



# Electric Vehicle Transportation Center

## Savings and Peak Reduction Due to Optimally-Timed Charging of Electric Vehicles on the Oahu Power System

Mr. Paritosh Das  
Dr. Matthias Fripp  
University of Hawaii, Department of Electrical Engineering  
E-mail: [mfripp@hawaii.edu](mailto:mfripp@hawaii.edu)

*For:*  
Hawaii Natural Energy Institute, University of Hawaii at Manoa  
1680 East West Road, POST 109  
Honolulu, HI 96822

*Submitted to:*  
Dr. David Block  
Florida Solar Energy Center  
University of Central Florida  
1679 Clearlake Road  
Cocoa, FL 32922  
E-mail: [block@fsec.ucf.edu](mailto:block@fsec.ucf.edu)

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## ABSTRACT

Electric Vehicles (EVs) – including both plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) – could help increase energy security and reduce greenhouse gas emissions, by using electricity produced from clean, domestic sources instead of imported oil. This benefit could be enhanced if EVs are adopted in high-renewable power systems and are charged at the times when renewable power is most abundant, producing a win-win arrangement in which EVs are charged with lower-cost power, and in turn enable greater adoption of renewable power in the grid.

With its unique geography and current fossil fuel based energy infrastructure combined with its aggressive renewable energy goals, Hawaii forms an ideal site for large scale adoption of EVs in the future. The research study presented here develops an in-depth, Hawaii-specific EV model which is then integrated with the Oahu power system to study the effects of large scale EV integration into the grid, and also intends to provide a better understanding as to how different optimally-timed EV charging strategies can benefit such a unique power system.

The EV model developed in this study uses actual driving pattern data collected from the 2009 National Household Travel Survey (NHTS) to develop nationally representative profiles of vehicle usage patterns. It then constructs a fleet of appropriate size for Hawaii, which has the same vehicle usage pattern. This provides a reasonable model of how EVs might be used in Hawaii, including realistic charging profiles for individual vehicles. Using the driving pattern distributions, potential EV charging windows/timeslots were calculated by determining the maximum possible time a vehicle is parked in a potential charging location (i.e. home and workplace). These potential charging timeslots provide the EV owner the most comprehensive and realistic charging options available, as each option is unique to that particular vehicle and is derived from its driving pattern behavior.

Rather than assuming all vehicles drive the same distance as each other, each vehicle is modeled individually, which creates a realistic distribution of vehicle charging requirements.

Half-hourly EV charging electricity demand profiles were calculated for each individual modeled vehicle by depending on different shares of charging locations (workplace/home charging) and different rates of charging (1.4kW/3.3kW/6.6kW). Two different optimized charging models of the power system were implemented. One model assumed EV owners paid dynamic electricity prices equal to the historical hourly marginal cost for the Oahu power system in 2014, and that EV charging did not change these prices. The other model used a supply curve for electricity based on the properties of the Oahu generation system (including existing wind and solar equipment), and optimized EV charging throughout the day based on this supply curve. Finally, using each of these models the load profiles, and costs of the business-as-usual and optimized charging approaches were compared. This work found that that smart recharging strategies were successfully able to mitigate the amount of power drawn during the peak periods of the day, and also provide savings to the EV owners by reducing the EV charging costs by 8-35% compared to the business-as-usual (BAU) charging scenario.

This research study could help researchers and policymakers to develop an optimal plan for power system expansion and operation, considering large scale adoption of EVs, and show how to develop better time-of-use electricity pricing schemes to incentivize EV owners in order to obtain a smarter and more efficient grid.

Note: The contents of this report were previously included in Das, Paritosh, *Savings and Peak Reduction Due to Optimally-Timed Charging of Electric Vehicles on the Oahu Power System*, M.S. Thesis. University of Hawaii, Manoa, Fall 2015.

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## TABLE OF CONTENTS

<b>ABSTRACT.....</b>	<b>i</b>
<b>TABLE OF CONTENTS .....</b>	<b>iv</b>
<b>LIST OF FIGURES .....</b>	<b>vi</b>
<b>LIST OF TABLES .....</b>	<b>viii</b>
<b>CHAPTER 1. INTRODUCTION .....</b>	<b>1</b>
<b>1.1 Role of Transportation in GHG Emissions Reduction .....</b>	<b>2</b>
<b>1.2 Hawaii Energy Scenario .....</b>	<b>4</b>
<b>1.3 Hawaii Clean Energy Goals and Targets .....</b>	<b>6</b>
<b>1.4 Global EV Scenario .....</b>	<b>9</b>
<b>1.5 Research Objectives .....</b>	<b>11</b>
<b>CHAPTER 2. LITERATURE REVIEW .....</b>	<b>12</b>
<b>2.1 Studies on PHEV Electricity Load (Energy) Impacts Using Different Charging Scenarios .</b>	<b>12</b>
<b>2.2 Studies on PHEV Economic and Emission Impacts.....</b>	<b>15</b>
<b>2.3 Electric Vehicle Charging Studies in Oahu .....</b>	<b>15</b>
<b>2.4 Research Contribution towards Literature .....</b>	<b>17</b>
<b>CHAPTER 3. MODEL DESIGN AND DESCRIPTION .....</b>	<b>20</b>
<b>3.1 Electric Vehicle Data Characteristics .....</b>	<b>20</b>
<b>3.1.1 Electric Vehicle Data and Assumptions.....</b>	<b>21</b>
3.1.1.1 NHTS Dataset Characteristics .....	21
3.1.1.2 Data Extraction from 2009 NHTS Dataset .....	23
3.1.1.3 Identification of Location of Charging .....	27
3.1.1.4 Identification of Times When EVs Were Parked at Home or Work .....	27
<b>3.1.2 Vehicle Characteristics/Driving Pattern Analysis .....</b>	<b>30</b>
3.1.2.1 Vehicle Type .....	30
3.1.2.2 Daily Vehicle Miles of Travel .....	30
3.1.2.3 Driving Range .....	31
3.1.2.4 Battery Capacity .....	32
3.1.2.5 Potential Charging Windows/Time Slots .....	34
3.1.2.6 Timestamp Transformation.....	34
<b>3.1.3 Charging Characteristics.....</b>	<b>35</b>
3.1.3.1 State Of Charge (SOC).....	35
3.1.3.2 Energy Requirement for Battery Charging .....	35
3.1.3.3 Charging Levels.....	35
3.1.3.4 Charging Infrastructure/Mode .....	37

<b>3.2 Oahu Grid Characteristics .....</b>	<b>40</b>
<b>3.2.1 Hawaii Electricity Load Profile.....</b>	<b>40</b>
<b>3.2.2 Hawaii Electricity Price Profile .....</b>	<b>41</b>
<b>3.2.3 Existing Power Plants.....</b>	<b>41</b>
<b>3.3 Model Notations .....</b>	<b>43</b>
<b>3.4 EV Recharging Scenarios.....</b>	<b>43</b>
<b>3.4.1 Price-Taker Model .....</b>	<b>43</b>
3.4.1.1 Optimized Charging.....	43
3.4.1.2 Business-As-Usual (BAU) Charging .....	46
<b>3.4.2 Supply Curve Model.....</b>	<b>47</b>
3.4.2.1 Optimized Charging.....	47
3.4.2.2 Business-As-Usual (BAU) Charging .....	52
<b>CHAPTER 4. EXPERIMENTAL RESULTS AND ANALYSIS.....</b>	<b>53</b>
<b>4.1 Impact on Load Profile.....</b>	<b>54</b>
4.1.1 Price-Taker Model .....	54
4.1.2 Supply Curve Model.....	55
<b>4.2 Savings .....</b>	<b>56</b>
4.2.1 Price-Taker Model .....	56
4.2.2 Supply Curve model.....	57
<b>CHAPTER 5. CONCLUSION .....</b>	<b>59</b>
<b>REFERENCES .....</b>	<b>60</b>

## LIST OF FIGURES

Figure 1. U.S. GHG Emissions by Economic Sector in 2013.....	2
Figure 2. U.S. GHG Emissions by Transportation Sector in 2013 .....	2
Figure 3. U.S. Sector Contributions towards Emissions Reductions .....	3
Figure 4. U.S. Technology Contributions towards Emissions Reductions .....	4
Figure 5. Annual Average Electricity Price in Dollar per kWh .....	5
Figure 6. Hawaii Electricity Production by Source, 2013 .....	5
Figure 7. Hawaii Petroleum Use by Sector in 2013.....	6
Figure 8. Hawaii Renewable Energy Portfolio Standards (RPS) Levels.....	7
Figure 9. Hawaii Renewable Energy Production Status 2008-2014 [20].....	8
Figure 10. Hawaii Renewable Energy Efficiency Portfolio Standards (EEPS) Status 2008-2014 [22] .....	8
Figure 11. Global EV and EVSE Stock [23].....	9
Figure 13. Global EV Sales [23] .....	10
Figure 14. Registered Electric, Hybrid and total passenger vehicles in Hawaii.....	10
Figure 15. NHTS 2009 Data File Structure [50] .....	22
Figure 16. Miles Driven per Day .....	31
Figure 17. Electric Vehicle Driving Ranges .....	32
Figure 18. Battery Size (kWh) and Electricity Consumption (kWh/100 mile) .....	34
Figure 19. Electric Vehicle Charging Rates.....	37
Figure 20. Distribution of vehicles parked at Home .....	39
Figure 21. Distribution of vehicles parked at Workplace.....	39
Figure 22. Oahu Electricity Load Profile.....	41
Figure 23. Oahu Electricity Price Profile .....	41
Figure 24. Supply Curve of the Oahu Power System .....	48
Figure 25. Average System Load Profile using Price-Taker model.....	55
Figure 26. Average System Load Profile using Supply curve model.....	56

Figure 27. EV Savings from Price-Taker model.....	57
Figure 28. EV Savings from Supply curve model.....	58
Figure 29. Total Savings from Supply Curve Model.....	58



## LIST OF TABLES

Table 1. Description of the PHEV Charging Profiles used in Parks et al. [29] .....	13
Table 2. Description of the PHEV Charging Profiles used in [36] and [37] .....	14
Table 3. Description of the PHEV Charging Profiles used in Kang and Recker [38] .....	14
Table 4. Description of the EV Charging Profiles used either in studies [43]–[45] .....	17
Table 5. EV Charging Profiles used in studies [43]–[45] .....	17
Table 6. Description of Vehicle File Variables .....	22
Table 7. Description of VEHTYPE variable .....	23
Table 8. Description of VEHID variable .....	24
Table 9. Description of DRVR_FLG variable .....	24
Table 10. Description of BESTMILE variable .....	24
Table 11. Description of STRTTIME variable .....	25
Table 12. Description of ENDTIME variable .....	25
Table 13. Description of TDAYDATE variable .....	25
Table 14. Description of TRAVDAY variable .....	25
Table 15. Description of WHYTO variable .....	26
Table 16. Description of WHYFROM variable .....	26
Table 17. Description of DWELTIME variable .....	26
Table 18. Description of CHARGE_LOCATION variable .....	27
Table 19. Description of PARKING_STARTTIME variable .....	28
Table 20. Description of PARKING_ENDTIME variable .....	28
Table 21. Description of TIME_PARKED variable .....	28
Table 22. Distribution of vehicles in the processed NHTS 2009 dataset .....	30
Table 23. Average Vehicle Miles Travelled in U.S – 2013 .....	30
Table 24. Energy Efficiency and Battery Size according to Vehicle Type .....	33
Table 25. Levels of Charging .....	36
Table 26. Charging options .....	37

Table 27. Charging Infrastructure .....	38
Table 28. Feasible EV fleet Charging Distribution .....	39
Table 29. Decision variables in Price-Taker Model .....	44
Table 30. Sets used in Price-Taker Model .....	44
Table 31. Parameters used in Price-Taker Model .....	44
Table 32. Sets used to define EV Constraints .....	45
Table 33. Parameters used to define EV Constraints (a) .....	46
Table 34. Parameters used to define EV Constraints (b) .....	46
Table 35. Parameters in the Business-As-Usual Model .....	47
Table 36. EV Decision variable in Supply Curve Model .....	48
Table 37. Parameters in Supply Curve Model .....	49
Table 38. EV Decision variable in Supply Curve Model .....	50
Table 39. Sets used to define EV Constraints in Supply Curve Model .....	50
Table 40. Parameters used to define EV Constraints (a) Supply Curve Model .....	50
Table 41. Parameters used to define EV Constraints (b) in Supply Curve Model .....	51
Table 42. Parameters used to define Load Serving Constraints in Supply Curve Model .....	51
Table 43. Parameters used to define Maximum Dispatch Constraints in the Supply Curve Model .....	52
Table 44. Parameters used in BAU charging of the Supply Curve Model .....	53
Table 45. Average Daily EV Load Distribution using Price-Taker model .....	54
Table 46. Average Daily Load Distribution using Supply curve model .....	56

## CHAPTER 1. INTRODUCTION

Advancing clean-energy, reducing dependence on foreign oil and reducing greenhouse gas (GHG) emissions (carbon emissions) have widely been recognized as some of the key components integrated in the current U.S. energy policy [1]. Rapid increase in oil demand in emerging economies and increasing global oil price volatility have further motivated policymakers to move towards energy independence which has been critical for achieving energy security.

Increasing environmental concerns about the adverse effects of greenhouse gas (GHG) emissions driving climate change have caused U.S. and various other countries to propose and launch aggressive and comprehensive plans to address this serious global concern. In accordance with the Intended Nationally Determined Contribution (INDC) submitted to the United Nations Framework Convention on Climate Change (UNFCCC), the United States has proposed greenhouse gas (GHG) reduction targets in the range of 17 percent by 2020 and 26-28 percent by 2025, relative to its 2005 emission levels, and to make best efforts to reduce by 28 percent [2]–[5].

According to the Inventory of U.S. Greenhouse Gas Emissions and Sinks 1990-2013 [6], the transportation sector is the second largest contributor to U.S. greenhouse gas (GHG) emissions, after the electricity generation sector. As shown in Figure 1, the transportation sector accounts for almost 27 percent of the total GHG emissions in 2013 and has increased more in absolute terms than any other sector between 1990 and 2013. When analyzed in detail, within the transportation end-use sector, passenger cars are the largest contributor to the total U.S. GHG emissions with 42 percent as shown in Figure 2. In order to address this problem, electrification of the transportation system has been considered by various studies [7]–[10] as one of the most feasible and promising solutions.

As illustrated by one of the outcomes in the study by Fripp (2012) [11], electric vehicles can help in achieving radical emission reductions by using demand-side flexibility, in which customers shift their electricity demands to those time periods of the day, where the surplus power produced by renewable energy resources could be best utilized. Thus well-timed charging of electric vehicles, by providing reschedulable loads, also helps the utility to integrate more renewable power into the transportation sector.

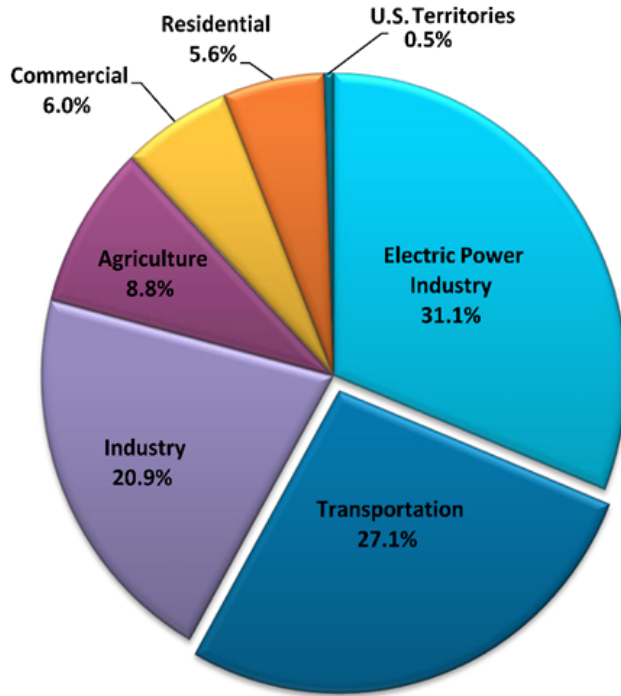


Figure 1. U.S. GHG Emissions by Economic Sector in 2013

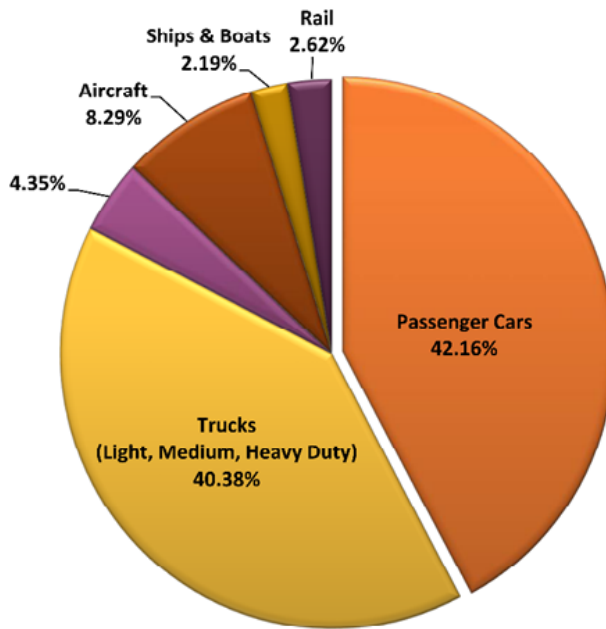


Figure 2. U.S. GHG Emissions by Transportation Sector in 2013

### 1.1 Role of Transportation in GHG Emissions Reduction

In order to understand the importance of transportation sector decarbonization, the International Energy Agency in its annual publication “Energy Technology Perspectives 2015”

[12], analyzes and presents various scenarios and strategies to guide policy makers in order to achieve the objective of limiting the average global temperature rise to 2° C. The 2° C has been identified as the necessary threshold required to avoid the worse effects of climate change in the Fourth Assessment Report of the Inter-governmental Panel on Climate Change which was agreed by various international governments including the U.S. in the Copenhagen Accord [13] and the Cancun Agreements [14], [15] organized by the United Nations Framework Convention on Climate Change (UNFCCC).

Based on the ETP 2015 modeling results, in order to achieve the carbon emissions goals/targets for limiting the average global temperature increase to 2° C (“2DS Scenario”) from the baseline 6° C Scenario (“6DS Scenario”) which is an extension of the current trends, the potential share of the transportation sector of the overall U.S. CO2 emissions needs to be 29 percent by 2050, as shown in **Figure 3**. Whereas in terms of technology as shown in **Figure 4**, renewables needs to potentially contribute 30 percent towards 2° C scenario emission reductions. In the absence of efforts to stabilize atmospheric concentration of GHGs, average global temperature rise above pre-industrial levels is projected to reach almost 5.5°C in the long term (i.e. after 2100) (Refer to [12], [16] for more details about scenarios and assumptions).

