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Clean Transportation: Effects of Heterogeneity and Technological Progress on EV Costs and CO2 Abatement, and Assessment of Public EV Charging Stations

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Clean Transportation: Effects of Heterogeneity and Technological Progress on EV Costs and CO_2 Abatement, and Assessment of Public EV Charging Stations

by

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A DISSERTATION

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CERTIFICATE OF APPROVAL

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Ph.D. DEGREE DISSERTATION

The Ph.D. Degree Dissertation of Ranjit R. Desai has been examined and approved by the dissertation committee as satisfactory for the dissertation requirement for the Ph.D. degree in Sustainability.

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ABSTRACT

The advent of Electric Vehicles (EV) in the private transportation sector is viewed as a means of reducing emissions and making significant efforts towards reducing climate change impacts. However, when it comes to adopting and/or promoting a new technology through subsidies, the consumers' needs are seldom given significant attention. Moreover, most analyses informing policy making assess the potential of new and cleaner technologies like EVs based on *an average consumer's* needs and behavior. Given heterogeneity, these analyses miss subpopulations that benefit (or lose) more than an average consumer. In fact, private transportation greatly depends upon how the diversity of consumers choose to commute and what kind of vehicles they choose to possess. Especially in the United States of America (U.S.), each consumer faces different needs for their daily commute, which dictates their preferences for vehicles. This behavioral heterogeneity in addition to the geographic locations of consumers makes the U.S. private transportation sector an intricate system. The locations of the U.S. define fuel prices as well as emissions from electricity production. Therefore, these behavioral and geographic heterogeneities are highly crucial while calculating the benefits and potentials of EVs. The analyses conducted for this dissertation consider these heterogeneities to accommodate the nuances in consumers. This consideration of heterogeneities is the most critical aspect of this work.

Chapter 2 of this dissertation builds a Marginal Abatement Cost Curve (MACC) for Electric Technology Vehicles (ETVs) which incorporates these heterogeneities, behavioral and geographical. With current gasoline and battery cell prices, result indicate that without federal tax credits, about 1.9% of the population would receive direct financial benefits from purchasing an ETV. This subpopulation drives over 4 times (over 48,000 miles annually) more than the average consumer (11,700 miles). The consideration of the heterogeneities has made it possible to recognize this subpopulation. The scenario analyses are conducted for different fuel and battery cell prices. These analyses shed light on how different subpopulations benefit financially and environmentally from ETVs. In this chapter, the impacts of federal tax credits with and without considering heterogeneities are estimated, suggesting why policy analyses need to incorporate consumer heterogeneities while assessing benefits of government subsidies.

Given these results on economic and carbon benefits of ETVs, Chapter 3 builds an integrated model of adoption that includes endogenous technological progress—through learning rates—where due to initial adopters the technology is made cheaper for the future ones. The feedback loop developed in this chapter takes into consideration the cumulative production of the technology and estimates price reductions using learning rates. Reduced capital costs then propel more consumers to adopt ETVs making the technology cheaper, again increasing the consumer base that benefits from them. The economic benefits of buying an ETV versus a conventional one costs depend on battery costs, non-battery EV costs, and the future of conventional vehicles. Results are that the future market penetration (share of consumers economically benefitting) is sensitive to two poorly understood quantities: non-battery EV costs and cost increases in conventional vehicles driven by future emission standards. Federal tax credits are also studied in how they stimulate adoption and in turn technological progress of ETVs.

Governments are not only investing in subsidies for consumer purchase of ETVs but also in installing public EV charging stations. These charging stations are expected to motivate

consumers to choose ETVs over conventional vehicles and help reduce range-anxiety. In Chapter 4 an assessment is conducted to understand how these public resources are being used. Results reveal the behavior of consumers at the public EV charging stations using empirical data collected in the City of Rochester. A data distillation is first conducted for the raw data to construct the daily charging profiles of the EV users. A pattern analysis is then performed to identify 5 distinct and homogenous clusters of daily charging profiles of the consumers. This work defines the operational inefficiency of the public charging station as the time spent in parking without charging out of the total time a PEV user accessed the public charging station. This analysis uncovers a significant inefficient operation of these public EV charging stations, i.e. EVs remained parked at stations long after charging is finished. An estimation of the opportunity cost of reducing this observed inefficiency in terms of Greenhouse Gas emissions savings is also conducted in this chapter.

