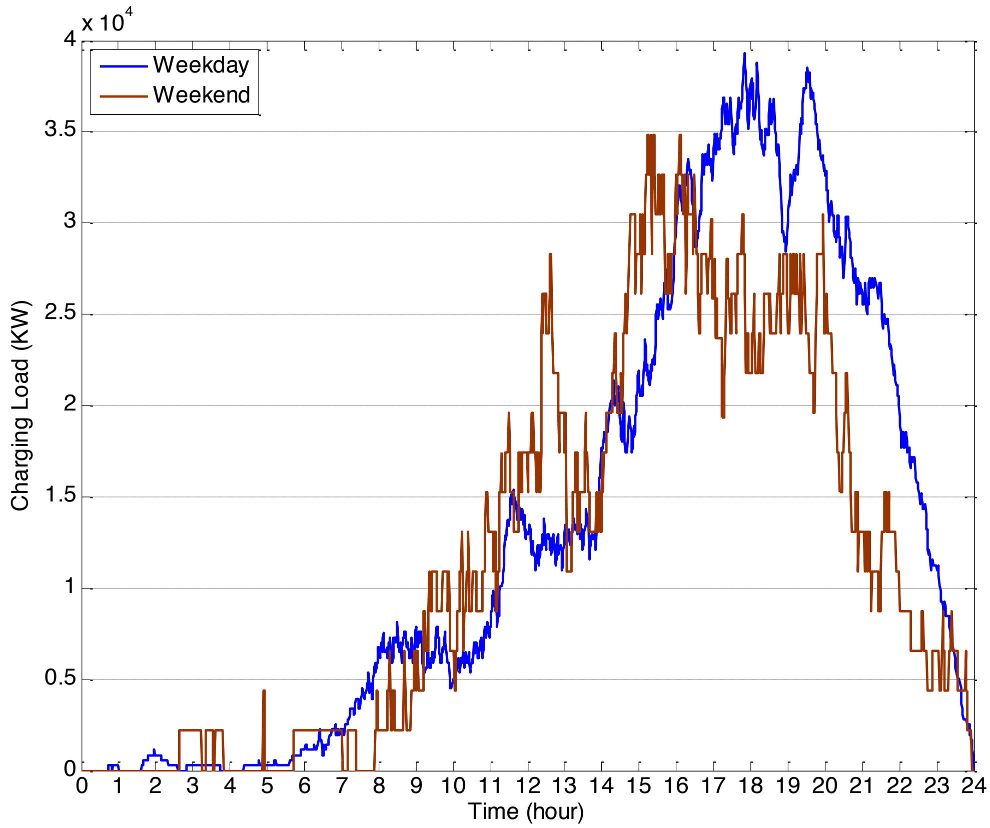


Fig. 25. The estimated current aggregated charging load in California based on 5 minutes parking event definition.

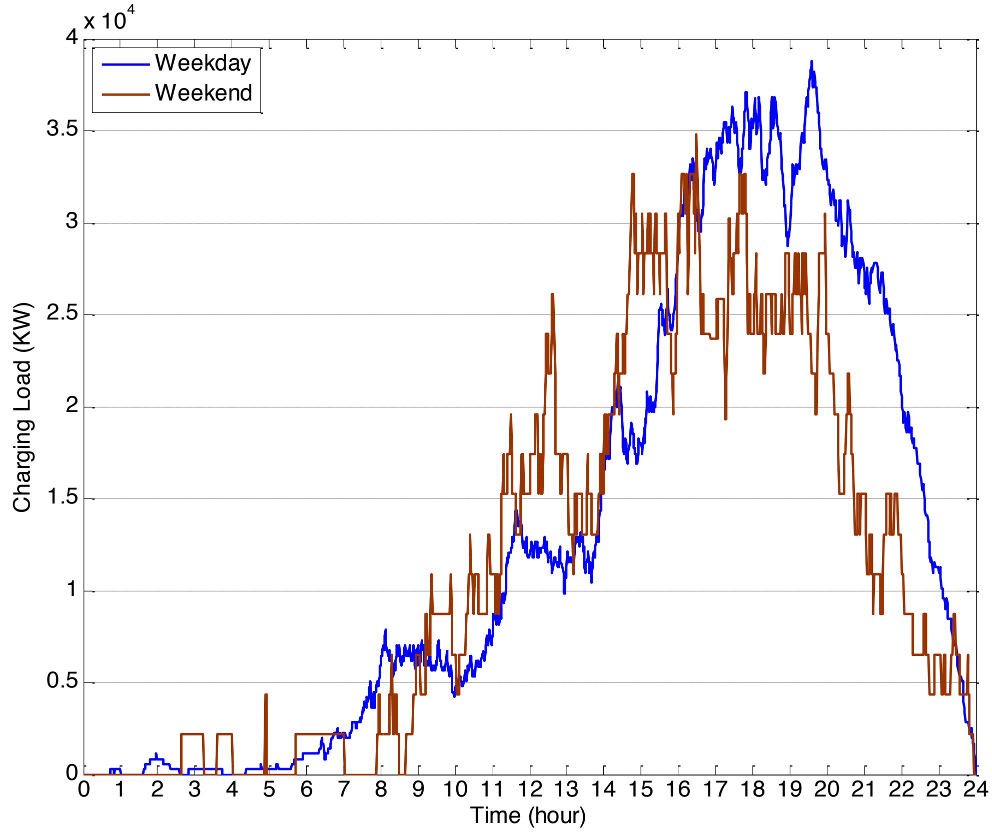


Fig. 26. The estimated current aggregated charging load in California based on 30 minutes parking event definition.