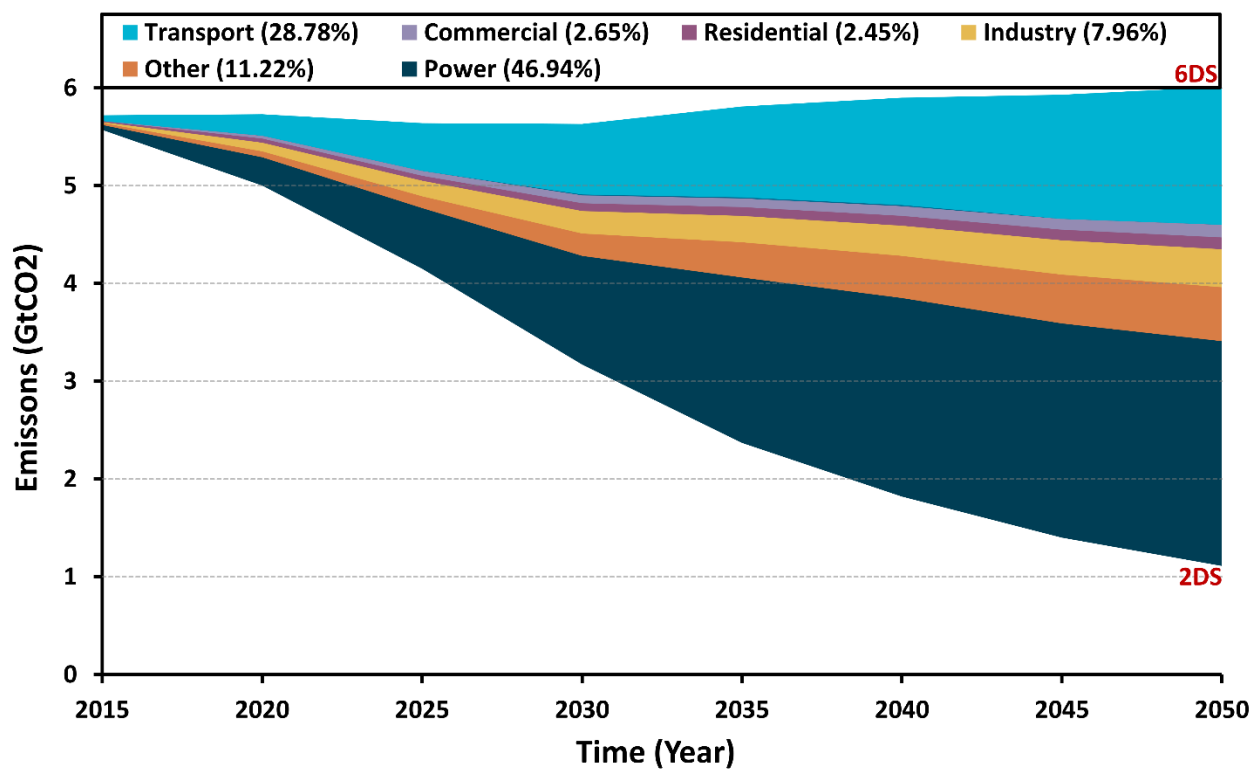


Figure 3. U.S. Sector Contributions towards Emissions Reductions

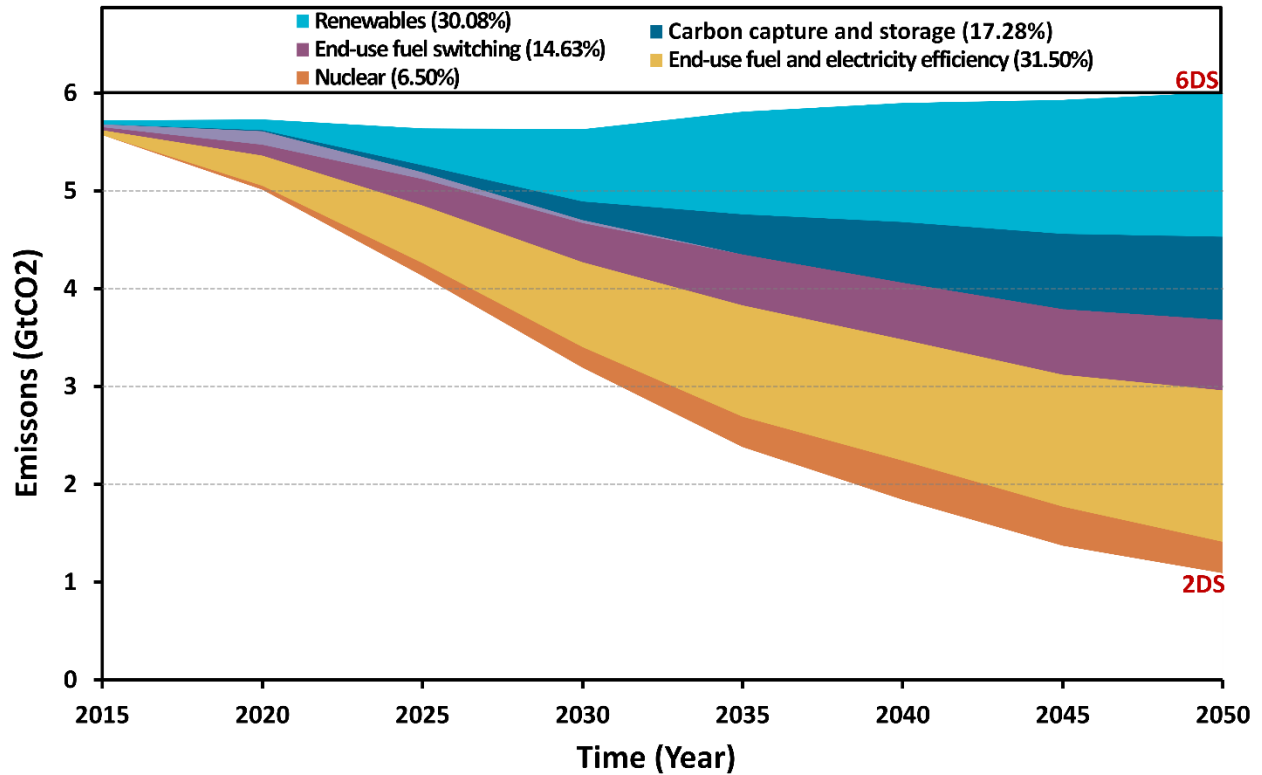


Figure 4. U.S. Technology Contributions towards Emissions Reductions

### 1.2 Hawaii Energy Scenario

With almost 84% of its energy demand in 2013, being fulfilled by imported fossil based fuels, Hawaii still continues to be the most petroleum dependent state in the U.S. Due to this high dependence on imported oil for power production, Hawaii continues to have the highest electricity prices in the nation [17] i.e. 3 times higher than the U.S. national average electricity price as shown in **Figure 5**.

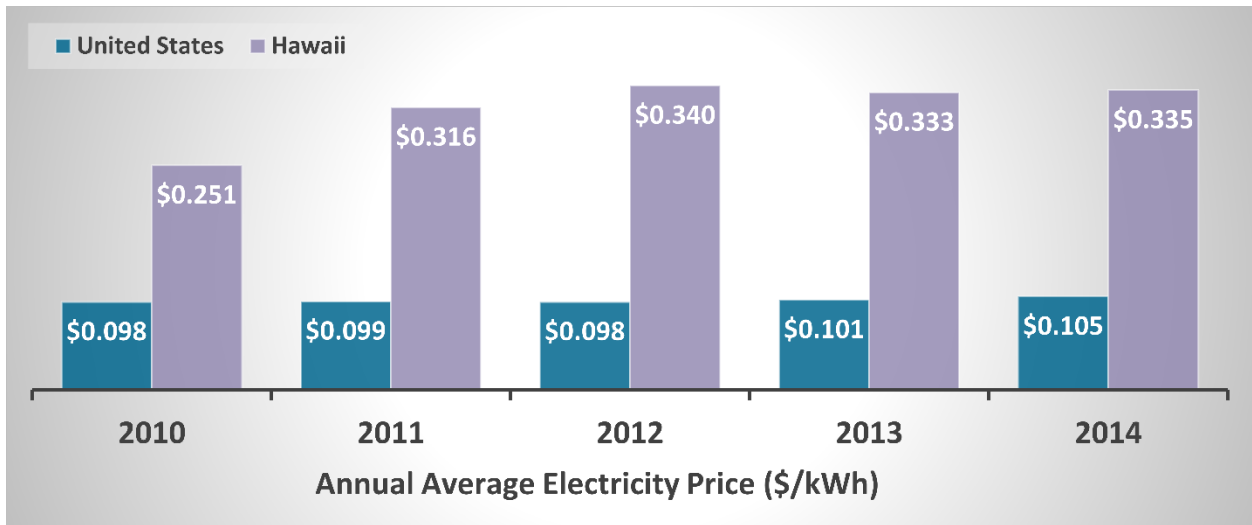


Figure 5. Annual Average Electricity Price in Dollar per kWh

Transportation sector continues to be the major consumer of the state’s oil consumption, accounting for almost 61 percent (includes ground transportation, commercial aviation and marine transport) of the total petroleum use for the year 2013, out of which ground transportation contributes around 28 percent.

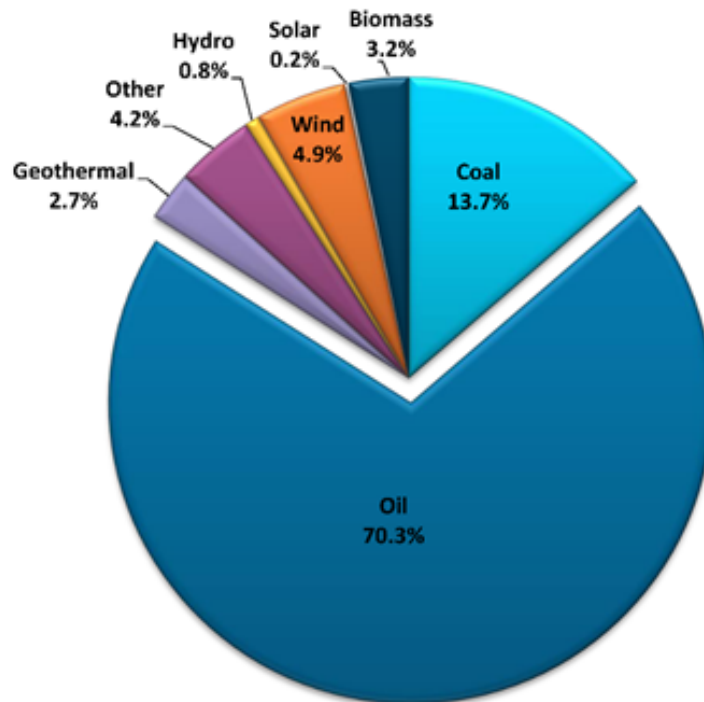


Figure 6. Hawaii Electricity Production by Source, 2013

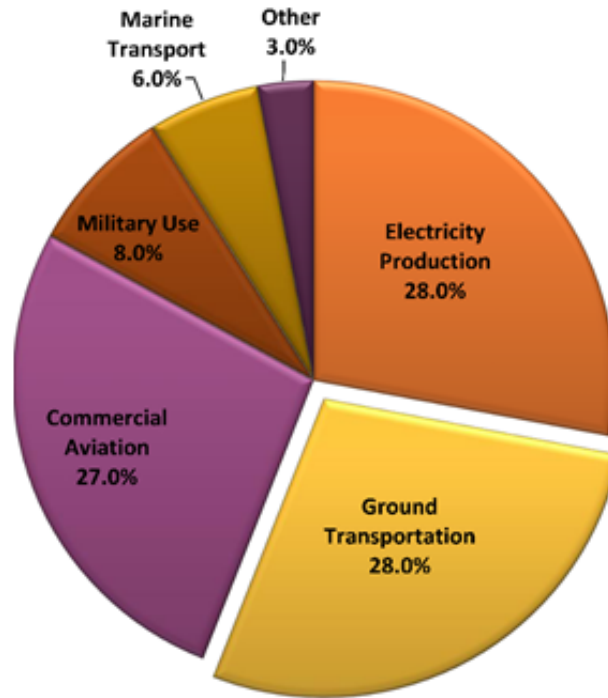


Figure 7. Hawaii Petroleum Use by Sector in 2013

### 1.3 Hawaii Clean Energy Goals and Targets

With the motivation to reduce dependence on fossil based sources, and the harmful effects of greenhouse gas emissions on the environment, states across the U.S. have started creating and implementing climate and clean energy policies and programs. Policies and measures such as renewable portfolio standards (RPS) and energy efficiency portfolio standards (EEPS) specify for utilities or third-party program administrators, multi-year specific mandatory or voluntary energy targets, in order to achieve that particular state's environmental, economic, and energy goals. These energy goals/targets vary from state to state and are dependent on each state's specific energy demands and the diversity of its energy supply.

In order to mitigate Hawaii's dependence on fossil based energy sources, the State of Hawaii and the U.S. Department of Energy established the Hawaii Clean Energy Initiative (HCEI) [18] in 2008. This Memorandum of Understanding (MOU) established aggressive goals to achieve 70% clean energy by the year 2030, with 30 percent from efficiency measures, and 40 percent coming from locally generated renewable sources. In June 2015, with the signing of House Bill 623 [19], Hawaii became the first U.S. state to enact a law that sets a goal of generating 100 percent of its electricity from renewable energy by 2045. This new RPS goal is currently the most aggressive clean energy goal in the country. The interim RPS goals as shown in **Figure 8** are also very challenging and will require significant efforts from both the policymakers and the utility.



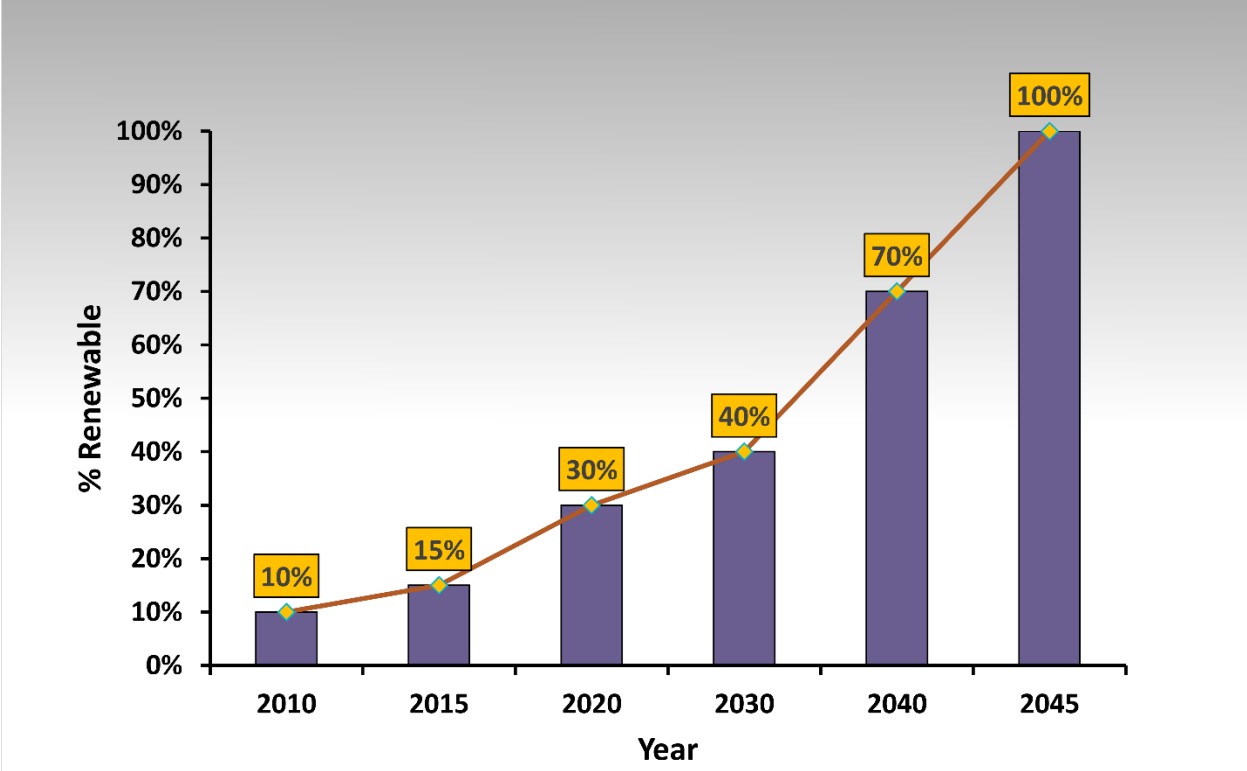


Figure 8. Hawaii Renewable Energy Portfolio Standards (RPS) Levels

The state has already achieved its mandated 15 percent RPS target for the year 2015 in the year 2013. For the year 2014, 21.1 percent of the state’s total electricity sales were contributed by renewable energy resources. The historical progression of the RPS levels for Hawaii from 2008 to 2014, are shown in **Figure 9**.

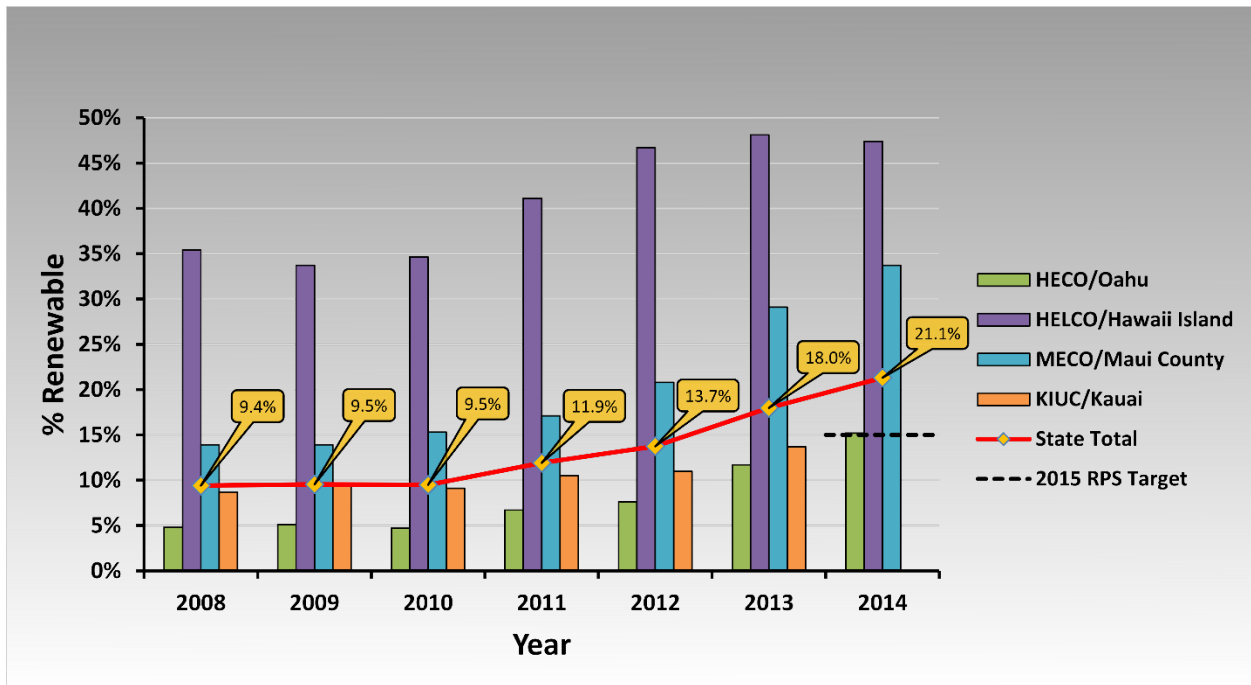


Figure 9. Hawaii Renewable Energy Production Status 2008-2014 [20]

Similarly Hawaii’s EEPS program has set a goal of reducing electricity use by 4,300 gigawatt-hours (GWh) by 2030, which is roughly equivalent to 30 percent of electric utility sales in 2030 [21]. For the year 2014, the EEPS level for the state of Hawaii was 16.8 percent.

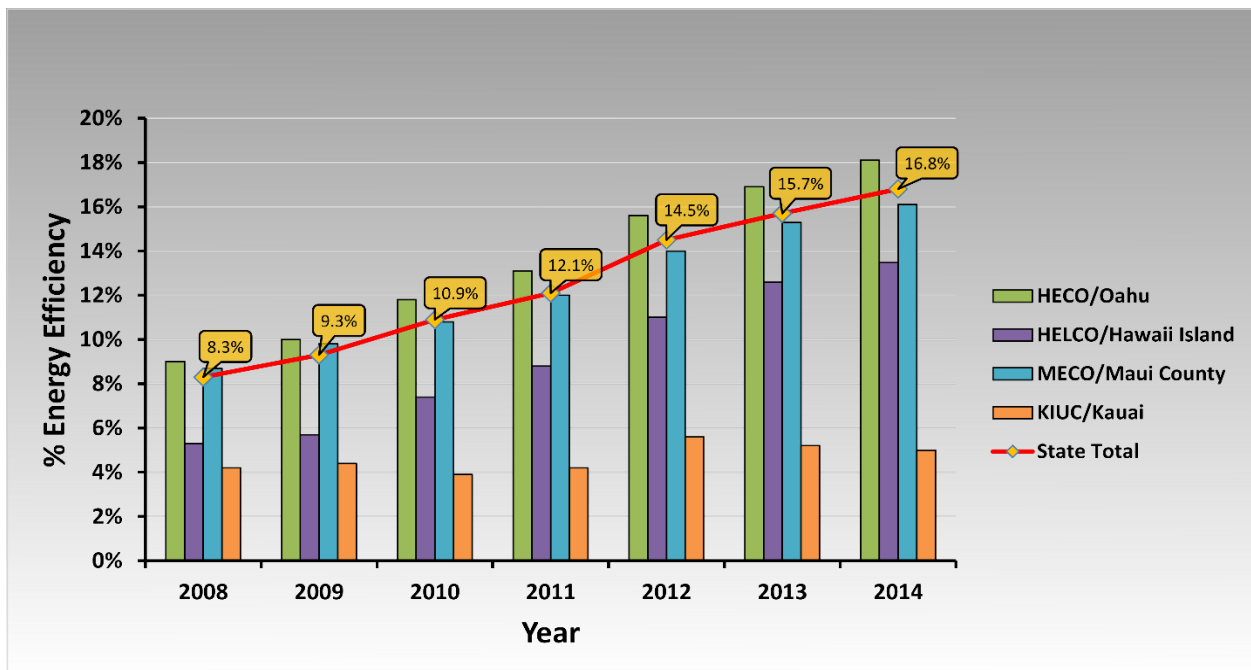


Figure 10. Hawaii Renewable Energy Efficiency Portfolio Standards (EEPS) Status 2008-2014 [22]

## 1.4 Global EV Scenario

EV sales globally has been on the rise and has increased by 50 percent from 2013 to 2014, whereas PHEV and BEV sales grew by 57 percent and 43 percent respectively [16]. According to EVI's 2015 update of its Global EV Outlook 2015 [23], U.S. with an EV and EVSE (Electric Vehicle Supply Equipment) stock of 276,104 and 21,814 respectively joins countries like Netherlands, Norway, and Sweden by being the only countries having EV sales in the year 2014 exceed market shares of 1 percent. Similarly 2014 also saw tremendous growth in EV charging infrastructure, the number of Level 1 and Level 2 chargers increased from 46,000 in 2012 to around 940,000 in 2014 and the number of fast chargers (Level 3, CHAdeMo, and SuperCharger) increased from 1,900 in 2012 to 15,000 in 2014 [16]. According to [24], among all countries, U.S. registered the highest number of PEVs (14,832 vehicles) in the first quarter of 2015.