The main policy takeaways of this dissertation are that identifying key subpopulations who benefit from the ETVs is highly significant and possible only by incorporating behavioral and geographical heterogeneities. This allows a more precise estimation of impacts of policies such as the federal tax credits. Secondly, the initial adopters make the technology cheaper for the latter adopters. However, the future market parity of ETVs with conventional vehicles depends on poorly understood factors such as current costs and learning rates of non-battery EV technologies and future cost increases in conventional vehicles driven by stricter emissions requirements. Lastly, the use of public resources, such as public charging stations needs to be studied. They are expensive to create, and inefficient use may deter possible EV adopters. Furthermore, the possible opportunity cost of reducing emissions by using the charging station more efficiently allows better use of a public resource.

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I am eternally grateful to my Ph.D. advisors Dr. Roger B. Chen and Dr. Eric Williams. As I look forward to my career ahead from here, it is because of their help, support, and encouragement. Dr. Chen accepted me to be one of his first Ph.D. students, and it has been a learning curve for me to say the least. The core topic of my dissertation, ‘Electric Vehicles’, started because I started working on the EV charging stations project. I must thank Dr. Chen for giving me this project. I had an opportunity to work on the marginal abatement cost (MAC) project with Dr. Williams. I believe it was undoubtedly a tide-turning project in my career. It has been an absolute pleasure to be his advisee. His guidance has been instrumental and played a pivotal role in guiding my dissertation work to be what it is today. It is not an exaggeration to say that the work done under his guidance has become a part of my identity as a researcher. I wish there was a way to express my gratitude to you. I must thank both Dr. Chen and Dr. Williams for supporting me financially throughout the Ph.D. and helping me to attend conferences to present my work. Thank you, Dr. Chen and Dr. Williams, for helping me achieve my goals and for being an integral part of the most crucial part of my academic career.

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I dedicate this dissertation to my parents. I understand all the hardships you have to go through to teach me and provide all the resources I needed to be successful. I do not think there is any way I can thank you enough or express my gratitude for everything that you have done for me. I feel proud to be your son. Mummy, Papa, thank you! I cannot thank you enough for your sacrifices and your support so that I could be where I am today. I love you from the bottom of my heart. Ravina, you are actually a younger sister, but time and again, you have proven to be an elder sister and taken care of everything at home while I was busy in my dissertation. I am incredibly proud of you and love you!

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1 CHAPTER 1: INTRODUCTION

1.1 *Background and Motivation*

Transportation is a necessity of daily life but it also accounts for a large share of greenhouse gas (GHG) emissions in the United States and the world, as the current levels indicate 410 parts per million (ppm) of CO2e (CO2-earth 2018). For these reasons, decarbonization of transportation is a critical part of controlling atmospheric GHG concentrations as the current Intergovernmental Panel for Climate Change (IPCC) report recommends "rapid and far-reaching" efforts in the transport sector to limit global warming to 1.5 degrees C (IPCC 2018a, 2018b) as well as to achieve the 2 degrees C target set in the Paris Accords (PPMC TRANSPORT 2018).

In the United States of America (U.S.), the transport sector emits 1,782 Million Metric Tons of CO2e (MMT CO2e) (28% of all U.S. emissions) with 69% of that due to light-duty vehicles (i.e., private transport) (U.S.-EPA 2018d, 2018c). Globally, transportation is accountable for 23% of the energy-related greenhouse gas emissions and 92% of total oil consumption (IEA 2018). The U.S. transport sector's dependence on oil is beyond argument. Oil prices are extremely volatile, and they impact almost every American household because of heavy reliance on gasoline-powered light-duty vehicles for private transportation. In such circumstances, it is imperative that the U.S. private transportation sector looks at alternative and cleaner modes of transportation such as Battery Electric Vehicles (BEVs) and Plug-in Electric Vehicles (PHEVs) instead of conventional fossil fuel vehicles. Compared to the incumbent technologies, these cleaner technologies have the potential to contribute to air quality and climate goals of the nation by tapping into cleaner sources of electricity. These modern technologies, therefore, hold great promise to make the transportation systems cleaner and more sustainable.

As per the National Household Travel Survey 2009 (NHTS), 83% of the daily vehicle miles traveled (VMT) per driver were under 60 miles, and 95% were under 120 miles. Moreover, the results from NHTS 2017 have also confirmed similar travel trends (Methipara, Reuscher, and Santos 2016). Most of the current E.V.s, moreover, have a range of 60-120 miles on a single charge (Kane 2017). Therefore, 99% of the vehicle trips in the U.S. can, theoretically, be completed by Plug-in Electric Vehicles (PEV include BEVs and PHEVs). In 2017, the U.S. stock of PEVs was 762,000. This, although, amounts to only 1.2% of the total private transportation market share, the PEV stock has risen by over 35% compared to the previous year (International Energy Agency 2018). It will be, thus, safe to assume that the PEV market share will keep on increasing rapidly in the near future. PEVs, therefore, hold the key to mitigate the impacts of transportation. As sustainability must compete with other needs for the finite resources all the time, it is essential to know the cost of adopting PEVs to mitigate the impacts of transportation on the environment.