Chapter 6

Locational Marginal Price Information

Given that a key aspect of this thesis, which makes it unique, is to address the locational aspects, in this section, we analyze the locational as well as temporal diversity in the price of electricity in wholesale electricity market. Note that, combining the electricity price data sets and the type of data sets that we developed in this thesis is the key to conduct a comprehensive charging cost analysis for EVs.

The analysis in this section is particularly based on the Locational marginal Prices (LMPs) in the day-ahead electricity market that is operated by the California Independent System Operator [24]. For the purpose of our study, we generated a list of grid nodes for each of the six counties, and obtained the hourly LMP prices for each node. The goal of this section is to show the price diversity of different nodes within each county, and price diversity across the six counties for which we analyzed the SCAG data set.

Table VIII

NUMBER OF NODES IN EACH COUNTY

County	**Ventura**	**Los Angeles**	**Orange**	**San Bernardino**	**Riverside**	**Imperial**
Number of Buses	5	36	16	51	37	2

The number of power grid nodes / buses in each county is shown in table VIII, and for the purpose of investing the electricity price diversity within each county. We generated a figure that shows the LMP price traces of each node in Orange County during a time interval of one week, as show in Fig. 27.

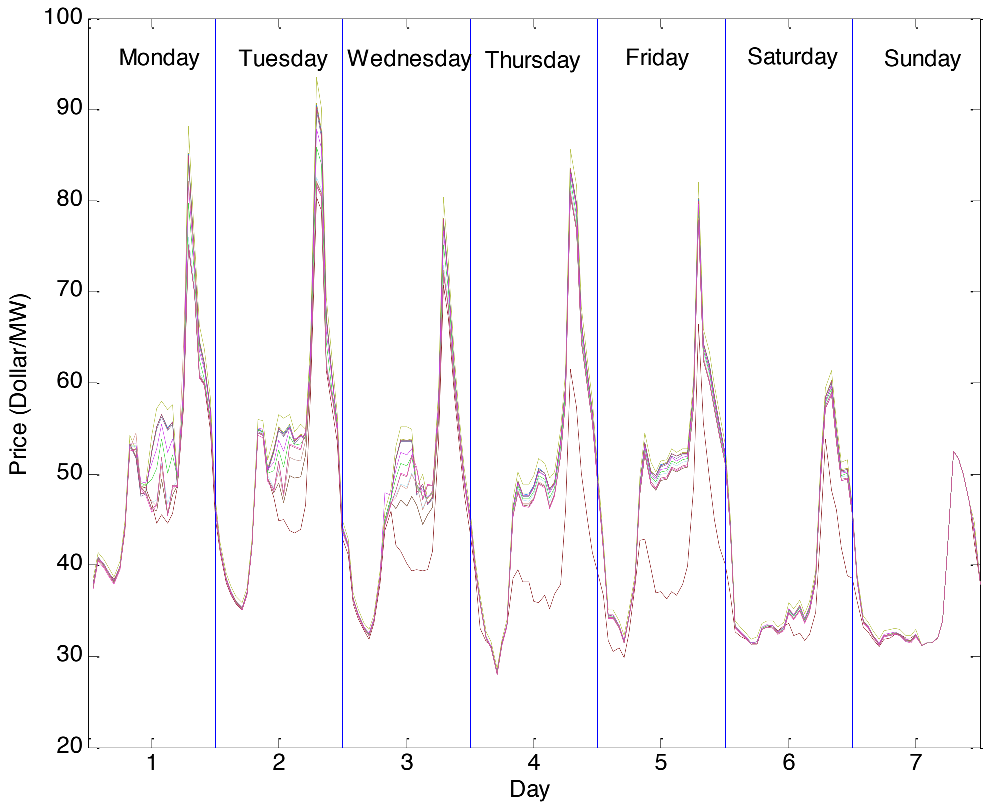


Fig. 27. Diversity of LMP Prices at Different Nodes in Orange County

From Fig. 27, even within one county, we still have price differences at various locations.

Next, we observe that there is also price diversity across counties; the comparison is made based on the yearly average of LMP prices in each county in time interval of one day. The results are shown in Fig. 28.