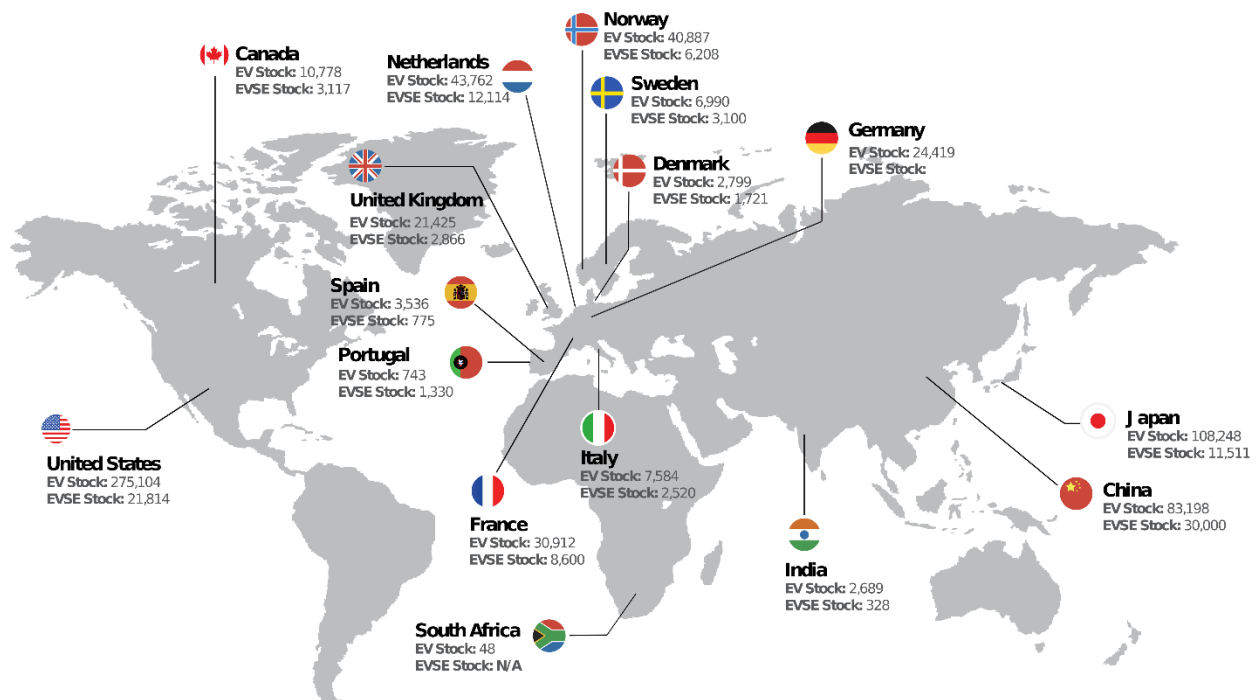


Figure 11. Global EV and EVSE Stock [23]

(Source: Based on IEA data from the Global EV Outlook 2015 © OECD/IEA 2015, IEA Publishing; modified by Paritosh Das. License: <http://www.iea.org/t&c/termsandconditions/> )

Hawaii has also shown a lot of promise in terms of EV growth. For the year 2014, Hawaii ranked second behind California among all the states in the number of plug-in electric light vehicle registrations per thousand people. Registration of passenger electric vehicles in Hawaii grew by 46% from January 2014 to January 2015. There has also been good development in EV charging infrastructure in Hawaii; at the end of the year 2014, Hawaii had 192 electric charging stations and 431 electric charging units [25] (Data does not include residential (“wall outlets”) or private electric charging infrastructure (EVSE); one charging station can have multiple number of charging units/outlets).

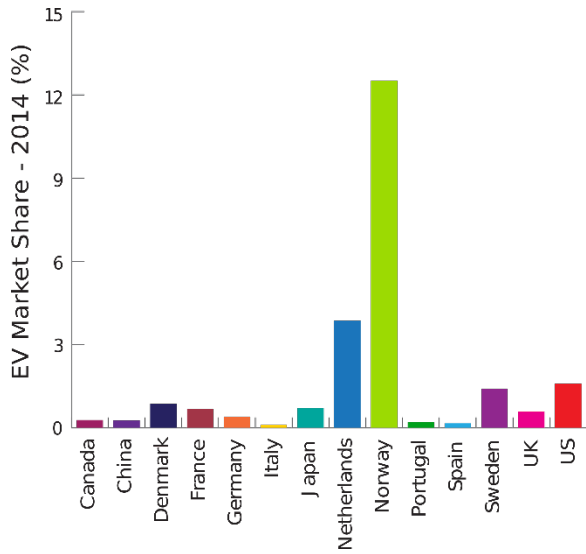


Figure 12. Percentage EV Market Share in 2014 [23]

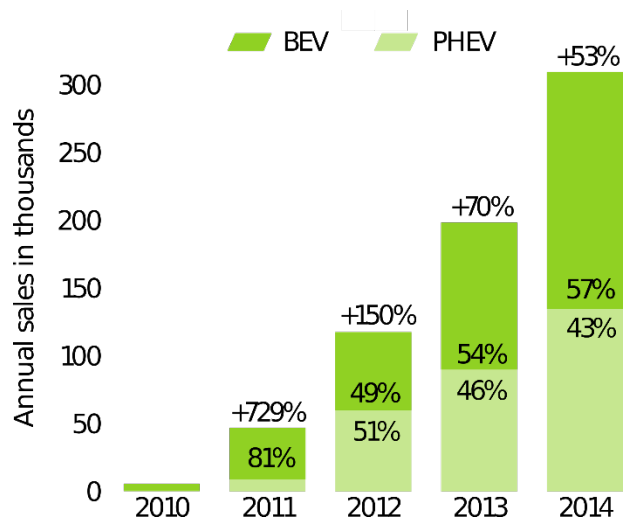


Figure 13. Global EV Sales [23]

(Source: Based on IEA data from the Global EV Outlook 2015 © OECD/IEA 2015, IEA Publishing; modified by Paritosh Das. License: <http://www.iea.org/t&c/termsandconditions/> )

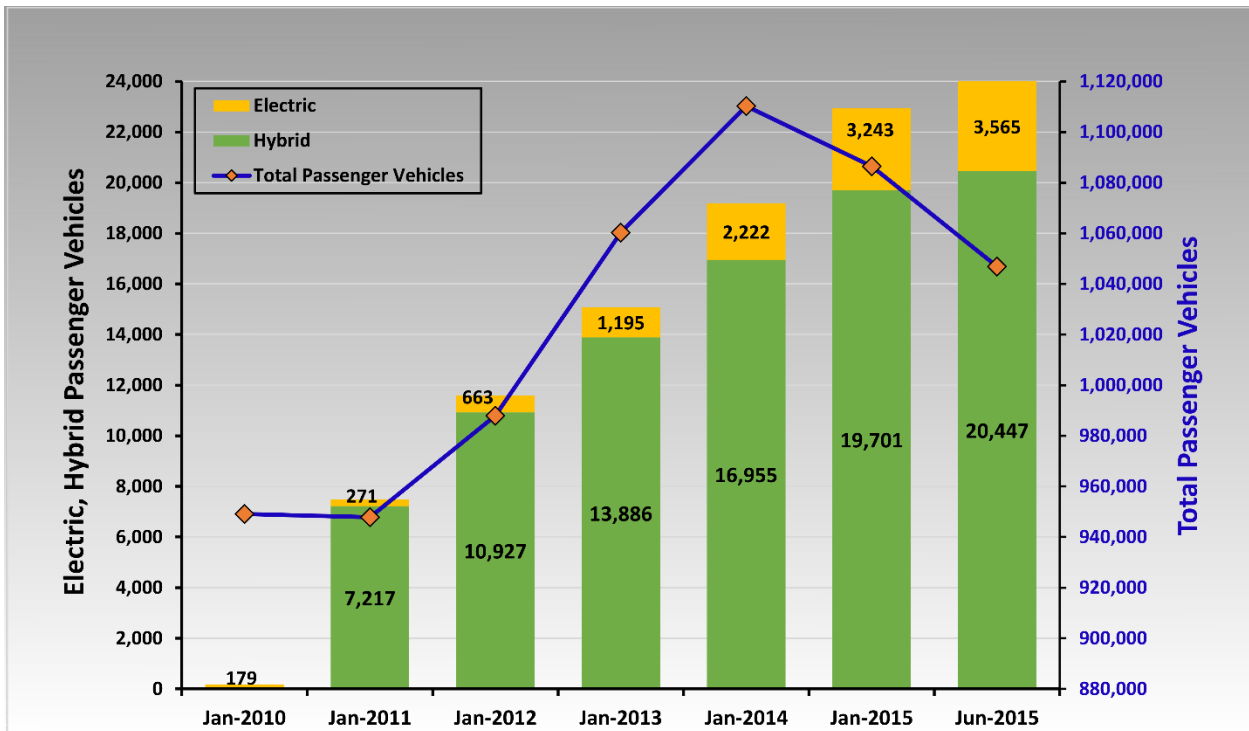


Figure 14. Registered Electric, Hybrid and total passenger vehicles in Hawaii

## 1.5 Research Objectives

The main purpose of this research is to examine the impacts of electric vehicles on the Hawaii electric power system by identifying and evaluating different EV charging scenarios which would provide a more accurate and realistic representation of potential consumer behavior. With the increasing penetration of renewable energy resources such as wind and solar into the Oahu Power system for the ultimate goal of achieving 100 percent of its electricity from renewable energy by 2045, there is a need to understand how electrification of the transport sector (primarily passenger) would affect the electrical grid.

This research work develops a simple power system model and configures it with Hawaii specific data to evaluate the benefits of optimally-timed EV charging, and the impacts of these charging scenarios on the power system, in order to serve different types of vehicle fleets. The primary goal can be broadly classified into the following three interrelated objectives:

- A. Design and develop a comprehensive EV Model which involves the following:
  1. Develop detailed EV charging windows/timeslots that are available for each individual vehicle considered in the study, by analyzing individual vehicles' driving pattern behavior, as shown in the NHTS. The work identified potential charging windows/timeslots that are representative of actual passenger vehicle travel behavior and provide realistic schedules of charging options available for different passenger vehicle classes at likely charging locations (i.e., home and workplace).
  2. Develop daily electricity demand profiles for each modelled EV by considering different shares of charging locations (workplace/home charging) and different rates of charging (1.4kW/3.3kW/6.6kW). Charging behavior is considered under business-as-usual (BAU) and two optimized recharging scenarios: a) Price-Taker Model, and b) Supply Curve Model. The EV adoption is constrained by type of charger used, location and duration of charger access, vehicle size and daily mileage.
- B. Develop a unit commitment and dispatch production cost model of the Oahu power system, which can identify optimal power system operation plans based on the half hourly behavior of renewable resources, system load, demand response, and conventional power plants.
- C. Integrate the power system production cost model with the EV fleet model to evaluate and study the impact of the two different EV fleet recharging scenarios on system load, and power system costs. The study also compares the benefits of scheduling EV charging at optimal times of each day with the business-as-usual (BAU) scenario.

## CHAPTER 2. LITERATURE REVIEW

### 2.1 Studies on PHEV Electricity Load (Energy) Impacts Using Different Charging Scenarios

To study the impact of EVs on the grid, an estimate of how much energy each vehicle needs each day, when they will be plugged in and the rate at which they will draw power is needed. In order to determine each of the characteristic, various research studies have used different methods and assumptions.

The study by Kintner-Meyer et al. [26] estimated the threshold of PHEV penetration that can be achieved using the idle generation capacity of the existing electric infrastructure for 12 modified North American Electric Reliability Council (NERC) regions. The idle generation capacity is represented by the difference between the installed system capacity and the system load. The modelled vehicles were assumed to be PHEVs which had an all-electric driving range of 33 miles, before re-charging, or the use of gasoline becomes necessary. The energy requirements per mile for the selected light duty vehicle classes were used to determine the maximum number of vehicles that can be charged successfully from the available idle generation after satisfying the system load demand.

Similarly, the study by Schneider et al. [27] focused on the impacts of high penetration of PHEVs on the Pacific Northwest distribution Systems. From among the vehicle energy requirement assumptions for different vehicle classes as mentioned in [26], they chose a battery size of 10 kWh. In-order to model the PHEV load profile, two charging scenarios were selected. The first charging profile was obtained from the study [28], in which charging occurs at all times of the day, with majority of the charging occurring during off-peak hours, in residential locations having input voltage ratings of 120V. The second charging profile also known as a “rapid-charging” profile assumes that all the charging to occur in residential locations having a 240V connection, within a 3 hour time slot (5 pm – 8 pm).

The study by Parks et al. [29] which models the impacts of PHEV charging on the Xcel Energy Colorado service territory, assumed a PHEV with an all-electric driving range of 20 miles for modelling simulations. The vehicle design and performance characteristics were based on the Advanced Vehicle Simulator (ADVISOR) vehicle simulation tool, developed by [30]. The performance assumptions of the vehicle fleet data was obtained from the driving pattern data from 227 vehicles in St. Louis in 2002, which were tracked using GPS. In-order to determine the PHEV load profile, four charging scenarios were evaluated as shown in the table below **Table 1**. The hourly PHEV load profile obtained from the EV charging scenarios were added to the system load to study the impact of EV adoption.

**Table 1. Description of the PHEV Charging Profiles used in Parks et al. [29]**

<b>EV Charging Profile</b>	<b>Description</b>	<b>Charging Rate</b>
<b>Uncontrolled Charging</b>	Charging doesn't follow any pattern and occurs whenever within reach of a residential outlet.	1.4 kW
<b>Delayed Charging</b>	Similar to uncontrolled charging, but charging is delayed until 10 pm.	1.4 kW
<b>Off-Peak Charging</b>	Overnight charging occurs during 11pm to 7am.	3.2 kW
<b>Continuous Charging</b>	Similar to uncontrolled charging but also includes public charging stations.	1.4 kW

Previous studies by Sioshansi and Denholm [31][32], Sioshansi and Miller [33], and Sioshansi et al. [34] have used specific regional empirical driving data to determine the PHEV load profile to be used in their analyses. They model the Electricity Reliability Council of Texas (ERCOT) electric power system whereas Sioshansi et al. [34] model the Ohio power system. In all the 4 studies, vehicle driving pattern data collected from 227 vehicles in the St. Louis, Missouri metropolitan area by the East-West Gateway Coordinating Council's (EWGCC) household travel survey has been used. The Advanced Vehicle Simulator (ADVISOR) vehicle simulation tool, developed by [30] uses this data along with the various PHEV charging profile scenarios, to provide battery energy requirement usage data for creating the PHEV charging profiles.

A study by Lemoine et al. [35] determined various PHEV load charging profiles according to 3 different charging scenarios. The "Optimal charging" scenario assumes charging during periods of lowest demand which is limited just to the nighttime hours. The "Evening charging" scenario assumes charging to begin between 6 pm and 8 pm and is assumed to charge continuously for 4 hours whereas the "Twice per day" scenario uses the evening charging timings along with charging at the morning between 8 am and 9 am. Their assumption included that each PHEV has an all-electric-range (AER) of 20 miles for the first two scenarios and 40 miles for the last scenario.

The studies by Axsen and Kurani [36] and Axsen et al. [37] analyzed the PHEV energy impacts in California by creating PHEV recharge scenarios that have been constructed from survey data collected from a sample of 877 new vehicle buyers in California. The survey respondents were assigned a day of the week, and reported travel information for that particular 24 hour period. In order to determine the recharge profiles, both the studies evaluated four PHEV recharging scenarios as shown in **Table 2**.

**Table 2. Description of the PHEV Charging Profiles used in [36] and [37]**

<b>EV Charging Profile</b>	<b>Description</b>
<b>Plug and Play</b>	Drivers are assumed to charge whenever they are parked within 25ft of an electrical outlet.
<b>Universal\Enhanced workplace access</b>	Similar to “plug and play” charging and also includes charging at workplace.
<b>Off-Peak Only</b>	Similar to “plug and play” charging but assumes no charging between 6 am and 8 pm.

The study by Kang and Recker [38] used the vehicle travel data collected from the 2000-2001 California Statewide Household Travel Survey, to study the potential energy and emission impacts of PHEV adoption in the California power system. PHEVs having all-electric ranges of 20 miles and 60 miles have been considered in this study. In order to determine the charging demand due to the adoption of PHEVs, four charging scenarios were considered.

**Table 3. Description of the PHEV Charging Profiles used in Kang and Recker [38]**

<b>EV Charging Profile</b>	<b>Description</b>
<b>End-of-day Recharging</b>	Charging occurs after the last trip of the day.
<b>Uncontrolled home Charging</b>	Charging occurs each time the vehicle is parked at home.
<b>Controlled Charging</b>	Charging is allowed only from 10 pm through the next morning.
<b>Publicly-available electricity Charging</b>	Charging occurs whenever a vehicle is parked at any public location.

In order to perform an well-to-wheels analysis of energy use and greenhouse gas emissions of PHEVs, the study by Elgowainy et al. [39] used 2001 NHTS travel data to develop PHEV load profiles for four different electric power systems in the U.S. The simulation model divided the PHEV population in each of these four geographical areas according to AERs of 10, 20, 30, and 40 miles, depending on the vehicle travel data. Various assumptions about battery energy requirement usage and fuel economy were determined using Argonne’s Powertrain System Analysis Toolkit (PSAT) model. Three different charging scenarios i.e. unconstrained charging, constrained charging, and smart charging, have been considered to determine the PHEV load profiles for the simulation calendar year 2020. The unconstrained charging scenario assumes charging at home after the final trip of the day whereas in the constrained charging scenario, charging at home occurs 3 hours after the final trip of the day. The smart charging scenario assumes charging to occur only during the time-period having lowest system loads.

The study by Weller [40] performed a more detailed analysis in determining different PHEV load profiles according to various different charging behaviors, using the 2001 National



Household Travel Survey (NHTS) data for determining the daily vehicle usage pattern. Weller (2011) evaluated various charging scenarios depending upon the vehicle charging location and charging power and validated that managing the time of PHEV charging over a day is critical in alleviating the impact of uncontrolled PHEV charging which coincides and affects the normal evening peak system electricity load.

## **2.2 Studies on PHEV Economic and Emission Impacts**

The study by Wang et al. [41] used game theory models to study the PHEV charging impacts on the locational marginal prices (LMPs). After evaluating their model on the Pennsylvania-New Jersey-Maryland Interconnection, they found that the extra load due to PHEV recharging has a significant undesirable effect on the LMP and future recharging infrastructures such as real-time pricing, battery stations, or vehicle-to-grid technology would be useful in mitigating this effect. PHEV recharging loads have been calculated depending on the various assumed charging profiles which are broadly divided into 2 categories: price-insensitive and price-sensitive recharging. The price-insensitive recharging profiles considers either daytime or nighttime recharging, in which charging is allowed from 8 am to 7pm, or from 8 pm to 7 am respectively. The price-sensitive recharging scenarios represent the benefits of future recharging infrastructures.

The study by Sioshansi [42] analyzes the cost and emission impacts of PHEV charging under different electricity pricing tariffs. The vehicle model and the driving pattern data used in this study has been adopted from previous work done by Sioshansi and Denholm [31][32] which uses the ADVISOR vehicle simulation model, with the driving data obtained from survey conducted on 227 vehicles in the St. Louis, Missouri metropolitan area. The modelling is carried out on the Electricity Reliability Council of Texas (ERCOT) power system. The five different PHEV charging scenarios evaluated in this model represent PHEV charging under different electricity pricing tariffs. The study concluded that in this particular case study, contrary to common expectation, real-time pricing performed worse in terms of impacts on both the net cost and emissions than all the other considered electricity tariff scenarios.

The Electric Power Research Institute's (EPRI) (Duvall et al.) [28] study analyzed the impact of PHEV adoption on the GHG emissions over a time period of 2010 to 2050. The study modelled two sets of scenarios representing varying levels (low, medium, and high) of CO<sub>2</sub> intensity and PHEV penetration. The PHEV charging load profile was calculated assuming maximum charging during late night and early morning hours, and modest charging during the middle of the day. The analysis concluded that the adoption of PHEVs can significantly reduce the consumption of petroleum fuels in the U.S. thereby achieving a cumulative GHG reduction, ranging from 3.4 to 10.3 billion metric tons of CO<sub>2</sub> emissions from 2010 to 2050.

## **2.3 Electric Vehicle Charging Studies in Oahu**

The Hawaii Natural Energy Institute (HNEI) in collaboration with GE have conducted studies [43][44] which analyzed the potential of various electric vehicle charging scenarios in

order to better utilize and reduce the curtailed renewable energy during time periods of high generation and low demand in the Oahu power system.