Electric technology vehicles (ETVs) are a leading solution for decarbonizing transportation (Sustainable Mobility for all 2017; Bloomberg New Energy Finance 2017; International Energy Agency 2018). In this dissertation, the term Electric Technology Vehicle (ETVs) is used to include Hybrid Engine Vehicle (HEV), Battery Electric Vehicle (EV) and Plug-in Hybrid Vehicles (PHEV). An electric drivetrain, common to all three types, improves efficiency. It is essential to understand that there is significant variability in the U.S. consumers' use of private transportation. Therefore, this dissertation takes a deeper dive into understanding the outlook of Electric Technology Vehicles by incorporating behavioral and geographic heterogeneity of consumer usage, technological progress (through the learning rate), and operational efficiency of the public charging stations—installed to increase the market share of PEVs.

1.2 *Marginal Abatement Cost Curve (MACC)*

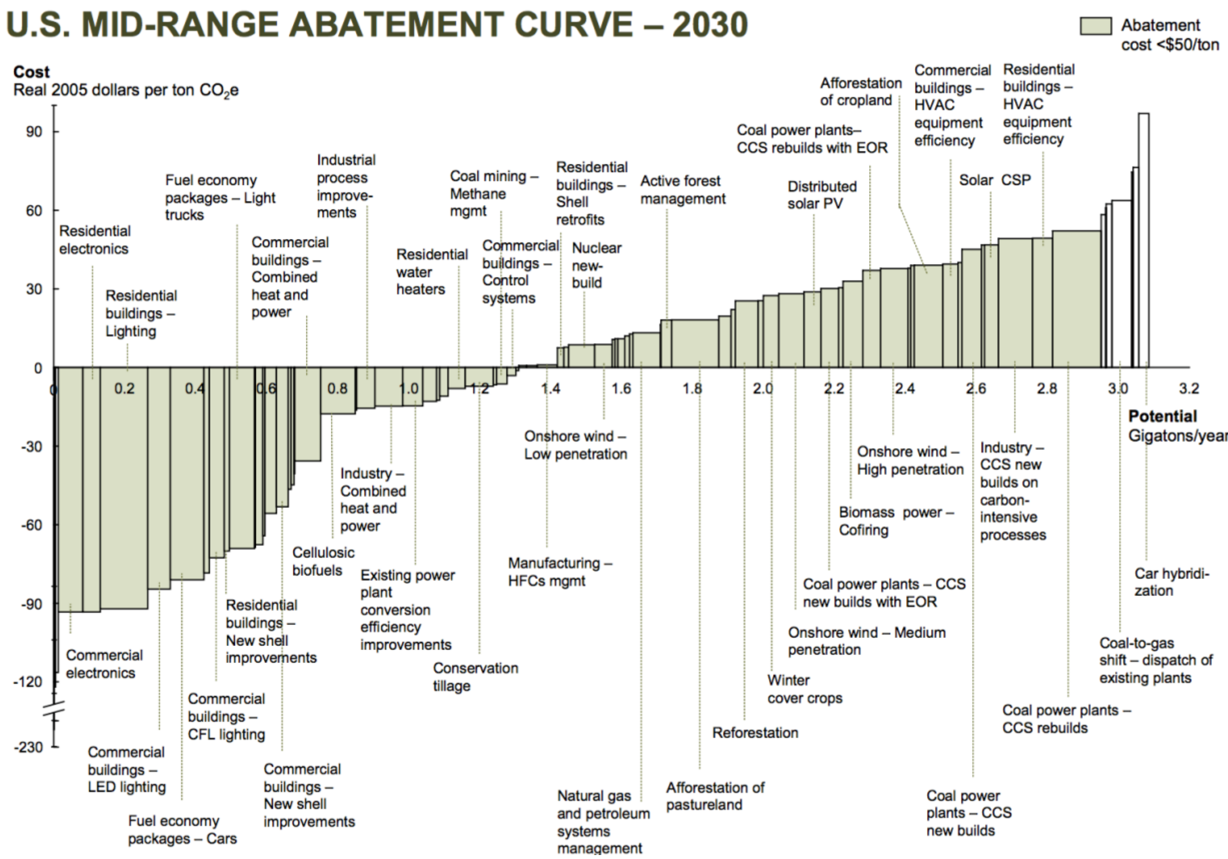


Figure 1-1: U.S. Carbon Marginal Abatement Cost Curve (McKinsey&Company 2009)