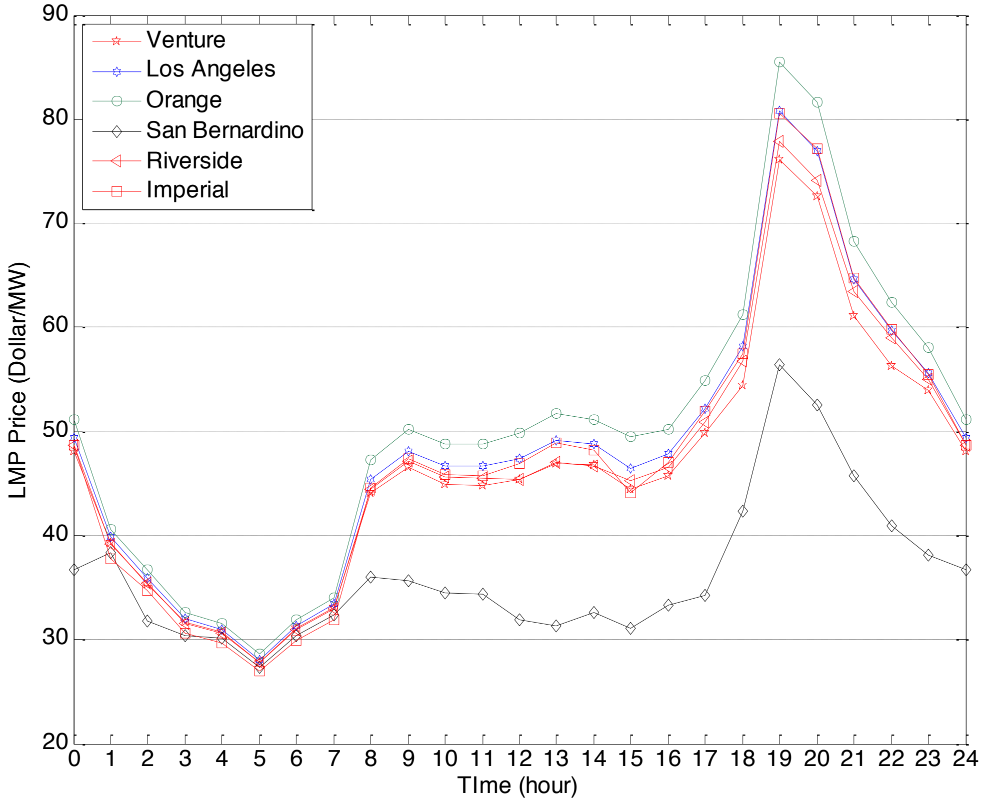


Fig. 28. Diversity of LMP Prices between Each County

We can see in Fig. 28 that the price diversity across different neighboring counties could be quite significant, suggesting that the cost of charging EVs could noticeably differ at different counties.

Of course, the exact cost of EV charging in each location also depends on whether the driver starts charging right away after it parks its vehicle at home or at a charging station, or whether it rather optimizes the time of its charging schedule based on the electricity price data. Addressing these aspects is beyond the scope of this thesis. However, the type of analysis that we conducted in this thesis could pave the way to enable more specific charging cost optimization as we point out in the next section.

Chapter 7

Conclusion and Applications in Future Smart Grid Research

In this thesis, we synthesized a new Plug-in Hybrid Electric Vehicle (PHEV) data set based on 1005 daily driving data samples for residential vehicles in Southern California. The core of our study was to estimate the per-PHEV state-of-charge (SoC) traces, the per-PHEV charging load traces under different charging scenarios, and distribution of per-PHEV initial SoC information were investigated in our analysis. Our analysis addressed the factor of location with respect to six Southern California counties: Ventura County, Los Angeles County, Orange County, San Bernardino County, Riverside County, and Imperial County. Our analysis also separately investigated charging load on weekdays and weekends.

Three key data types were used in our analysis: first, the features of four PHEVs, namely Chevrolet Volt, Honda Accord Plug-in, Ford Fusion Energi, and Toyota Prius Plug-in; second, the data on EV sales in California; third, the data on locational price of electricity in the California wholesale electricity market. Our analysis also separately investigated charging load on weekdays and weekends.

Two major assumptions were made in our analysis: first, we assumed samples within the data set leave home in the morning and went back home at night. Second, we assumed PHEVs get charged under a fixed charging rate, which was their maximum charging rate.

Three main conclusions could be made based on our study: first, different PHEV charging scenarios might have different impacts on power system, specifically, in this study, charging scenario 2 is batter than scenario 1, even though it may use more energy. Second, because of the difference of driving pattern across different counties, same PHEV penetrations may have different impacts on the grid at different locations. Third, the electricity price is not only different during different time, but also different across different locations, so when working on PHEV charging strategy, we should not only consider charging intervals, but also take charging locational optimization into account.

The study in this thesis could be linked to three general research areas in smart grid:

1. Forecasting EV charging load in California in the coming years and decades, both on transmission level and distribution levels. This can be done by extending our analysis based on EV sale forecasts.
2. Optimizing the charging schedule of EVs with respect to various design objectives. The key design objective from the viewpoint of EV owner is to minimize the cost of EV charging. From the viewpoint of the utility company, the aggregator company, or the ISO, the design objectives may include lowering the peak-demand, integrating renewable energy resources, reducing wholesale price of electricity, and improving power grid efficiency.
3. Optimizing the potential grid-connection discharging schedule of EVs under the vehicle-to-grid (V2G) paradigm, tailored around the driving habits of people in each country in California.

Conducting the above studies will add to the values of the results in this thesis.

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