The study [44] builds on one of the base case scenarios of high penetration of wind and solar resources, modelled in the Oahu Wind Integration Study (OWIS) for the Oahu grid. The high renewable energy scenario of 600 MW from OWIS, was extended to include 800 MW and 1000 MW, to study the impact of various electric vehicle charging scenarios, electric vehicle adoption rates and storage support, in order to minimize the curtailed renewable energy in the Oahu grid. On a fixed load system, the increase in the renewable energy generation capacity in the various base case scenarios also gives rise to the increase in the percent of curtailed energy. This analysis assumes that the total amount energy needed for the EV fleet charging is exactly equal to the total amount of curtailed renewable energy considered in a particular base case scenario, i.e., the daily EV charging energy has been calculated by equally distributing the annual curtailed renewable energy over 365 days. This study evaluated 7 EV charging profiles which could achieve the maximum reduction in curtailed renewable energy. The model simulations showed that for a base case scenario of 1000 MW of renewable energy (700 MW wind, 300 MW solar), the potential reduction in the curtailment of renewable energy ranged from 40% to 53%, with the “daily perfect tracking” and “annual uniform charging” EV charging profiles being the best-case and the worst-case options respectively. The “daily perfect tracking” profile has been considered as a theoretical upper boundary which assumes perfect synchronization between renewable energy and the load.

The study [43] builds on the basic data structure of [44], to study in detail the impact of different EV charging profiles on the Oahu power system, in order to minimize the curtailed renewable energy. The model considers four base cases with no EV charging and 6 scenarios of different EV charging profiles for each of the base case. For the first four EV charging scenarios, modelling was done using a production cost simulation model (GE-MAPS) whereas the remaining two charging profiles were modelled using a spread-sheet model. The charging profiles used in this study are shown in the **Table 5**. The study concluded that although considered “unrealistic”, the “Daily Perfect Tracking” charging scenario captured most of the potentially curtailed renewable energy.

The study [45] uses the future base case scenarios with high penetration of wind and solar resources developed by GE in the study [43] to analyze the effect of EV charging scenarios to reduce the curtailment of renewable energy in Oahu. The study validated the results obtained in the study done by GE and suggested that out of the 4 considered EV charging scenarios, the EV charging profile “**Annual, Profile 2**” is more practical and hence can be implemented by using various incentive programs.

**Table 4. Description of the EV Charging Profiles used either in studies [43]–[45]**

EV Charging Profile	Description
<b>Annual Uniform Charging</b>	Daily charging is equally distributed all year
<b>Annual Perfect Tracking</b>	Daily charging tracks the annual average of any hour
<b>Annual, Profile 1</b>	70% night charging, 30% day, including 5:00-9:00 pm Peak
<b>Annual, Profile 2</b>	70% night charging, 30% day, excluding 5:00-9:00 pm Peak
<b>Annual, 85%</b>	85% of charging between 9:00 pm – 7:00 am
<b>Monthly Perfect Tracking</b>	Daily charging for each hour set at monthly average curtailed for that month
<b>Daily Perfect Tracking</b>	Charging is proportional to daily curtailed load shape

**Table 5. EV Charging Profiles used in studies [43]–[45]**

Reference Source EV Charging Profile	Electric Vehicle Charging as an Enabling Technology [44]	Oahu Electric Vehicle Charging Study [43]	Strategic Use of Electric Vehicle Charging to Reduce Renewable Energy Curtailment on Oahu [45]
<b>Annual Uniform Charging</b>	x	x	x
<b>Annual Perfect Tracking</b>	x	x	x
<b>Annual, Profile 1</b>	x	x	x
<b>Annual, Profile 2</b>	x	x	x
<b>Annual, 85%</b>	x	x	
<b>Monthly Perfect Tracking</b>	x		
<b>Daily Perfect Tracking</b>	x	x	

#### 2.4 Research Contribution towards Literature

The simulation model developed in this study uses actual driving pattern data collected from the 2009 National Household Travel Survey (NHTS) conducted by the U.S. Department of Transportation (DOT). This national survey provides one of the most recent and comprehensive dataset on transportation and travel pattern behavior in the United States, which is publicly available. Prior PHEV load profile studies such as Kintner-Meyer et al. [26], Schneider et al. [27], Stephan and Sullivan, Lemoine et al. [35], Denholm and Short, Duvall et al. [28], Hadley and Tsvetkova, Wang et al. [41], HNEI/GE studies [43], [45] have generally assumed a fixed number

of miles as the daily travel distance driven by vehicles and thus do not address the different prominent driving pattern variations.

This study on the other hand evaluates individual driving patterns in a much detailed level, in which trip by trip driving pattern distributions were determined for each individual vehicle. These detailed distributions provide an accurate and realistic representation of the actual driving pattern in the United States, which were used to determine potential EV charging scenarios. These charging scenarios thus provide a more reasonable and accurate representation of the impact of EVs in the current and future passenger transportation sector.

Using these driving pattern distributions, EV charging windows/timeslots were calculated by determining the maximum possible time a vehicle is parked in a potential charging location (i.e. home and workplace). These potential charging timeslots provide the EV owner the most comprehensive and realistic charging options available, as each option is unique to that particular vehicle and is derived from thorough analysis of its driving pattern behavior.

Although many of the PHEV impact studies have been performed on localized regional power system grids such as Colorado, Texas, Ohio, California, PJM (Pennsylvania–New Jersey–Maryland) electric power systems, but very little study has been done on the Oahu power grid except the ones by HNEI/GE. The HNEI/GE studies mainly concentrated on analyzing how best the different assumed EV Charging profiles perform in reducing the curtailment (i.e., spillage) renewable energy in the Oahu power grid. The most important assumption used by them was to limit the total electricity demand due to EV charging to be equal to the amount of curtailed renewable energy considered in each base case scenario, where the maximum annual curtailed energy ranges from 201 GWh to 736 GWh for base case scenarios in which future renewable power generation projects ranging from 600 MW to 1000 MW were assumed to be integrated into the Oahu power system.

The amount of energy needed for charging a particular EV valuated in this study are calculated as a function of charging location (i.e. home and workplace charging) and the charging rate for different designs of passenger vehicles (car, van, SUV, pick-up truck) UNDER business-as-usual and two optimized recharging scenarios: 1. Price-Taker Model, and 2. Supply Curve model.

Although the model can be customized to model both PHEVs and BEVs, but the vehicles simulated here have been assumed to only represent full battery electric vehicles (BEVs). This assumption is based broadly on the following factors which are specific for niche markets such as like Hawaii.

Due to its unique geographical location as compared to all other states in the U.S, the Hawaiian Islands and especially the island of Oahu, which with a total land area of just 600.7 square miles (i.e. 1555.9 square kilometers) and with almost 70% of the resident population of the state [46], forms an ideal site to analyze the impacts of large scale adoption of EVs and how different optimal EV charging can benefit such an unique power system.

With the extreme dimension of Oahu ranging from 44 miles (71 km) long and 30 miles (48 km) across, the work assumed that all simulated vehicles can have a maximum travel range of 100 miles, which is very much consistent with the maximum number of miles that can be travelled with a single electric charge (AER) of some of the current BEVs in the market today. As

suggested by the study in [47], with the current increase in the all-electric ranges of BEVs and with more charging facilities\infrastructure becoming available, BEVs tend to mitigate consumers range anxiety and thus project themselves as a forerunner to out compete PHEVs in the future scenario of large-scale mass adoption of EVs. This adoption behavior can also be inferred from the 2013 electric vehicle registrations data analyzed in the study [48], in which apart from California, Hawaii had the highest new vehicle share of BEVs with about 1.2%, whereas the new vehicle share of PHEVs in Hawaii tended to be around 0.3%.

## CHAPTER 3. MODEL DESIGN AND DESCRIPTION

In order to understand the impacts of EVs on the Hawaii electric power system, it is necessary to develop a comprehensive EV model which takes into consideration critical EV characteristics. The EV model developed in this study assumed that Hawaii might have a large number of electric vehicles, which were driven in similar patterns to the nationally representative vehicle-day data given by NHTS 2009.

Charging availability and requirements profiles were then created for all these vehicles based on the driving pattern behavior determined from NHTS 2009. Each vehicle was then assigned a feasible charging strategy (Level 1, Level 2a, or Level 2b) depending upon the charging location (home or work), battery capacity and time available for charging. Vehicle charging simulations were then performed under two scenarios: business-as-usual (charge as fast as possible as soon as they reach their charging location) or optimal (charge at the best times during the window when they are plugged in at the charging location).

In this study, two models of the power system were implemented. One model assumed EV owners paid dynamic electricity prices equal to the historical hourly marginal cost in 2014, and that EV charging did not change these prices. The other used a supply curve for electricity based on the properties of the Oahu generation system (including existing wind and solar equipment), and optimized EV charging throughout the day based on this supply curve. Finally, using each of these models the load profiles, and costs of the business-as-usual and optimized charging approaches were compared.

### 3.1 Electric Vehicle Data Characteristics

The EV model developed in this model, identifies and develops several important vehicle and travel characteristics. These characteristics are important in simulating a vehicle model to represent a large EV fleet. Using the NHTS 2009 dataset, a sequence of pre-processing operations extracted data on all the trips made by individual vehicles on individual days. Several important travel characteristics such as: how far each vehicle traveled on each day; and when would have been the best opportunities for a replacement EV to charge at work or home, were identified. Simple models of EV replacements for the fossil fuel vehicles were then created, with one model corresponding to each vehicle size class. Each EV was assumed to have a 100 mile electric range, and an efficiency based on standard models for each vehicle size. Based on the miles driven and the type of vehicle, the amount of electricity that would be required on each vehicle-day if the gasoline/diesel vehicle were replaced by an EV was determined. All possible EV vehicle-days were then assigned to a feasible charging strategy (Level 1, Level 2a, or Level 2b) depending upon the location of charging (home or work). These steps are described in more detail below. These vehicle fleets are then modelled in section 3.4 as loads to be served by the power system.

### **3.1.1 Electric Vehicle Data and Assumptions**

The National Household Travel Survey (NHTS) is a national survey sponsored by the U.S. Department of Transportation (DOT). NHTS provides comprehensive data on travel and transportation patterns in the United States. This detailed transportation data inventory is publicly available and can be obtained from the NHTS website [49] for the study year 2009. NHTS transportation data helps transportation planners, academic researchers, and policy makers to understand personal travel behavior at the individual and household level, and analyze the trends in travel characteristics over time, relate the travel behavior with the demographics of the traveler, and the demographics with travel over time.

#### **3.1.1.1 NHTS Dataset Characteristics**

The NHTS 2009 survey was conducted over a 13-month period from March 2008 through April 2009 so that the seasonal travel variations are aptly represented. The survey covered all members of selected households for one day, asking them to list all the trips they made on that particular study day. The result is a collection of snapshots of one day of travel for 150,147 households. The survey had travel days assigned for all seven days of the week, including holidays, to represent travel across weekday and weekend variations. The data was collected from survey interviews from almost 150,147 households and 351,275 persons in all 50 states and the District of Columbia, in-order to represent all geographical areas [50]. A typical 24-hour travel day is from 4:00 AM of the day assigned until 3:59 AM of the following day.

Four main data files are associated with the 2009 NHTS dataset:

- 1. Household File:** Data collected from each household (one record per household).
- 2. Person File:** Data collected from each interviewed household member (one record per person).
- 3. Vehicle File:** Data collected from each household's vehicles (one record per household vehicle).
- 4. Travel Day Trip File:** Data collected for each trip a household member made on a particular travel day (one record per travel day person trip).

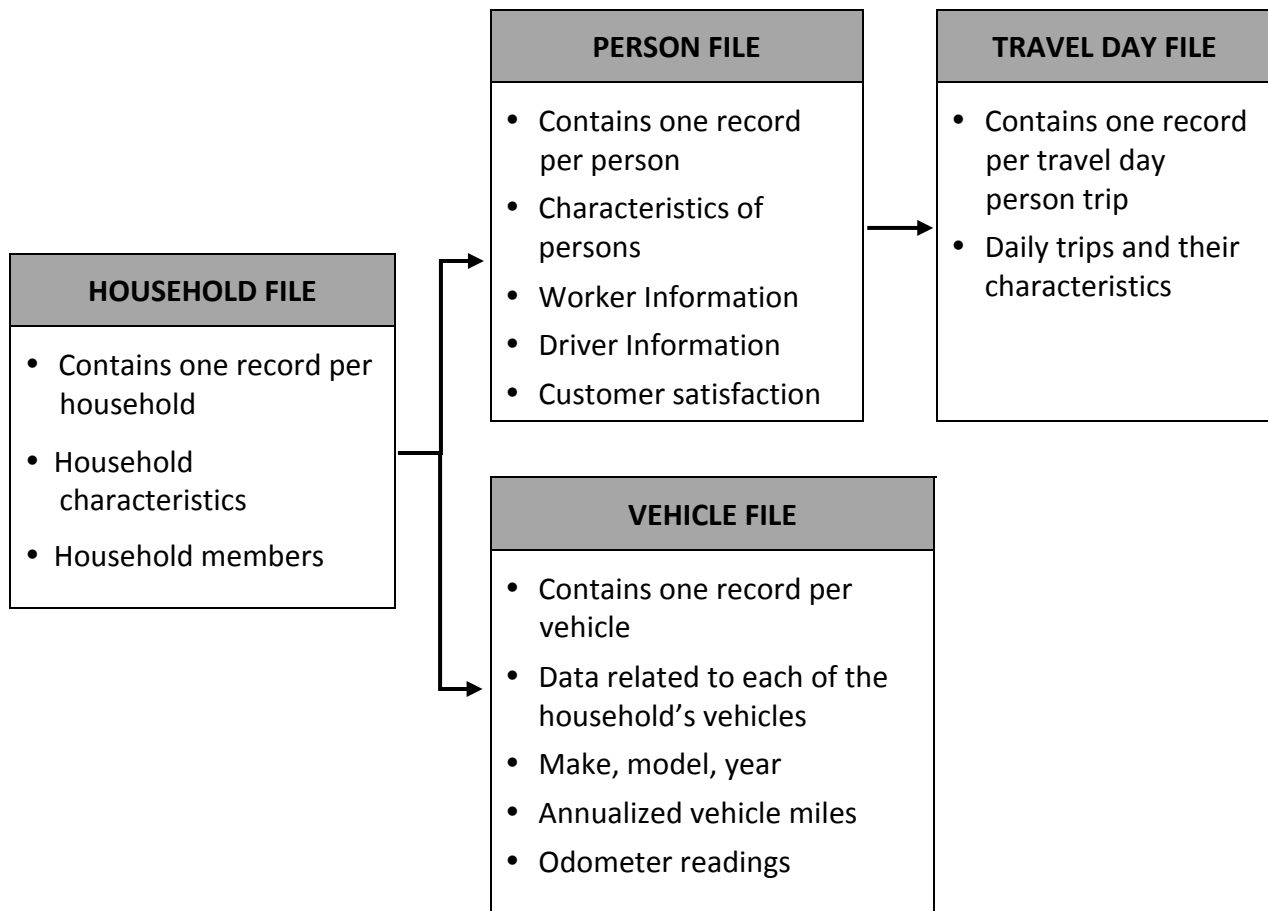


Figure 15. NHTS 2009 Data File Structure [50]

For the research analysis presented here, the dataset files Vehicle file and Travel day trip file have been used. These files in the Dbase format were obtained from the NHTS 2009 website.

- 1. Vehicle File (VEHV2PUB):** The sample size of the dataset is 309,163 records. This dataset contains around 61 unique data attributes to represent each household vehicles characteristics. From among all the attributes, six attributes as shown in Table 6 have been utilized in this study (HOUSEID, VEHID, VEHTYPE, TRAVDAY, TDAYDATE, and BESTMILE). Although this is a national dataset, 465 vehicle records from Hawaii are also included in the dataset.

Table 6. Description of Vehicle File Variables



Variable Name	Variable Description
HOUSEID	Eight digit household ID number
VEHID	Vehicle number used for trip
VEHTYPE	Vehicle type
TRAVDAY	Travel day date with month and year
TDAYDATE	Travel Day – Day of Week
BESTMILE	Best estimate of annual miles

- 2. Travel Day Trip File (DAYV2PUB):** The sample size of this dataset is 1,167,321 records. This dataset contains 112 unique data attributes to represent each trip a household member made on a particular travel day. From among all the attributes, only 15 have been utilized in this study. (HOUSEID, VEHID, VEHTYPE, DRVR\_FLG, TDAYDATE, TRAVDAY, STRTTIME, ENDTIME, DWELTIME, TRPMILES, TRVL\_MIN, AWAYHOME, TRIPPURP, WHYTO, WHYFROM). Although this is a national dataset, 1,973 trip records from Hawaii are also included in the dataset. These fields are discussed in more detail below.

The two essential dataset files collected from the NHTS 2009 travel survey database were linked with each other using the common variables HOUSEID, VEHID, and VEHTYPE as also shown in references [51], [52]. Our goal was to obtain a complete list of trips made by each vehicle in the survey. According to [50], Vehicle file and Travel day trip files can be linked with each other using the HOUSEID and VEHID common variables. A sequence of pre-processing operations, as mentioned in the next section were performed on the above dataset in order to extract the required data, that are necessary in the scope of this research study.

### 3.1.1.2 Data Extraction from 2009 NHTS Dataset

- 1. VEHICLE TYPE:** In this study, the types of vehicles that are considered are divided into four categories [53] as shown in Table 7. The household vehicle fleet which represent a major portion of the transportation sector fleet are responsible for around 50% of the U.S Greenhouse gas emissions. All these vehicles are good candidates for electrification, and thus were chosen in this study.

Table 7. Description of VEHTYPE variable

Variable Name	Description	Code/Range
VEHTYPE	Type of Vehicle	01 = Automobile/car/station wagon 02 = Van (mini, cargo, passenger) 03 = Sports utility vehicle 04 = Pickup truck

- 2. VEHICLE ID:** Individual vehicles within each household are identified by a unique two-digit number. This variable can be found in both the Vehicle file and the Travel Day Trip file. In

the pre-processing phase all trip records corresponding to values “-1” (Appropriate skip), “-7” (Refused) and “-8” (Don't know) have been discarded.

Table 8. Description of VEHID variable

Variable Name	Description	Code/Range
VEHID	Household Vehicle ID	01-28 = Household Vehicle used for trip

3. **DRIVER IDENTIFICATION FLAG:** The respondents were asked to self-report if they were the driver or a passenger in that particular trip in the personally owned vehicle (POV). Only the records having variable values of “01” (self-reported as driver) were considered for this study. This was done to ensure that each trip by each vehicle was included only once, eliminating additional records reported by non-driving passengers.

Table 9. Description of DRVR\_FLG variable

Variable Name	Description	Code/Range
DRVR_FLG	Subject was driver on this trip	01 = Self-reported as driver for the Travel Day trip

4. **ANNUAL VEHICLE MILES:** The best estimate of the annual miles driven by each vehicle is obtained from the “BESTMILE” variable. This is a derived variable which was developed by the Oak Ridge National Lab. Derived variables are those variables which are not present in the NHTS 2009 survey questionnaire but are created later by either renaming questionnaire variables, or combining multiple variables, or by deriving the variable from external sources other than the survey questionnaire. Additional detailed explanation about how each of the derived variables in the NHTS dataset was created can be obtained from the ‘Derived Variables Descriptions’ section of [50].

Table 10. Description of BESTMILE variable

Variable Name	Description	Code/Range
BESTMILE	Best estimate of annual miles	0 - 200000

5. **TRIP START TIME:** The travel day trip start time is obtained from the 'STRTTIME' variable and is represented in the military time format (0001 through 2400 hours).

Table 11. Description of STRTTIME variable

Variable Name	Description	Code/Range
STRTTIME	Trip START time in military	0000-2359

6. **TRIP END TIME:** The travel day trip end time is obtained from the 'ENDTIME' variable and is represented in the military time format (0001 through 2400 hours).

Table 12. Description of ENDTIME variable

Variable Name	Description	Code/Range
ENDTIME	Trip END time in military	0000-2359

7. **TRIP TRAVEL DATE:** The 'TDAYDATE' variable gives the year and month of the Travel day on which that particular trip was made. The values are represented in YYYYMM format. The values range from March 2008 to April 2009.

Table 13. Description of TDAYDATE variable

Variable Name	Description	Code/Range
TDAYDATE	Date of Travel Day (YYYYMM)	200803 – 200812, 200901 – 200904

8. **TRIP TRAVEL DAY:** The 'TRAVDAY' variable gives the day of the week of the Travel day on which that particular trip was made. The values range from 01 to 07 representing Sunday to Saturday, respectively.

Table 14. Description of TRAVDAY variable

Variable Name	Description	Code/Range
TRAVDAY	Travel day - day of week	01 = Sunday 02 = Monday 03 = Tuesday 04 = Wednesday 05 = Thursday 06 = Friday 07 = Saturday

9. **TRIP DESTINATION:** Based on the trip destination, the 'WHYTO' variable gives the purpose of the trip.

Table 15. Description of WHYTO variable

Variable Name	Description	Code/Range
WHYTO	Purpose or destination of trip	01 = Home 10 = Work 11 = Go to work 12 = Return to work 13 = Attend business meeting/trip 14 = Other work related

10. **TRIP START LOCATION:** The 'WHYFROM' variable gives the location from which the trip originated.

Table 16. Description of WHYFROM variable

Variable Name	Description	Code/Range
WHYFROM	Location from which the trip started	01 = Home 10 = Work 11 = Go to work 12 = Return to work 13 = Attend business meeting/trip 14 = Other work related

11. **DWELTIME:** This variable gives the calculated time at destination (in minutes) which is calculated from the trip start time (STRTTIME) and the trip end time (ENDTIME).

Table 17. Description of DWELTIME variable

Variable Name	Description	Code/Range
DWELTIME	Calculated Time (minutes) at Destination	0-1439 -9 = Not ascertained

### 3.1.1.3 Identification of Location of Charging

- 1. CHARGING LOCATION:** This is a field created to explicitly identify locations which could be used for EV charging. A pre-processing operation was used to identify locations where charging could potentially occur, either at work or at home. Other potential charging locations, such as shopping centers have not been considered in this study.

Table 18. Description of CHARGE\_LOCATION variable

Variable Name	Description	Code/Range
CHARGE_LOCATION	Location of EV charging	'Home' 'Work'

The pre-processing operations classified the vehicle trips dataset broadly into two domains ('Home', 'Work'). The main purpose of this classification was to identify the vehicles which could potentially be replaced by EVs. The NHTS 2009 dataset provides trip purposes of each trip on the survey day, which are represented by the variable 'WHYTO' as shown in Table 15. The vehicle trips which have trip destination as home (WHYTO = 01) and were parked there for more than 2 hours have been considered as candidates for home charging. In order to specifically identify these trips, the CHARGE\_LOCATION variable was updated to 'Home'. Similarly, vehicle trips which have their trip destinations reported as 'Work' (WHYTO = 10), 'Go to work' (WHYTO = 11), 'Return to work' (WHYTO = 12), 'Attend business meeting/trip' (WHYTO = 13), 'Other work related' (WHYTO = 14), have been considered as candidates for work-place charging. The CHARGE\_LOCATION variable was updated to 'Work', in order to represent these particular vehicle trip records.

### 3.1.1.4 Identification of Times When EVs Were Parked at Home or Work

In order to explicitly identify times when the vehicle was parked for an extended duration at work or at home, the fields 'PARKING\_STARTTIME', 'PARKING\_ENDTIME', and 'TIME\_PARKED' were created and added to the travel day table. These fields are used to identify the single longest at-home and at-work charging windows that could potentially occur each day.

Table 19. Description of PARKING\_STARTTIME variable

Variable Name	Description	Code/Range
PARKING_STARTTIME	Parking START time in military	0000-2359

Table 20. Description of PARKING\_ENDTIME variable

Variable Name	Description	Code/Range
PARKING_ENDTIME	Parking END time in military	0000-2359

Table 21. Description of TIME\_PARKED variable

Variable Name	Description	Code/Range
TIME_PARKED	Total Time (minutes), the vehicle was parked at charging location	0-1439

Based on the location of charging, the methods and assumptions used to determine these parking windows/timeslots to be used for charging, have been described in more detail below.

1. **Workplace Parking:** The vehicle trips which have been identified as candidates for charging at work (CHARGE\_LOCATION = Work) and were parked there for more than 2 hours have been considered here. The start (PARKING\_STARTTIME) and end time (PARKING\_ENDTIME) of the timeslot the vehicle is parked at workplace is determined from the end time (ENDTIME) of the vehicle's current trip to reach work and the start time (STRTTIME) of the vehicle's immediate next trip. Only those trips for that particular vehicle were selected in which the trip destination (WHYTO) matches exactly to the start location (WHYFROM) of the next immediate trip. Parking at workplace included the following subdivisions:
  - A. **Over-day Parking:** These are the vehicles that are parked at work and their parking start time (PARKING\_STARTTIME) starts sometime between 12:00 am - 11:59 pm and ends (PARKING\_ENDTIME) between 12:00 am - 11:59 pm of the same day. The total amount of time parked at work is calculated from the parking start time (PARKING\_STARTTIME) and parking end time (PARKING\_ENDTIME) fields. The 'TIME\_PARKED' field is accordingly updated and is compared with the value from the 'DWELTIME' field for consistency. The calculation of the 'TIME\_PARKED' field value is important as in some

instances the 'DWELTIME' value obtained from the initial NHTS 2009 dataset might not have been ascertained (DWELTIME = -9).

- B. Overnight Parking:** These are the vehicles that are parked at work and their parking start time (PARKING\_STARTTIME) starts sometime between 12:00 am - 11:59 pm and ends up in the next travel day. The total amount of time parked at work is calculated from the parking start time (PARKING\_STARTTIME) and parking end time (PARKING\_ENDTIME) fields. The 'TIME\_PARKED' field is accordingly updated and is compared with the value from the 'DWELTIME' field for consistency. The calculation of the 'TIME\_PARKED' field value is important as in some instances the 'DWELTIME' value obtained from the initial NHTS 2009 dataset might not have been ascertained (DWELTIME = -9).
- 2. Home Parking:** The vehicle trips which have been identified as candidates for charging at home (CHARGE\_LOCATION = Home) and were parked there for more than 2 hours have been considered here. The start (PARKING\_STARTTIME) and end time (PARKING\_ENDTIME) of the timeslot the vehicle is parked at home is determined from the end time (ENDTIME) of the vehicle's current trip to reach home and the start time (STRRTIME) of the vehicle's immediate next trip. Only those trips for that particular vehicle were selected in which the trip destination (WHYTO) matches exactly to the start location (WHYFROM) of the next immediate trip. Parking at home included the following subdivisions:
- A. Over-day Parking:** These are the vehicles that are parked at home and their parking start time (PARKING\_STARTTIME) starts sometime between 12:00 am - 11:59 pm and ends (PARKING\_ENDTIME) between 12:00 am - 11:59 pm of the same day. The total amount of time parked at work is calculated from the parking start time (PARKING\_STARTTIME) and parking end time (PARKING\_ENDTIME) fields. The 'TIME\_PARKED' field is accordingly updated and is compared with the value from the 'DWELTIME' field for consistency. The calculation of the 'TIME\_PARKED' field value is important as in some instances the 'DWELTIME' value obtained from the initial NHTS 2009 dataset might not have been ascertained (DWELTIME = -9).
  - B. Overnight Parking:** These are the vehicles that are parked at work and their parking start time (PARKING\_STARTTIME) starts sometime between 12:00 am - 11:59 pm and ends up in the next travel day. The total amount of time parked at work is calculated from the parking start time (PARKING\_STARTTIME) and parking end time (PARKING\_ENDTIME) fields. The 'TIME\_PARKED' field is accordingly updated. The calculation of the 'TIME\_PARKED' field value is extremely important in this particular case of overnight home parking, as the 'DWELTIME' value for these specific type of trips obtained from the initial NHTS 2009 dataset is 'Not ascertained' (DWELTIME = -9).

### 3.1.2 Vehicle Characteristics/Driving Pattern Analysis

#### 3.1.2.1 Vehicle Type

In this study, the types of vehicles that are considered are divided into four categories. The passenger vehicle fleet which represent the major chunk of the transportation sector fleet are responsible for around 50% of the U.S Greenhouse gas emissions are thus the perfect candidates for this study.

Table 22. Distribution of vehicles in the processed NHTS 2009 dataset according to vehicle type

Vehicle Type	Number of Vehicles	Percentage
Automobile/car/station wagon	107643	53.90%
Van (mini, cargo, passenger)	16517	8.27%
Sports utility vehicle	44076	22.07%
Pickup truck	31476	15.76%

#### 3.1.2.2 Daily Vehicle Miles of Travel

The number of miles driven by a vehicle is an important criterion in understanding and planning the vehicle characteristics. According to the Highway Statistics 2013, released by the U.S. Department of Transportation – Federal Highway Administration [54], the average number of miles travelled per vehicle for the year 2013 in U.S. was 11,346 miles which is around 31 miles per day. In the dataset used for the research study, the annual number of miles travelled per vehicle in the whole U.S was determined to be around 11,455 miles which comes to around 31 miles per day. In comparison, for Hawaii the annual vehicle miles of travel per vehicle (includes all classes of vehicles) is reported by the State of Hawaii Data Book-2014 [46] to be around 9,006, which is around 24.67 miles per day. Almost 53% of the total vehicles included in this study drive less than 30 miles per day, with the most common daily mileage range being 20-25 miles as shown in **Figure 16**. This is an important parameter in the study as the number of miles driven by vehicles is needed to calculate the energy required for charging the vehicle battery.

Table 23. Average Vehicle Miles Travelled in U.S - 2013

Average vehicle miles travelled per vehicle U.S. - 2013	DOT FHWA [51]	2009 NHTS processed Dataset
Annual	11,346	11,445
Daily	31.08	31.36



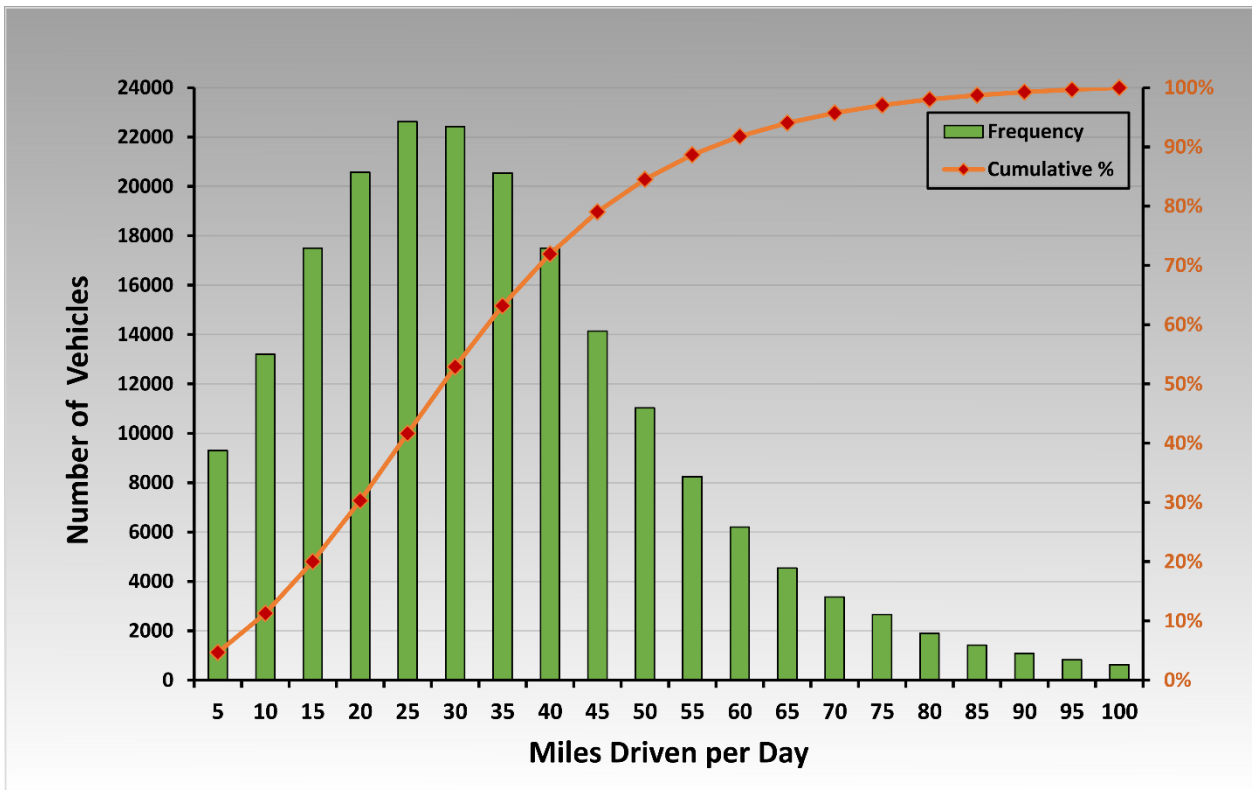


Figure 16. Miles Driven per Day

### 3.1.2.3 Driving Range

Compared to the continental U.S., Hawaii being a chain of islands have limited driving ranges. Based on [55], most light, medium, and heavy duty EVs tend to target a range of about 100 miles on a fully charged battery, although range may depend on specific driving conditions and habits. An analysis done in comparing the driving ranges of most of the current Plug-In Electric Vehicles models of 2014 and 2015, which includes both Battery EVs (BEVs) and Plug-in hybrid EVs (PHEVs) have all-electric driving range of 11-38 miles and 62-265 miles respectively [56] [57]. Although most of the mainstream affordable EV market primarily falls under the 100-mile EV range, Tesla with its Model S has managed to break into the 200 mile range EV market, although the price has been on the expensive end. With recent advances in research in battery technologies, the automobile industry’s goal is to bring down the cost and also increase the driving range so as to make electric cars more alluring to potential customers. In order to represent the mainstream EV market, the driving range for EVs and the All-Electric Range (AER) in the case of PHEVs, was fixed to a maximum of 100 miles.

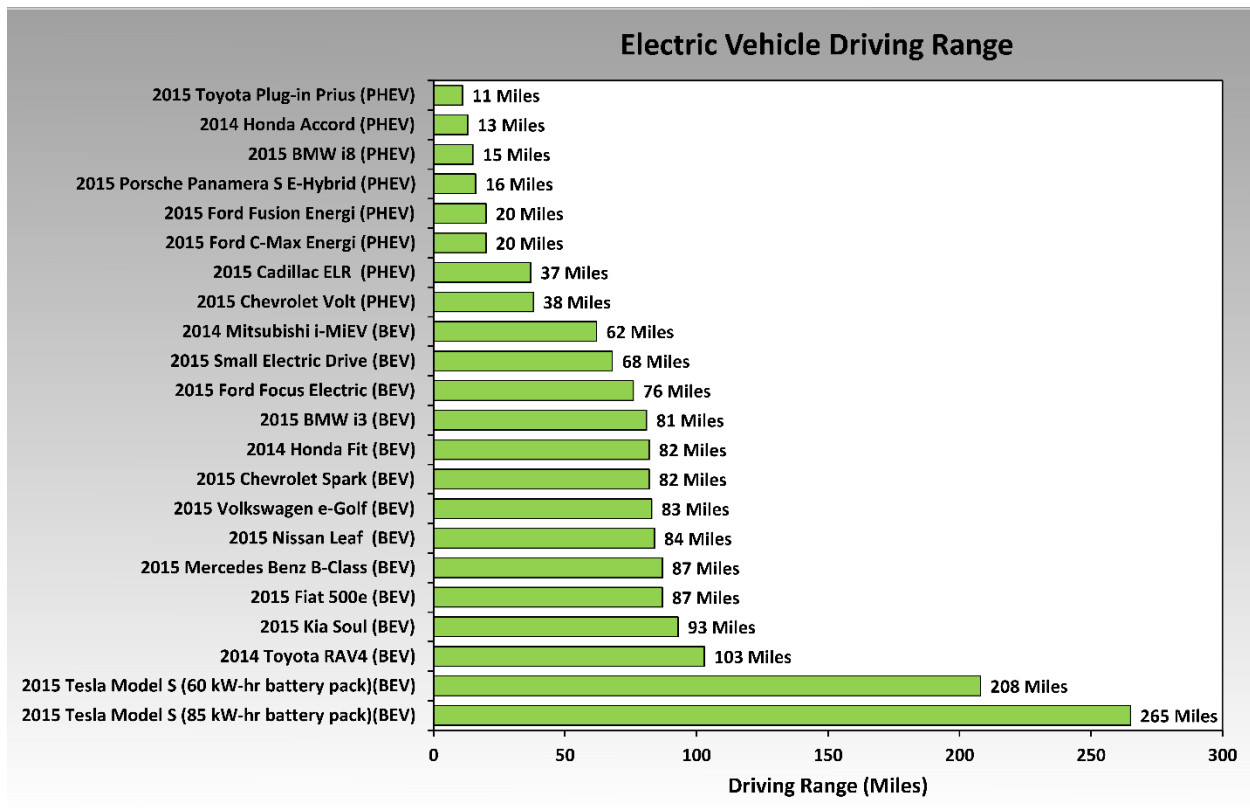


Figure 17. Electric Vehicle Driving Ranges

### 3.1.2.4 Battery Capacity

The type of Electric Vehicle has a direct impact on the battery capacity of a vehicle. Battery sizes differ according to the type of the vehicle. For example, the battery size of a SUV such as Tesla S is considerably higher than a compact hatchback like Nissan Leaf. Therefore, assigning a battery capacity to the different classes of vehicle (as shown in the section 3.1.2.1) considered in this study is important in-order to determine the energy needed to charge the EVs. Reports [26] [53] published by The Pacific Northwest National Laboratory (PNNL) have used “Energy Efficiency” and “optimal range” of different vehicle classes to calculate the battery capacity of that particular vehicle. Thus, now battery capacities for each vehicle class can be determined by combining the “energy efficiency” with the optimal driving range as determined in the driving range section above. The size of battery for various classes of EVs used in this study is shown in **Table 24**.

Table 24. Energy Efficiency and Battery Size according to Vehicle Type

Vehicle Class	Energy Efficiency [kWh/mile]	Battery Size of EV with 100 miles range [kWh]
Compact Sedan	0.26	26
Mid-size sedan	0.30	30
Mid-size SUV	0.38	38
Full-size SUV/Pickup Truck	0.46	46

Figure 18 shows the variations in Battery Size and the electricity consumption in kWh per 100 miles for most Electric Vehicle models available in the U.S. market. The chart is arranged in increasing order of the EV model's electricity consumption in kWh/100 miles. With 27 kWh of electricity consumption per 100 miles, the 2015 BMW i3 model tends to have the best efficiency in the current market. As shown, the electricity consumption in kWh/100 miles varies between the various models depending on the type of vehicle and ranges from 27 kWh to 52kWh per 100 miles. The data for this comparative analysis was collected from [56].

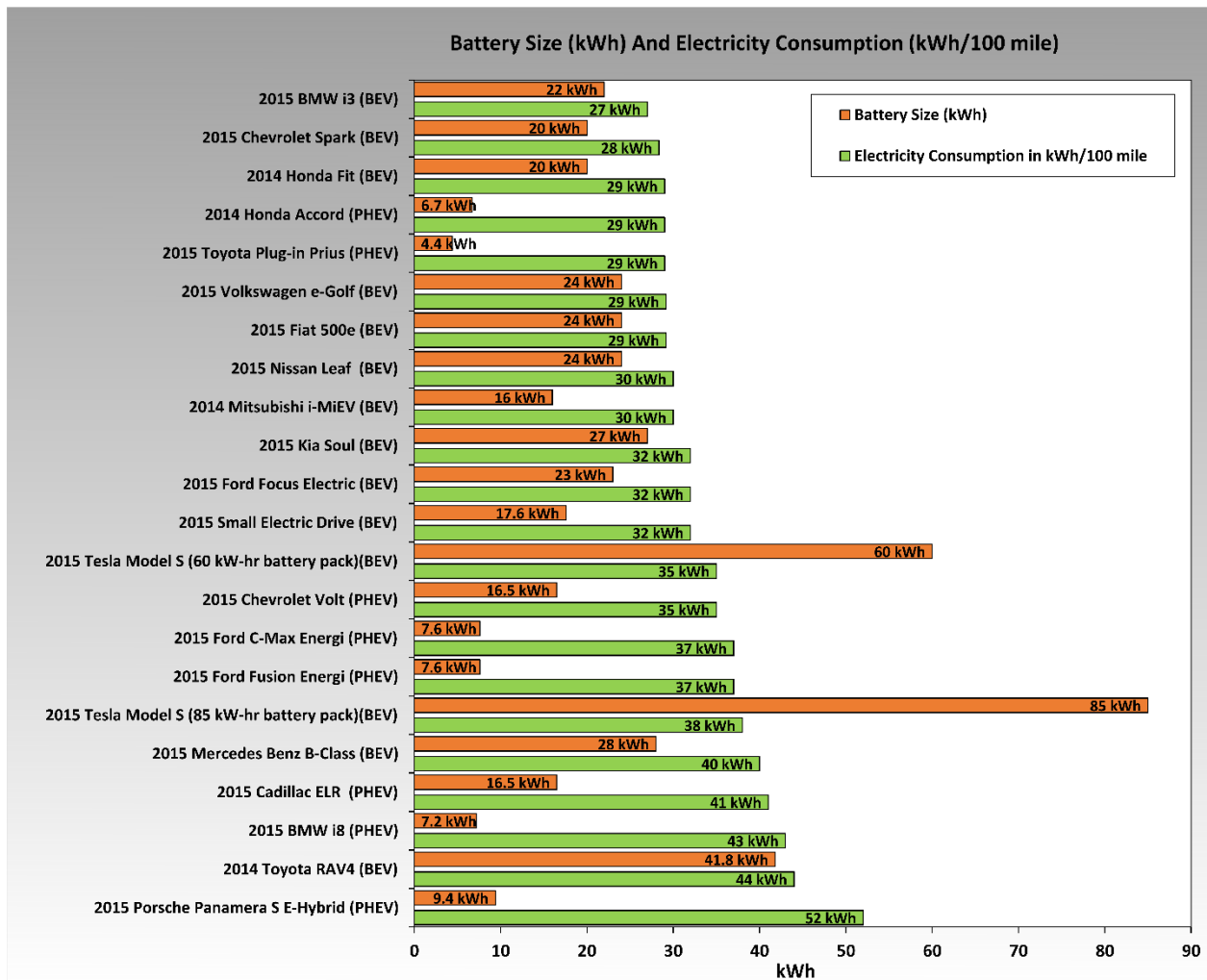


Figure 18. Battery Size (kWh) and Electricity Consumption (kWh/100 mile)

### 3.1.2.5 Potential Charging Windows/Time Slots

From the historical vehicle travel data, pre-processing algorithms were used to perform operations in order to determine the list of all potential charging timeslots/windows available for two categories of charging place options: 1] home charging and 2] workplace charging. The methods used are described in section 3.1.1.4. The potential charging timeslots/windows were obtained from analyzing the data about time when the vehicle is parked, at home or at the workplace after a home trip or work trip respectively.

### 3.1.2.6 Timestamp Transformation

The timeslots/windows which have a start time and an end time in which the EV is parked at home or at the workplace are potential candidates for either home or workplace charging. These start and end times are expressed here in the format of military timestamps and have a granularity level of each minute. For the work reported here, the event time points

have been rounded to the nearest 30-minute timestamp. This aligns the potential charging windows to 48 time intervals of each 30-minute duration, for any particular travel day.

### 3.1.3 Charging Characteristics

#### 3.1.3.1 State Of Charge (SOC)

SOC is defined as the ratio of the amount of energy remaining in the battery to the total energy in the battery when fully charged. It can be determined based on the number of miles driven by the vehicle and the vehicle range of the EV. Assuming that at the beginning of each travel day, the battery of the particular EV must be fully charged (SOC= 100%), estimation of SOC is important as that would help us to estimate the state of the battery after a trip is undertaken.

$$\text{SOC} = \left( \frac{\text{Total Driving Range} - \text{Distance Driven}}{\text{Total Driving Range}} \right) \times 100$$

In this study the driving pattern analysis shows the number of miles travelled in each travel day by a particular EV. Using this, the total amount of energy needed by the battery for that particular travel day can be determined.

#### 3.1.3.2 Energy Requirement for Battery Charging

The amount of energy used by the battery to travel the total number of miles driven in that particular travel day can be calculated using the following expression below.

$$\text{Energy Used} = \left( \frac{\text{Distance Driven}}{\text{Total Driving Range}} \right) \times \text{Battery Capacity}$$

$$\text{Energy Needed for Charging} = \left( \frac{\text{Energy Used}}{\text{Battery Charging Efficiency}} \right)$$

The total energy needed to fully charge the EV battery is calculated using the above equation where the efficiency for the battery charger and battery over a round-trip of full charge cycle is assumed to be 88% [28]. It is also assumed that the total battery capacity is fully available for use instead of the usual industry practice of using threshold bands of 20% to 80% [53] [58], in order to extend the battery life. The study also assumes that vehicles charge only once per day and the sampled day is representative of their typical driving pattern, so the charge they need on this vehicle-day is equal to the total amount of electricity consumed during this vehicle-day.

#### 3.1.3.3 Charging Levels

Various charging levels have been used in multiple different studies. Studies conducted in [59] [60] have used 3 charging levels such as a) 1.4 kW (120 VAC, 15A) b) 2.0 kW (120 VAC, 20A) and c) 6kW (208/240 VAC, 30A). Similarly the study performed in [61] have introduced

levels of 1.4 kW (120V,15 A) , 1.9 kW (120V,20A) and 7.7 kW (240V,40A). Study in [62] identifies three levels of charging based on the voltage and power levels as shown in Table 25.

Table 25. Levels of Charging

Type	Power Level
Level 1: 120 VAC	1.2 – 2.0 kW
Level 2 (low): 208-240 VAC	2.8 - 3.8 kW
Level 2: (high): 208-240 VAC	6 – 15 kW
Level 3: 208-240 VAC	>15 KW-96KW
Level 3: DC Charging: 600VDC	>15KW-240KW

The Society of Automotive Engineers (SAE) have been instrumental in developing major standards for Electric Vehicles and Plug-in Hybrid Electric Vehicles. The SAE J1772 [63] standard introduces a common EV/PHEV and supply equipment vehicle conductive charging method to facilitate conductive charging of EV/PHEV vehicles in North America. The SAE J1772 standard defines the following levels of charging [58] [64]:

- **AC Level 1:** On-board charger with 120 VAC, 1-phase 12 A rate with a 15 A Circuit or 120 VAC, 1-phase 16 A rate with a 20 A Circuit with configuration powers of 1.44 kW and 1.92 kW respectively.
- **AC Level 2:** On-board 208 to 240 VAC, 1-phase up to and including 80 A. The on-board charger configuration power levels of 3.3 kW and 6.6 kW have current settings of 16 A and 30 A respectively.
- **DC Level 1:** The EV Supply Equipment (EVSE) includes an off-board charger with 200 to 450 VDC with a rated current up to and including 80 A, with configuration power levels of 19.2 kW (residential) and 36 kW (public).
- **DC Level 2:** The EV Supply Equipment (EVSE) includes an off-board charger with 200 to 450 VDC with a rated current up to and including 200 A, with configuration power up to and including 90kW.

Although charging levels can potentially reach up to 19.2 kW, most of the EVs currently available in the U.S. market have on-board chargers of 3.3 kW and 6.6 kW, as shown in Figure 19 [56] [57]. Higher end luxury SUVs like Tesla S, Toyota RAV4, Mercedes Benz B-Class have on-board charger of 10 kW. In-order to represent the larger EV market and both the residential and commercial EV charging options, the Level 1 and Level 2 charging levels shown in Table 26 have been used in this study.

Table 26. Charging options

Charging Level	Charging Location	Power Supply	Power Level (kW)
Level 1	Residential	120V AC Single Phase, 12 Amp	1.4 kW
Level 2	Residential/ Workplace/ Commercial	240V AC Single Phase, 16 Amp, 30 Amp	A] 3.3 kW On-Board Charger
			B] 6.6 kW On-Board Charger

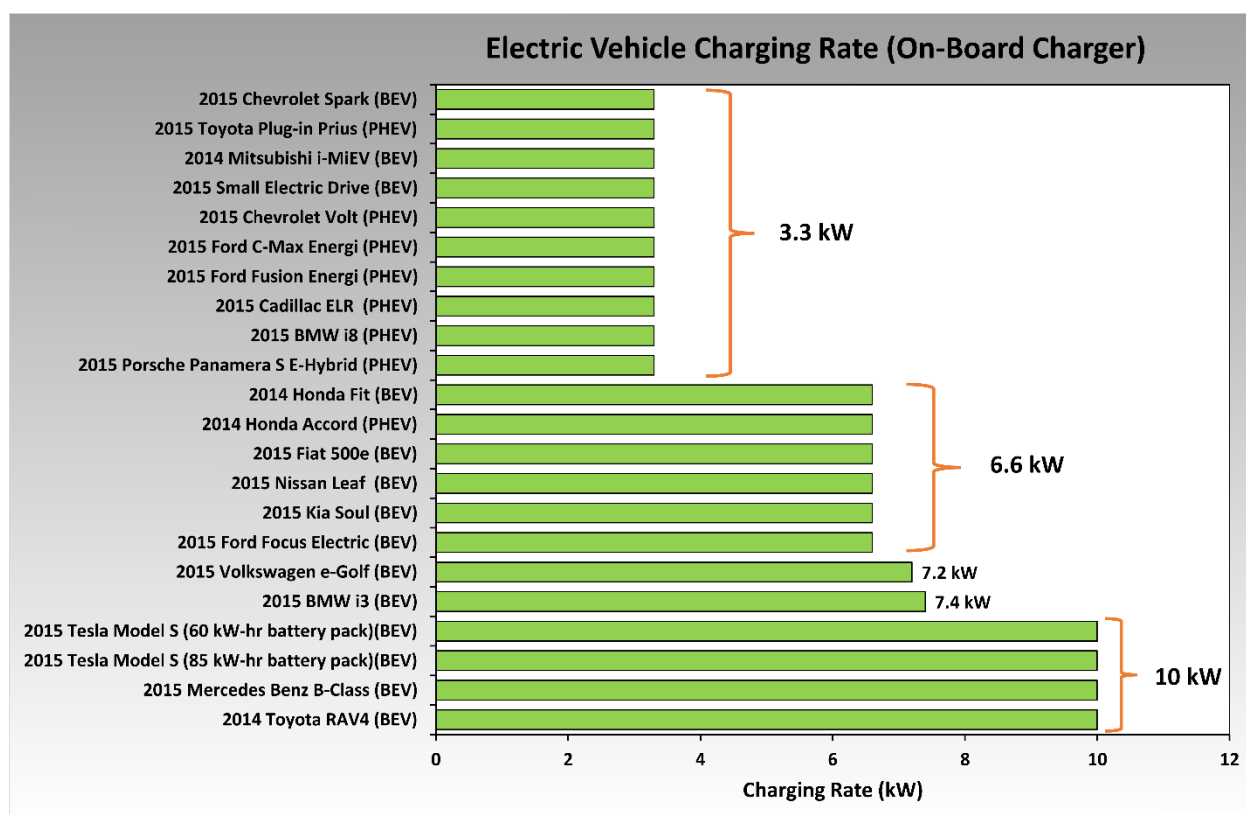


Figure 19. Electric Vehicle Charging Rates

### 3.1.3.4 Charging Infrastructure/Mode

AC Level 1 and Level 2 charging levels are more practically suitable for home environment whereas DC Level 3 charging (commonly called DC Fast Charging) is most suitable for public or commercial charging environments. Level 1 charging generally refers to the use of a standard household outlet whereas Level 2 charging typically offers charging for residential applications through a 240 V AC/ 40 Amp electrical circuit, (common in household circuits used for heavy-duty appliances such as dryer, stove outlet) [29] or 208 V electrical service line for commercial applications [65].

Table 27. Charging Infrastructure

Charging Level Mode	Charging Procedure	
	Home Charging	Workplace Charging
Level 1 – 1.4kW	10%	0%
Level 2a – 3.3kW	15%	20%
Level 2b – 6.6kW	75%	80%

In-order to have a definite charging option, it is important to assign various modes of charging to either home or workplace charging scenarios/options. The vehicle charging approach structure that was implemented in this study is shown in **Table 27**. AC Level 2 charging has often been considered the most common overnight charging option in households [66] considering the faster charging speeds and the advantage of not needing any extra charging infrastructure. According to [64], customers use residential chargers for around 60-80% of their charging sessions and AC Level 2 is the preferred choice. The shares of charging level mode as shown in **Table 27** were chosen to be broadly consistent with [64] [66] and informal discussions with EV users.

Analysis done on the data sample used in this study as shown in **Figure 20**, shows that almost 5.57% and 5.21% of the total vehicles, which are potential candidates for home charging, are parked in households uninterruptedly for 14 hours and 14.5 hours respectively, which is primarily the time the vehicle was parked overnight in the household after a person returns home from work. Similarly as shown in **Figure 21**, almost 10.88% and 10.62% of the total vehicles, which are potential candidates for workplace charging, are parked in workplaces uninterruptedly for 8.5 hours and 9 hours respectively, which is consistent with standard office timings. Thus although EV owners charge their vehicles at home primarily, utilizing charging at work could potentially extend their electric driving range (not discussed here) [67] and also allows them to use lower-cost electricity during the day.

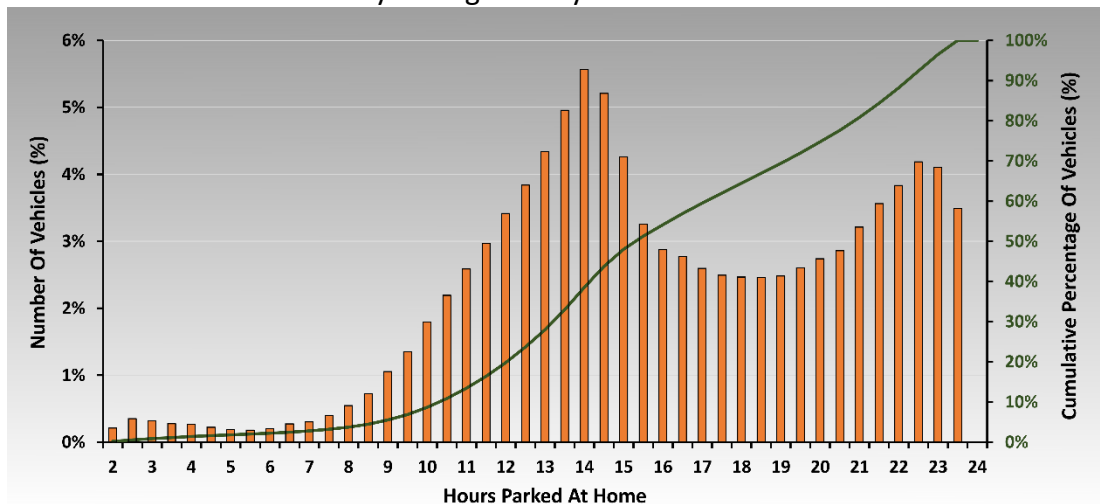




Figure 20. Distribution of vehicles parked at Home

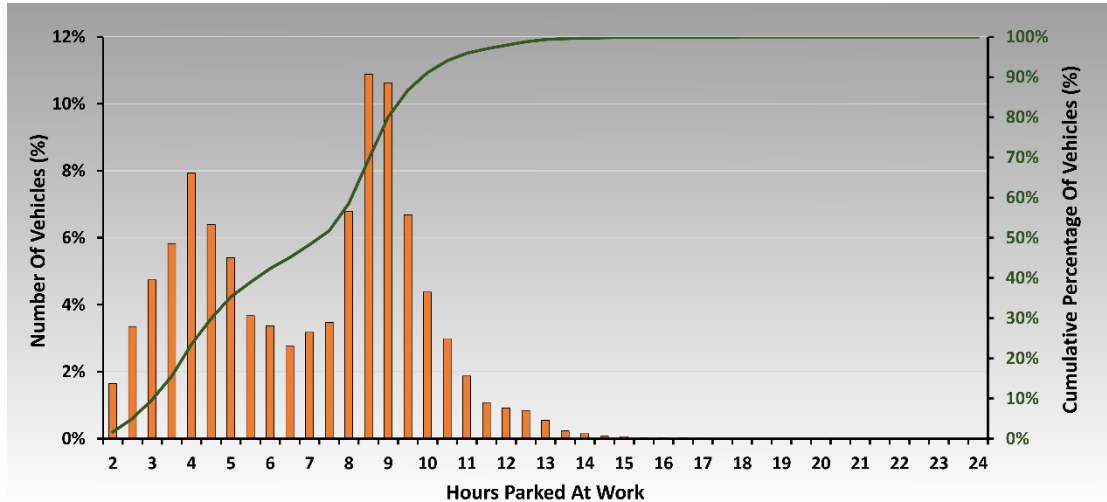


Figure 21. Distribution of vehicles parked at Workplace

The following steps summarize the operations performed:

1. A list of standardized EV models was created that could be used to replace gasoline/diesel vehicles. Each of these vehicles has a 100-mile range and a particular efficiency.
2. Using a range of pre-processing operation, analysis of the trip table was performed and the longest periods when each vehicle is parked at home or at work during the study-date was determined.
3. For the vehicles that could be replaced by EVs, the most similar standard EV in the list was assigned based on vehicle type/class.
4. The total amount of energy that is needed by each EV during the study day was then calculated.
5. It was assumed that each vehicle could be replaced by an EV, with two exceptions: vehicles that drove more than 100 miles during the vehicle-day, and the vehicles that need more energy than they could obtain from a Level 2b charger during their longest time parked at home or at work. The total resulting EV fleet distribution according to the location of charging is shown in Table 28.

Table 28. Feasible EV fleet Charging Distribution

Charging Location	Number of Vehicles	% of Total
Home Charging	137146	68.67%
Workplace Charging	62566	31.33%

Total	199712	100%
-------	--------	------

6. Depending on the total amount of energy needed by a particular EV, and the longest available parking time at home or at work, feasibility of charging each individual EV using level 1, 2a or 2b chargers was determined. For example, if an EV needs 12 kWh of charging and is parked at work for 3 hours, it can't be assigned to a 3.3 kW (level 2a) workplace charger and can only be assigned a 6.6 kW (level 2b) charger). Similarly, if an EV needs 10 kWh of charging and is parked at home for 8 hours, charging is feasible using either level 1 (1.4 kW), 2a (3.3 kW) or 2b (6.6 kW) chargers.
7. The 199,712 EVs were randomly assigned to a one of the 3 feasible charging strategy, according to the charging distribution shown in **Table 27**.
8. The assignment of a feasible charging strategy to each EV in the EV fleet was performed as follows:
  - a) All the EVs that could be charged at home at Level 1 were identified. Randomly assign from among the vehicles assigned to home charging to achieve the H1 percentage.
  - b) All the remaining EVs that haven't been assigned to H1 that could feasibly be charged at home on Level 2a were identified and were assigned to achieve the H2a percentage.
  - c) All the remaining EVs that could feasibly be charged at home on a Level 2b charger were assigned a Level 2b charger to make the H2b percentage.
  - d) The above process was repeated for EVs that are parked at work with W2a and W2b, at which point the fleet was allocated appropriately according to **Table 27** and **Table 26**.

## 3.2 Oahu Grid Characteristics

### 3.2.1 Hawaii Electricity Load Profile

The hourly electricity load data for Oahu, were obtained from filings of FERC form 714 [68] for the year ending 2014. Electric utilities with annual peak demand over 200MW are required to electronically file this form to the Federal Energy Regulatory Commission (FERC) at the end of each year. For the purpose of modeling the EV charging load (represented in half-hourly time intervals) in the same time scale as that of system demand, time-averaged half hourly demand data were obtained from the hourly dataset.

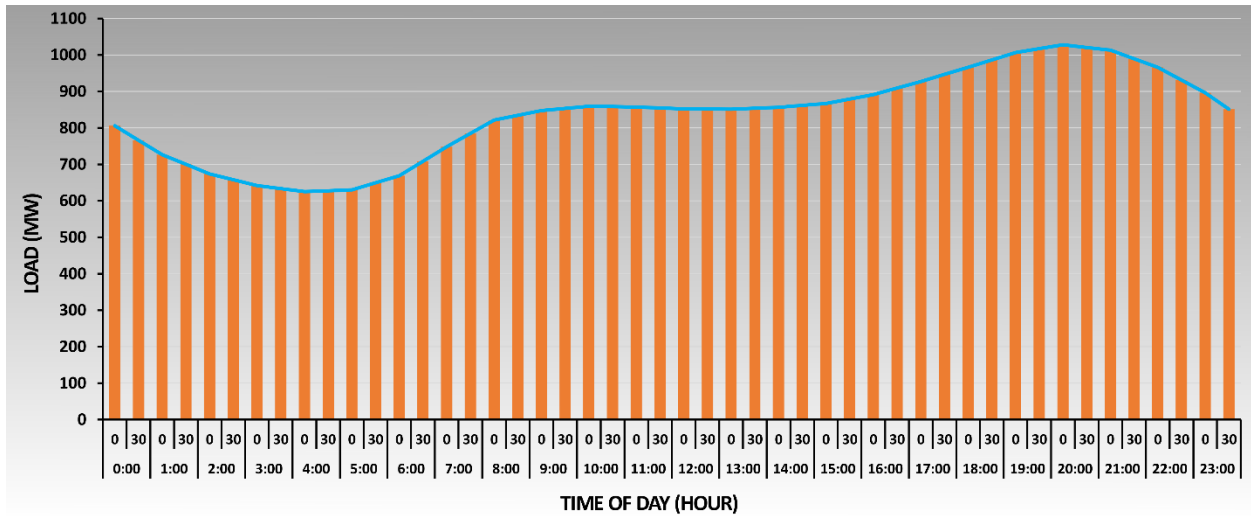


Figure 22. Oahu Electricity Load Profile

### 3.2.2 Hawaii Electricity Price Profile

The hourly marginal cost of electricity was obtained from the hourly balancing authority area system lambda data, provided in the FERC form 714 [68] for the year ending 2014, filed by the electric utilities, which for the Island of Oahu is the Hawaiian Electric Company (HECO), Inc. For this work, assume that customers face hourly dynamic prices that are equal to the marginal cost of production. These price values are expressed in units of \$/MWh. For the purpose of modeling, time-averaged half hourly electricity price data were obtained from the hourly dataset.

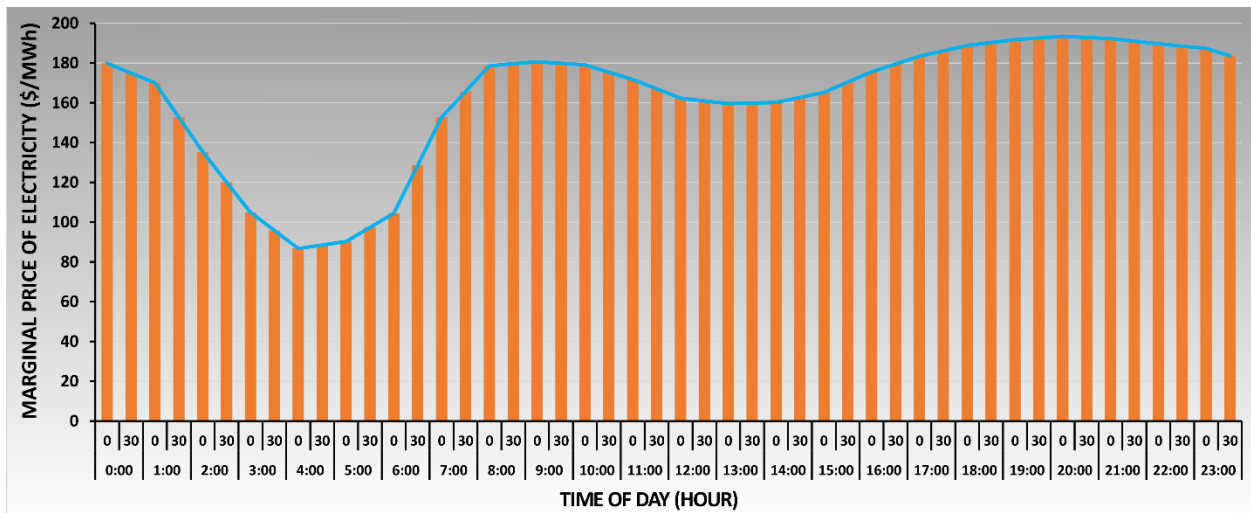


Figure 23. Oahu Electricity Price Profile

### 3.2.3 Existing Power Plants

In-order to the study the effect of large scale EV deployment to the electricity grid, the knowledge about the current electricity grid is vital. Data about all existing power plants and

generator data such as capacity, heat rate and technology (prime mover and energy source) for Oahu were obtained for the year ending 2012, from the form EIA-860 [69] and EIA-923 [70] which are the Energy Information Administration's (EIA) power plant survey databases.

For all the plants providing intermittent supply of power (e.g., wind or solar), the amount of power produced is dependent on the specified hourly capacity factor. These hourly capacity factors depend on the amount of wind or sunlight at a particular site for a corresponding time of the day. Thus, the total supply of power from an existing intermittent renewable generation project is a fraction of the installed capacity of the plant (installed capacity \* hourly capacity factor). The hourly power production (capacity factor) for the existing wind and solar (Distributed PV and Central Station PV power plants in Oahu were derived from the datasets used in the report [71]. The existing renewable energy projects included 210 MW of customer-sited solar (distributed PV), 5 MW of commercial solar and 99 WM of wind.

Data about the price of the fuel used in the existing power plants in Oahu was also obtained from [71]. The report [71] used fuel prices of biodiesel, bio-crude, high sulfur diesel, ultra-low sulfur diesel (ULSD), liquefied natural gas (LNG), low sulfur fuel oil (LSFO), medium sulfur fuel oil (MSFO), and low sulfur industrial fuel oil (LSIFO) from Appendix E-11: Fuel Costs Forecast Data of the 2013 Integrated Resource Planning ("IRP") Report published by the Hawaiian Electric Companies [72]. Coal price forecasts were obtained from Appendix A: Table A1 published in the U.S. Energy Information Administration's (EIA's) Annual Energy Outlook 2014 (AEO2014) [73]. Variable operation and maintenance costs of the various existing power projects (e.g., wear and tear costs) were obtained from the Consolidated Unit Information Forms in Appendix K (Supply-Side Resource Assessment) of the 2013 Integrated Resource Planning (IRP) Report, published by the Hawaiian Electric Companies [72] and from Table 8.2 of the 'Assumptions to the Annual Energy Outlook 2014' published by the U.S. Energy Information Administration (EIA) [73].

The actual variable cost per MWh of electricity generated by an existing power plant can be calculated as:

$$\text{variable\_cost } (\$/\text{MWh}) = \text{variable\_o\_m\_cost } (\$/\text{MWh}) + [\text{fuel\_cost } (\$/\text{MMBtu}) \times \text{heat\_rate } (\text{MMBtu}/\text{MWh})]$$

Where

variable\_o\_m\_cost = Variable operation and maintenance costs each existing power project (\$/MWh)

fuel\_cost = Fuel cost (\$/MMBtu)

heat\_rate = Heat Rate of each existing power plant (MMBtu/MWh)

### 3.3 Model Notations

The models are formulated using AMPL 12.2 and are solved using IBM ILOG CPLEX Optimization Studio 12.5.1. Some of the main elements that are needed to represent any constrained optimization problem are:

- **Sets:** Sets generally represent any unordered collection of objects related to the model. Individual members of the set are often represented by indexing variables.
- **Parameters:** Parameters represent any numerical value pertinent to the model. They provide input data for solving the optimization problem.
- **Decision variables:** Decision variables are a set of quantities that need to be determined in order to find an optimal solution to the problem.
- **Objective function:** Objective function of a linear programming model is a mathematical expression that indicates how each decision variable contributes to the value to be optimized. The goal of the objective function can be to maximize or to minimize some numerical value.
- **Constraints:** Constraints are mathematical expressions that combine the parameters and decision variables to express limits on the possible solutions.

### 3.4 EV Recharging Scenarios

#### 3.4.1 Price-Taker Model

##### 3.4.1.1 Optimized Charging

This model analyzes a scenario in which EV customers are offered time-varying prices depending on the marginal cost of producing electricity so that they can reduce their own cost by charging at times when the price of electricity is lower. This tests whether dynamic prices can help mitigate the amount of power drawn during the peak periods of the day. This optimal price-taker charging model aims to analyze the potential savings for EV customers by obtaining an optimal charging schedule for each vehicle with time-varying prices but not on a large enough scale to change the price of electricity.

The objective of this optimization is to derive an optimal charging schedule for each EV that minimizes the overall cost of charging using the marginal cost of electricity. The decision variable “EV\_Charge\_kw”, provides individual charging schedules for each EV during each of the 48 half-hourly timeslots to represent each of the 24 hour study date. This optimized EV charging schedule can potentially reduce costs for customers by using the time-varying nature of the electricity prices.

##### 3.4.1.1.1 Objective Function

The objective function of this method is:

$$\text{minimize } \sum_{\substack{(t,d) \in \text{TIMEPOINTS} \\ v \in \text{VEHICLES}}} (\text{EV\_Charge\_kw}_{v,t,d} \times \text{energy\_cost\_mwh}_{t,d} \times \text{length\_of\_tp\_hr}_{t,d})$$

Table 29. Decision variables in Price-Taker Model

Decision Variable Name	Indexing set	Description
EV_Charge_kw	(VEHCILES, TIMEPOINTS)	Number of KW of power required for charging each vehicle (v) during each timepoint (t, d) of a study date.

Table 30. Sets used in Price-Taker Model

Name	Indexing variable(s)	Description	Definition
DATES	d	Unique ID for each sample date included in the study.	Specified along with TIMEPOINTS: {d: (t, d) ∈ TIMEPOINTS}
TIMEPOINTS	(t,d)	Valid combinations of timeslot ID (t) and day (d) that are included in the model.	Specified exogenously.

Table 31. Parameters used in Price-Taker Model

Parameter Name	Indexed over	Description	Definition
energy_cost_mwh	TIMEPOINTS	The marginal cost of electricity derived from the “system lambda” values, expressed in units of dollars per MWh.	Specified exogenously. Used in ‘Fixed Price’ scenario only.
length_of_tp_hr	TIMEPOINTS	Length of timepoints.	Specified exogenously. Has been set to 0.5 to represent half hourly time intervals.

### 3.4.1.1.2 Constraints

The price-taker optimization model includes the following constraints:

#### 3.4.1.1.2.1 EV Constraints

The aim of the EV constraints is to do the following:

- a) The charging power level for each EV in a potential charging timeslot should be less than or equal to the maximum charging rate that is allowed for that particular vehicle. The maximum charging rates that have been considered in this research study 1.4 kW, 3.3 kW, and 6.6 kW and have been described in depth in the section 3.1.3.4. The maximum charging rate is assumed to be zero when the EV is not plugged in to the grid for charging.

subject to (for  $v$  in VEHICLES,  $(t, d)$  in TIMEPOINTS):

$$EV\_Charge\_kw_{v,t,d} \leq vehicle\_timepoint\_max\_power\_kw_{v,t,d}, \forall v \in VEHICLES, (t, d) \in TIMEPOINTS$$

The components have been described in the tables below.

Table 32. Sets used to define EV Constraints

Name	Indexing variable(s)	Description	Definition
VEHICLES	$v$	Unique ID assigned to each EV included in the study.	Specified along with VEHICLE_CHARGE_WINDOWS: $\{v: (v, d, dwl\_strt, dwl\_end) \in VEHICLE\_CHARGE\_WINDOWS\}$

Table 33. Parameters used to define EV Constraints (a)

Parameter Name	Indexed over	Description	Definition
vehicle_timepoint_max_power_kw	(VEHICLES, TIMEPOINTS)	Assigns the maximum allowed charging power for valid combinations of vehicle (v) in timepoints (t,d). This assignment handles both within-day charging and overnight charging schedules depending on the each vehicle’s potential charging windows.	1.4 kW-Level 1 Charger 3.3 kW-Level 2a Charger 6.6 kW-Level 2b Charger

- b) The main aim of this constraint is to make sure that the sum of the total charging done in all the potential time slots in any particular travel day is equal to the total energy needed for each individual vehicle, which has been pre-determined from the historical driving pattern data discussed in the earlier sections.

subject to (for v in VEHICLES, d in DATES):

$$\sum_{(t,d) \in \text{TIMEPOINTS}} (\text{EV\_Charge\_kw}_{v,t,d} \times \text{length\_of\_tp\_hr}_{t,d}) = \text{charge\_needed\_kwh}_{v,d}$$

Table 34. Parameters used to define EV Constraints (b)

Parameter Name	Indexed over	Description	Definition
charge_needed_kwh	VEHICLE_DATES_FOR_CHARGING	Amount of power needed to charge each vehicle (v) on a particular study date (d). Expressed in units of kWh.	Specified exogenously.

### 3.4.1.2 Business-As-Usual (BAU) Charging

In the business-as-usual charging scenario, EV owners are assumed to charge their EVs right after they reach their final destination (home or work). The charging is assumed to begin immediately at the start of the single longest period when each vehicle is parked at home or at work during the studied vehicle-day. This scenario is modelled to replicate the normal expected



charging behavior in which the time-varying prices offered in the price-taker model do not affect the EV owners charging decision.

The business-as-usual charging scenario is implemented in the price-taker model by manually setting the parameter ('EV\_Charge\_kw') to a default charging regime that charges at the maximum rate, starting at the earliest charge window and continues across timepoints and charge windows until the energy requirement is fulfilled. The maximum charging rate is assigned depending on the charger used i.e., either Level 1- 1.4kW, Level 2a -3.3 kW or Level 2b - 6.6 kW when plugged-in or 0 when not plugged-in. The same set of constraints and objective function are used as in section 3.4.1.1.1. The model is setup in the similar framework as in "optimized charging", except here the variable representing the number of kW of power required for charging each vehicle (v) during each timeslot (t, d) of a study date ('EV\_Charge\_kw') is a parameter instead of a decision variable.

Table 35. Parameters in the Business-As-Usual Model

Parameter Name	Indexed over	Description	Definition
EV_Charge_kw	(VEHCILES, TIMEPOINTS)	Number of KW of power required for charging each vehicle (v) during each timepoint (t, d) of a study date.	Calculated according to the energy required for charging, charger used, and charging window.

### 3.4.2 Supply Curve Model

#### 3.4.2.1 Optimized Charging

In the supply curve model, both the reschedulable load (EV load) and the power generated by each generator have the flexibility to change in each timepoint to provide the best optimized charging schedule for each vehicle, minimizing the cost of charging EVs. The model should satisfy the fixed system electricity demand during every timepoint of the day and also the various other constraints. The model selects power from the generators which have the lowest cost of generating electricity at that timepoint.

This model chooses an optimal charging schedule for each EV that minimizes the overall cost of charging using the variable cost of electricity from each existing generator, as represented by a stepped supply curve. The supply curve is obtained by stacking existing generators in ascending order of their variable cost (which is assumed not to vary with their output level). **Figure 24** represents the supply curve of the Oahu power system, which shows the marginal costs of power production and the generation capacities of generating plants, which are represented as a step in the curve. The generating plants are differentiated by the technology they use and/or the fuel they consume. The decision variable "EV\_Charge\_kw", provides individual charging schedules for each EV during each of the 48 half-hourly timeslots

to represent each of the 24 hour study date. In this model, the EVs charge at optimal times from the generators which have the lowest cost of generating electricity.

This optimized EV charging schedule can provide considerable savings for both customers and the system operator (utility) by allowing customers to charge at times when the electricity is generated from less expensive generators and the service provider by allowing it to serve loads using generators which are relatively less expensive and run on cleaner source of energy. More importantly, this model can show the optimal charging plan and cost savings when there are enough EVs to shift the marginal cost of power production each hour.

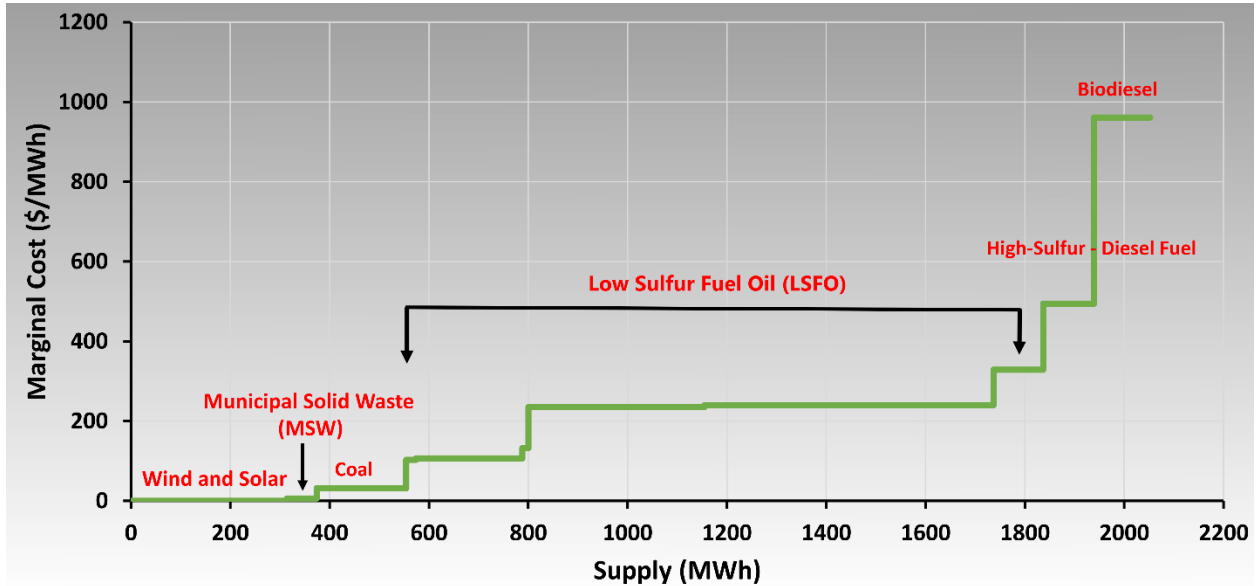


Figure 24. Supply Curve of the Oahu Power System

### 3.4.2.1.1 Objective Function

The objective function of this method is:

$$\text{minimize } \sum_{\substack{g \in \text{GENERATORS} \\ (t,d) \in \text{TIMEPOINTS}}} (\text{DispatchGen}_{g,t,d} \times \text{variable\_cost\_per\_mwh}_g \times \text{length\_of\_tp\_hr}_{t,d})$$

Table 36. EV Decision variable in Supply Curve Model

Decision Variable Name	Indexing set	Description
DispatchGen	(GENERATORS, TIMEPOINTS)	Number of MW of power to generate from each existing, dispatchable power project during each timeslot.

Table 37. Parameters in Supply Curve Model

Parameter Name	Indexed over	Description	Definition
variable_cost_per_mwh	GENERATORS	The variable cost per MWh of electricity associated with each generator. This includes fuel and variable O&M.	Specified exogenously. Calculated as $\text{variable\_cost\_mwh} = \text{variable\_o\_m\_cost} (\$/\text{MWh}) + [\text{fuel\_cost} (\$/\text{MMBtu}) \times \text{heat\_rate} (\text{MMBtu}/\text{MWh})]$

### 3.4.2.1.2 Constraints

The supply-curve optimization model includes the following 3 sets of constraints:

#### 3.4.2.1.2.1 EV Constraints

The aim of the EV constraints is to do the following:

- a) The charging power level for each EV in a potential charging timeslot should be less than or equal to the maximum charging rate that is allowed for that particular vehicle. The maximum charging rates that have been considered in this research study 1.4 kW, 3.3 kW, and 6.6 kW and have been described in depth in the section 3.1.3.4. The maximum charging rate is assumed to be zero when the EV is not plugged in to the grid for charging.

subject to (for  $v$  in VEHICLES,  $(t, d)$  in TIMEPOINTS):

$$\text{EV\_Charge\_kw}_{v,t,d} \leq \text{vehicle\_timepoint\_max\_power\_kw}_{v,t,d}, \forall v \in \text{VEHICLES}, (t, d) \in \text{TIMEPOINTS}$$

The components have been described in the tables below.

Table 38. EV Decision variable in Supply Curve Model

Decision Variable Name	Indexing set	Description
EV_Charge_kw	(VEHCILES, TIMEPOINTS)	Number of KW of power required for charging each vehicle (v) during each timepoint (t, d) of a study date.

Table 39. Sets used to define EV Constraints in Supply Curve Model

Name	Indexing variable(s)	Description	Definition
VEHCILES	v	Unique ID assigned to each EV included in the study.	Specified along with VEHICLE_CHARGE_WINDOWS: $\{v: (v, d, dwl\_strt, dwl\_end) \in \text{VEHICLE\_CHARGE\_WINDOWS}\}$

Table 40. Parameters used to define EV Constraints (a) Supply Curve Model

Parameter Name	Indexed over	Description	Definition
vehicle_timepoint_max_power_kw	(VEHCILES, TIMEPOINTS)	Assigns the maximum allowed charging power for valid combinations of vehicle (v) in timepoints (t,d). This assignment handles both within-day charging and overnight charging schedules depending on the each vehicle’s potential charging windows.	kW-Level 1 Charger 3.3 kW-Level 2a Charger 6.6 kW-Level 2b Charger

- b) The main aim of this constraint is to make sure that the sum of the total charging done in all the potential time slots in any particular travel day is equal to the total energy needed for each individual vehicle, which has been pre-determined from the historical driving pattern data discussed in the earlier sections.

subject to (for v in VEHICLES, d in DATES):

$$\sum_{(t,d) \in \text{TIMEPOINTS}} (\text{EV\_Charge\_kw}_{v,t,d} \times \text{length\_of\_tp\_hr}_{t,d}) = \text{charge\_needed\_kwh}_{v,d}$$

Table 41. Parameters used to define EV Constraints (b) in Supply Curve Model

Parameter Name	Indexed over	Description	Definition
charge_needed_kwh	VEHICLE_DATES_FOR_CHARGING	Amount of power needed to charge each vehicle (v) on a particular study date (d). Expressed in units of kWh.	Specified exogenously.

#### 3.4.2.1.2.2 Load-Serving Constraints

This constraint requires that power generated from the existing power plants must be able to satisfy the demand for power during each timepoint of the day. The total system load at each timeslot consists of the electricity load and the load due to charging EVs at that particular timepoint of the day. Reserve margins have not been considered in this work for simplicity but will be considered for future work.

subject to (for (t, d) in TIMEPOINTS):

$$\sum_{v \in \text{VEHICLES}} (\text{EV\_Charge\_kw}_{v,t,d}/1000) + \text{system\_load\_mw}_{t,d} = \sum_{g \in \text{GENERATORS}} \text{DispatchGen}_{g,t,d}$$

Table 42. Parameters used to define Load Serving Constraints in Supply Curve Model

Parameter Name	Indexed over	Description	Definition
system_load_mw	TIMEPOINTS	Fixed electricity loads during each timepoint (t,d).	Specified exogenously.

#### 3.4.2.1.2.3 Maximum Dispatch Constraints

This constraint ensures that the power produced by the existing dispatchable and baseload generators does not exceed their nameplate capacity. For plants providing intermittent supply of power (e.g., wind or solar), the maximum amount of power that can be generated at any particular timeslot is a fraction of the installed capacity of the plant (installed capacity \* capacity factor<sub>timeslot</sub>).

subject to (for g in GENERATORS, (t, d) in TIMEPOINTS):

$$\text{DispatchGen}_{g,t,d} \leq \begin{cases} \text{if intermittent}_g = 0 \\ \text{then gen\_size\_mw}_g \\ \text{else (gen\_size\_mw}_g \times \text{ip\_cap\_factor}_{g,t,d}) \end{cases}$$

Table 43. Parameters used to define Maximum Dispatch Constraints in the Supply Curve Model

Parameter Name	Indexed over	Description	Definition
gen_size_mw	GENERATORS	Maximum possible power output from each power plant.	Specified exogenously.
intermittent	GENERATORS	Flag to identify intermittent power plants (e.g., wind or solar).	Specified exogenously. 1 – intermittent, 0 – non-intermittent
ip_cap_factor	(GENERATORS, TIMEPOINTS)	Capacity factor (power production as a fraction of plant size) for each existing intermittent generation project (g) during each timepoint (t,d).	Specified exogenously

### 3.4.2.2 Business-As-Usual (BAU) Charging

In the business-as-usual charging scenario, EV owners are assumed to charge their EVs right after they reach their final destination (home or work). The charging is assumed to begin immediately at the start of the single longest period when each vehicle is parked at home or at work during the studied vehicle-day. This scenario is modelled to replicate the normal expected charging behavior in which the supply-curve model does not affect the EV owners charging decision.

The business-as-usual charging scenario is implemented in the supply-curve model by manually setting the parameter ('EV\_Charge\_kw') to a default charging regime that charges at the maximum rate, starting at the earliest charge window and continues across timepoints and charge windows until the energy requirement is fulfilled. The maximum charging rate is assigned depending on the charger used i.e., either Level 1- 1.4kW, Level 2a -3.3 kW or Level 2b - 6.6 kW when plugged-in or 0 when not plugged-in. The analysis uses the same set of constraints and objective function as used in section 3.4.1.1.1. The model is setup in the similar framework as in "optimized charging", except here the variable representing the number of kW of power required for charging each vehicle (v) during each timeslot (t, d) of a study date ('EV\_Charge\_kw') is a parameter instead of a decision variable.

Table 44. Parameters used in BAU charging of the Supply Curve Model

Parameter Name	Indexed over	Description	Definition
EV_Charge_kw	<i>(VEHICLES, TIMEPOINTS)</i>	Number of KW of power required for charging each vehicle (v) during each timepoint (t, d) of a study date.	Calculated according to the energy required for charging, charger used, and charging window.

## CHAPTER 4. EXPERIMENTAL RESULTS AND ANALYSIS

### 4.1 Impact on Load Profile

#### 4.1.1 Price-Taker Model

The impact of the EV fleet using the price-taker model on the total system demand is shown in **Table 45**. During the evening priority peak period (5:00 pm – 9:00 pm), EV charging using the business as usual charging plan, increases the evening peak load by an additional 1.35 GW on top of the normal system load whereas the optimized charging plan adds just around 79 MW in the same period. The price-taker optimized scenario is thus able to successfully shift the majority of the priority and mid peak period load to the off-peak period. The load in the off-peak period is mostly due to home charging whereas the mid-peak period load is strongly attributed to work-place charging.

The Business-As-Usual (BAU) charging schedule as shown in **Figure 25**, is able to closely model the common household driving pattern in the U.S. The morning charging peak is represented by the charging that is done prevalently when drivers reach their workplace and instantly plug-in their vehicles for charging. Similarly after the final trip of the day when drivers arrive home and the significant load due to EV charging is aptly represented by the large evening peak load.

The optimized charging schedule is able to successfully transfer/shift the bulk of the evening peak load to the off-peak periods of the day where the marginal price of electricity is considerably cheaper than the other periods of the day which is evident from **Figure 23**, represented in section **3.2.2**. A portion of the load in the priority peak period has been also shifted to the mid-peak period where the marginal prices of electricity are the second best favorable.

Table 45. Average Daily EV Load Distribution using Price-Taker model

Time-of-Day Rating Period	BAU Scenario (MW)	Optimized Scenario (MW)
5:00 pm – 9:00 pm (Priority Peak Period)	1354.42	78.80
7:00 am – 5:00 pm (Mid - Peak Period)	2154.60	1672.36
9:00 pm – 7:00 am (Off-Peak Period)	1089.21	2847.08



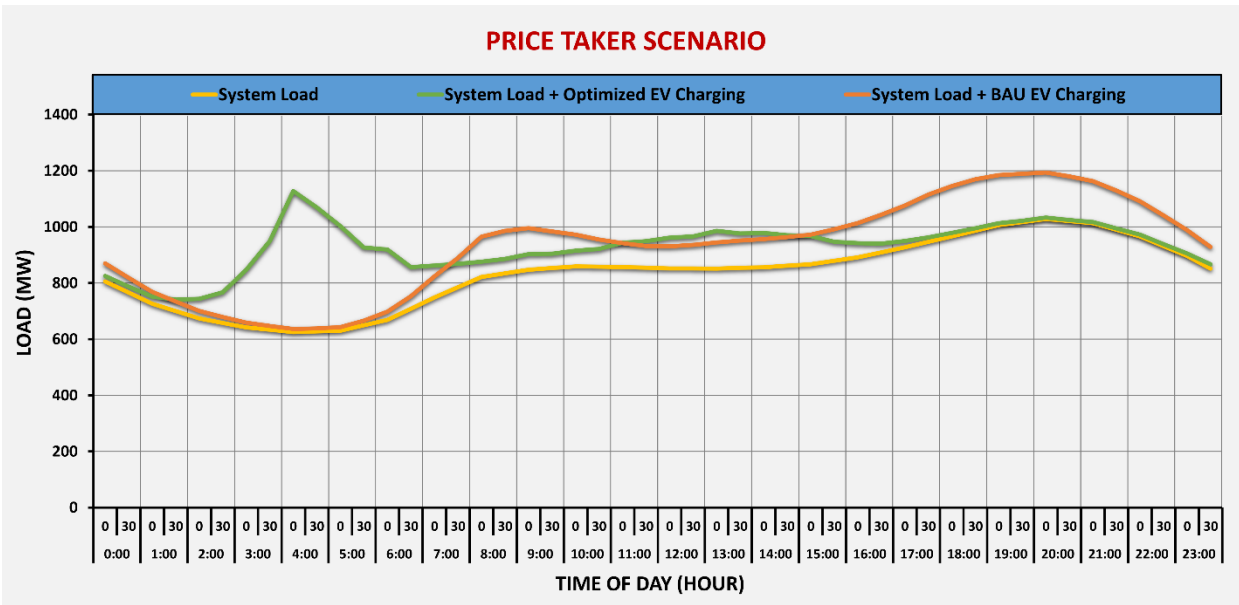


Figure 25. Average System Load Profile using Price-Taker model

#### 4.1.2 Supply Curve Model

The impact of the charging of the EV fleet using the supply curve model on the total system demand is shown in **Table 46**. During the evening priority peak period (5:00 pm – 9:00 pm), EV charging using the business as usual charging plan, further increases the evening peak load by an additional 1.35 GW load on the normal system load whereas the optimized charging plan adds just around 130 MW in the same period. The demand response optimized scenario is thus able to successfully shift the majority of the priority and mid peak period load to the off-peak period. The load in the off-peak period is mostly due to home charging whereas the mid-peak period load is strongly attributed to work-place charging.

The optimized charging schedule is able to successfully transfer/shift the bulk of the evening peak load to the off-peak periods of the day where only those particular generators generating electricity at a considerably cheaper rate are used than the other periods of the day where the cost of generating electricity is considerably higher.

This optimized model significantly flattens the peaks and the troughs in the demand curve as compared to the business-as-usual scenario as shown in Figure 26. Flattening of the demand curve helps the utility to get rid of peak demands which have a disproportionate effect on grid capital and operational costs, including transmission, generation, and fuel costs [74].

Table 46. Average Daily Load Distribution using Supply curve model

Time-of-Day Rating Period	BAU Scenario (MW)	Optimized Scenario (MW)
5:00 pm – 9:00 pm (Priority Peak Period)	1354.42	130.19
7:00 am – 5:00 pm (Mid - Peak Period)	2154.60	2096.36
9:00 pm – 7:00 am (Off-Peak Period)	1089.21	2371.68

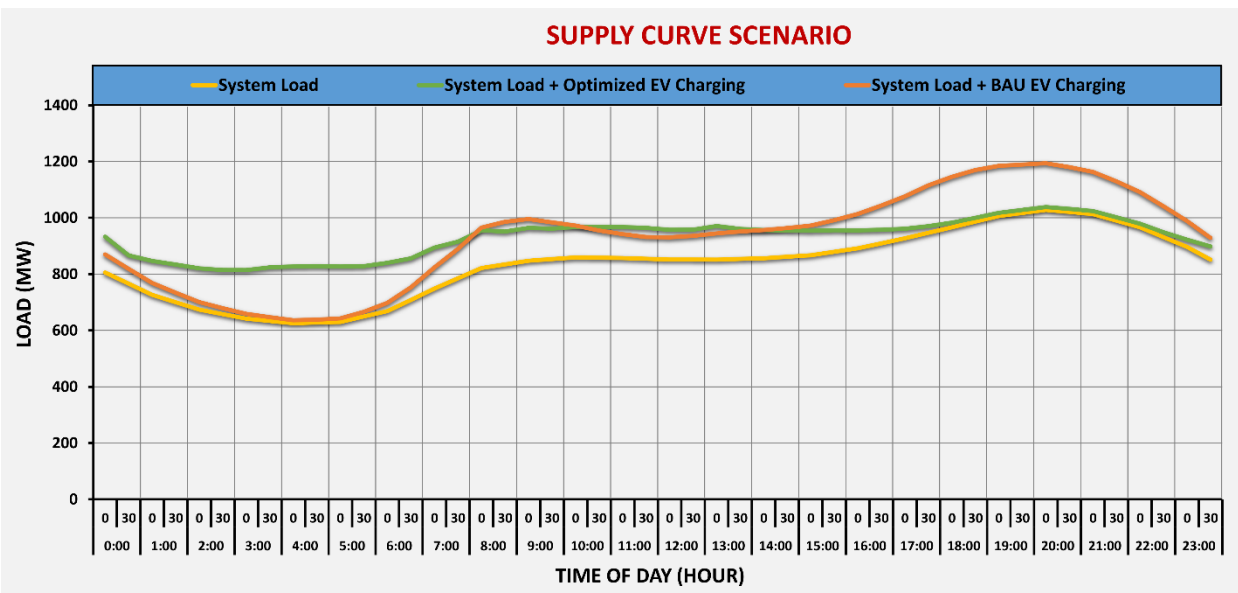


Figure 26. Average System Load Profile using Supply curve model

## 4.2 Savings

### 4.2.1 Price-Taker Model

The price-taker optimized scenario allows the residential households having EVs to align their charging schedules according to the time-varying prices available in a particular day. This time-varying electricity pricing incentivizes the consumers to follow an optimal charging schedule for each vehicle which would provide them with substantial savings as compared to charging EVs in the business-as-usual scenario. As reported in the earlier section, the optimal charging schedule shifts majority of the evening peak load into the off-peak periods of the day where the marginal price of electricity is considerably cheaper. For the study year 2014, this optimized charging profile reduces costs for EV owners by 35.45% compared to the business-as-usual (BAU) scenario. **Figure 27** depicts the EV charging costs in both Business-As-Usual (BAU)

and optimized scenario on a month by month basis for the study year 2014; it also shows the savings in the optimized scenario relative to business-as-usual. Depending on variation of the historical system load during different months of the year 2014, the percentage of EV savings also varies, ranging from a high of 57% to as low as 24%. For 199,712 vehicles, this would be a total savings of almost \$52 million for the year 2014, or about \$20 per month per vehicle. These are indicative of the savings that are available for the first few EVs added to the system, when there are too few to shift the cost of production; however, they are not likely to stay at this level with 200,000 EVs added; that is discussed in the next section.

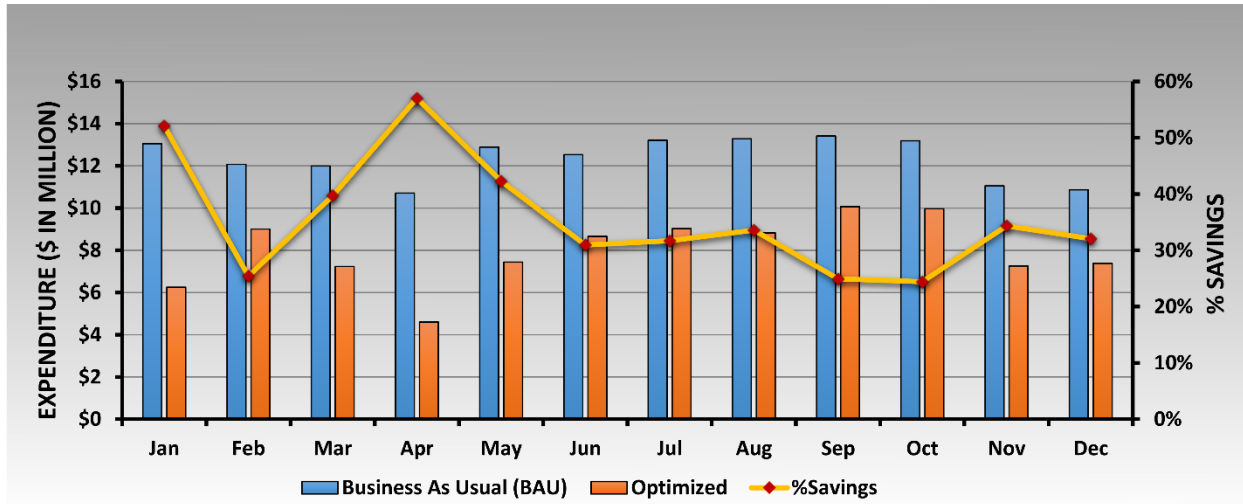


Figure 27. EV Savings from Price-Taker model

#### 4.2.2 Supply Curve model

By utilizing the optimized charging schedule, the supply curve model is successfully able to transfer bulk of the evening peak load to the off-peak periods of the day. This shift of peak load not only helps in flattening of the peaks in the demand curve but also provides incentives in terms of savings to both the EV owners and the utilities by allowing the EV owners to charge their EVs at those optimal time periods of the day which utilizes those particular set of generators which have a lower cost of generating electricity than the other periods of the day where the cost of generating electricity is considerably higher.

For the study year 2014, this optimized charging profile reduces EV charging costs by 8.10% compared to the business-as-usual (BAU) scenario. Figure 28 depicts the EV charging costs and the corresponding savings (percentage) associated in both Business-As-Usual (BAU) and optimized scenario on a month by month basis for the study year 2014. Depending on variation of the historical system load during different months of the year 2014, the percentage of EV savings also varies, ranging from a high of 9.3% to as low as 7.2%.

Figure 29 depicts the total costs incurred to supply electricity to satisfy both the fixed system electricity load and the reschedulable EV load in both Business-As-Usual (BAU) and optimized scenarios for different months of the year 2014. The optimized price-taker scenario

results in providing a system wide savings of 0.15% as compared to the Business-As-Usual (BAU) scenario for the year 2014.

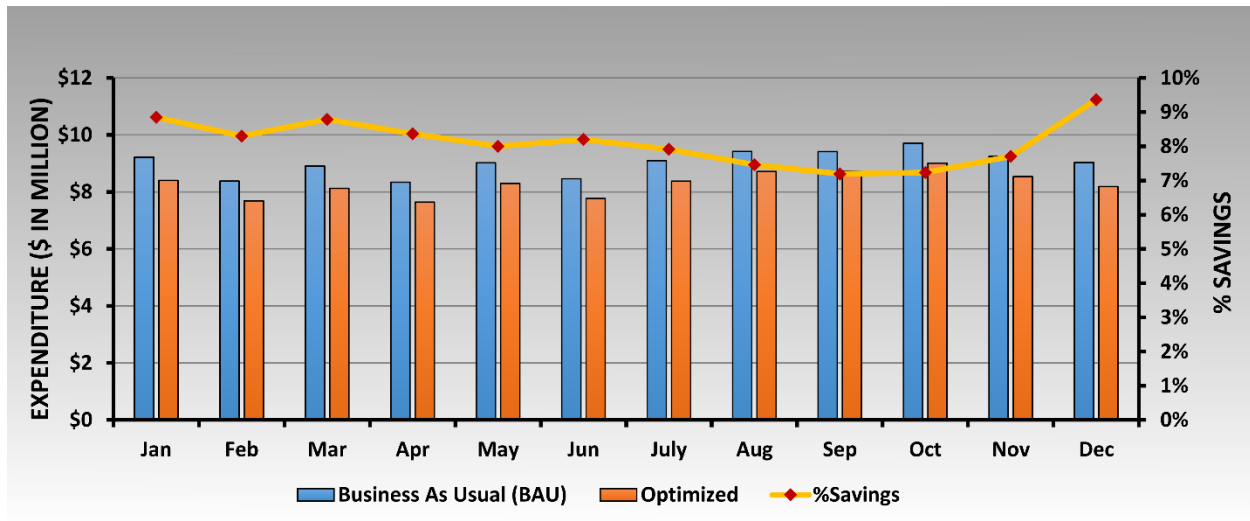


Figure 28. EV Savings from Supply curve model

These savings appear much lower than in the case of the price-taker model because EVs on this scale push up electricity production costs whenever they are charged, which was not factored into the price-taker model. Comparing the price-taker model with the supply curve model shows that EV scheduling must be included in the generator optimization each day, rather than simply computing prices without considering the EVs, and then hoping EVs will provide an optimal response [75].

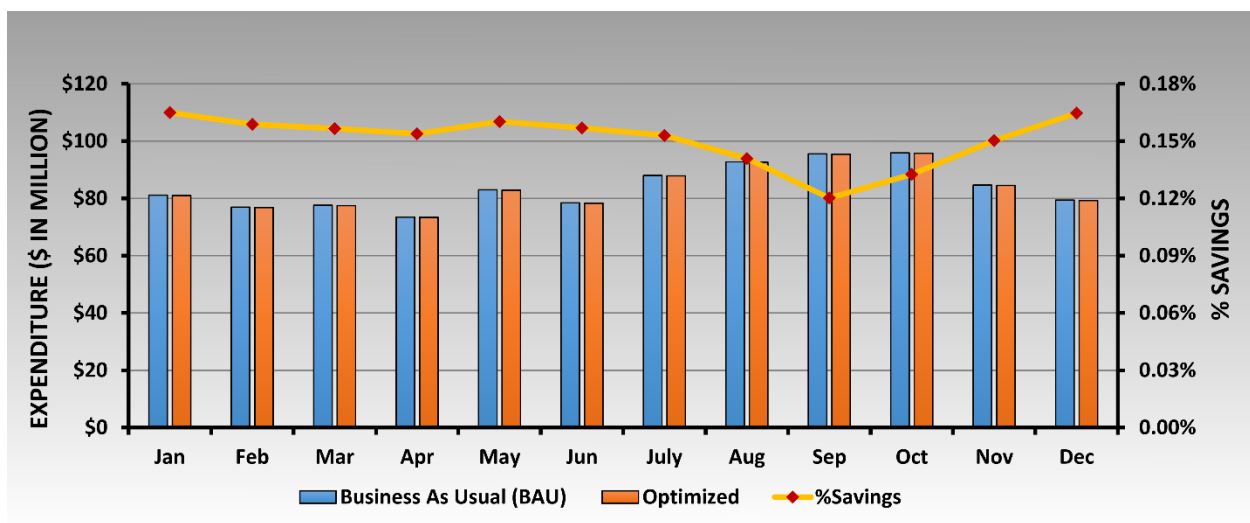


Figure 29. Total Savings from Supply Curve Model

## CHAPTER 5. CONCLUSIONS

The EV model developed in this study uses actual driving pattern data collected from the 2009 National Household Travel Survey (NHTS) to replicate the travel pattern behavior in Hawaii. For each individual vehicle, unique driving pattern distributions were obtained, based on which potential EV charging windows were determined. The study currently assumes two primary locations of charging i.e. home and workplace. It can be later extended to include other non-primary charging locations such as shopping centers etc. The detailed DISTRIBUTIONS OF individual EV charging windows developed for such a large sample data set of vehicles can serve as a useful data repository which can be directly used by other researchers and policymakers to analyze new charging scenarios in order to provide a more realistic representation of the EV electricity demand impacts on the electricity grid. The half-hourly EV load profiles derived can also be directly plugged into other integrated resource planning models to account for the EV charging load in the present or over a specified future planning period.

Rather than assuming all the vehicles drive the same daily distance, each vehicle is modelled individually, which helps in achieving a more accurate and realistic estimation of the amount of energy needed to charge each individual EV. The charging is also dependent on the different classes of passenger vehicles (car, van, SUV, pick-up truck), location of charging (i.e. home and workplace charging), charging rates (1.4kW/3.3kW/6.6kW) and plug-in times. Two different optimized smart recharging scenarios were then implemented and their effect on the system load, and power system costs were then compared with a business-as-usual (BAU) charging scenario.

The optimized price-taker model, which provides an optimal charging schedule by using time-varying prices depending on the marginal cost of electricity derived from the “system lambda” values, was able to successfully transfer bulk of the evening peak loads to the off-peak periods of the day, thus being able to achieve considerable EV savings as compared to the BAU scenario. This particular model would very much appeal to the residential households having EVs to readjust their charging schedules according to the time-varying prices available in a particular day. This reflects the opportunities available to early-adopters, but not for larger vehicle fleets.

As evident from results earlier, the integrated supply-curve model successfully flattens out the peak demand during the priority peak period (5:00 pm – 9:00 pm), without creating a new peak during the night. This is achieved by scheduling the EV owners to charge at times when electricity is generated from less expensive generators as compared to charging in those periods where the cost of generating electricity is considerably higher. This demand flattening not only helps the EV owners in residential households in terms of savings but also helps the utility by making the grid smarter and more efficient. This also gives a more realistic estimate of the savings available with high penetration of EVs (on the order of 200,000 among Oahu’s 310,000 households) [76].

As Hawaii strives towards becoming the first state in the U.S. to generate 100 percent of its electricity from renewable energy by 2045, but also in a global scenario, electrification of the

transportation sector combined with integration of more renewable energy resources into the power system have been considered to be the most promising solutions to achieve the carbon emissions goal of limiting the average global temperature to 2° C. With its unique geography and current fossil fuel based energy infrastructure combined with its aggressive energy goals, Hawaii forms an ideal site for large scale adoption of EVs in the future.

By developing a comprehensive Hawaii specific EV and power system model, this research study analyzed the impacts of large scale adoption of EVs on system load and provides a better understanding as to how different optimally-timed EV charging can benefit such a unique power system.

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