To understand the effects of heterogeneity, a Marginal Abatement Cost Curve (MACC) is developed incorporating the inherent heterogeneities in the system. The Marginal Abatement Cost Curve (MACC) is a framework used to characterize information of potential mitigation efforts and identify least and/or most cost-effective Greenhouse Gas (GHG) mitigation measures. A composite MACC is constructed by ordering technological interventions to mitigate a unit of emissions from lowest to highest cost, indicating the cumulative mitigation possible for each intervention. The earliest example of MACC goes back to 1980s when Meier A. K. in 1982 produced a cost curve for energy conservation. The MACC has become a popular and a handy tool for policy-makers, especially Marginal Abatement Cost Curve (MACC) developed by McKinsey for analyzing carbon mitigation costs for different sectors (McKinsey&Company 2007). Figure 1-1 shows a MACC developed by McKinsey (McKinsey&Company 2009) for the U.S. The figure shows the cost-effective and maximum emissions savings potential measures from left to right. The policymakers use the MACC to demonstrate which of these measures an economy can afford, and prioritize, in order to set and achieve GHG emissions reduction targets for the country.

1.2.1 Issues with Marginal Abatement Cost Curves

MACC, though, can provide a simplistic overview of available climate mitigation measures, it is an oversimplification of a complex techno-economic system. The MACC method has been criticized for neglecting various factors such as dynamics, consumer behavior, and interactions between the technologies as well as the hidden transaction and monitoring costs, and does not account for some of the mitigation costs which cannot be monetized (Kesicki and Ekins 2012) (Senatla et al. 2013). Further, it neither captures non-market barriers to the technology adoption nor treatment to underlying uncertainties related to assumptions and analyses (e.g. learning and discount rates, life spans of technologies and economics associated with technology) (Tilburg, Würtenberger, and Rivera Tinoco 2010)(Kesicki and Ekins 2012) (Senatla et al. 2013). However, as long as the limitations of the information provided by a MACC are understood, it does provide valuable and easily comparable information on costs and mitigation potential.

1.3 *Importance of Heterogeneity*

For this work, the MACC for Electric Technology Vehicles in the U.S. is developed with a new approach which accounts for heterogeneity. Figure 1-2 illustrates the new approach. When heterogeneity is not considered while analyzing a system, all the vehicles (or their owners) are considered to have the same characteristics. Once heterogeneity is introduced, for vehicle 2 and 3 the preferred technology changes as well as the abatement cost. Lastly, when technological progress is considered, the abatement costs for later adopters are less than the early adopters. In private transportation, the technological progress is for the learning rate of battery cell prices and non-battery EV technologies. The result, thus, is a disaggregated MACC that describes how carbon mitigation costs are affected by heterogeneity and technological progress. The final outcome indicates a path for dramatically lower carbon mitigation costs compared to the traditional approach. This MACC approach, while accounting for new factors such as learning rate, is still a partial view of a complex system combining economics, technology, behavior, and policy. Ultimately, it is important to understand factors such as interactions between technologies and decision-making processes of adopters.

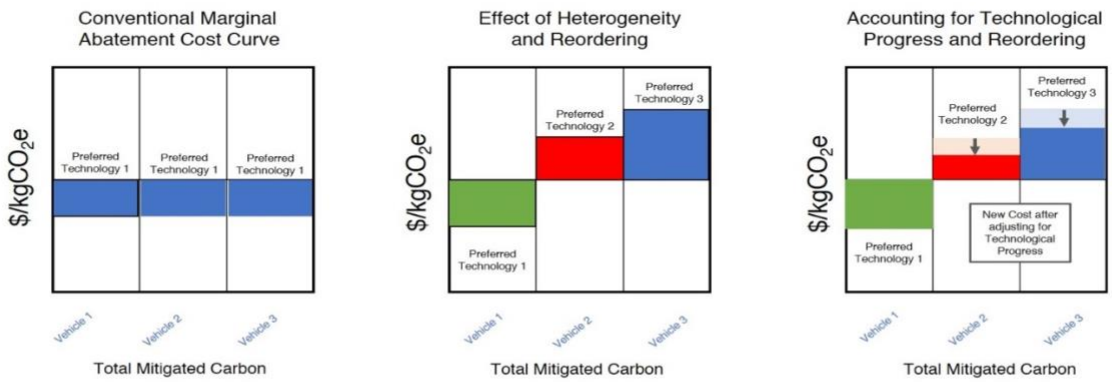


Figure 1-2: The core concept of this proposal - Marginal Abatement Cost Curve accounting for heterogeneity and technological progress, illustrated with hypothetical results for three vehicles in the U.S.

1.4 *Research Objectives*

This dissertation aims to mainly answer three key questions:

1. How heterogeneity affects the economic and carbon benefits of Electric Technology Vehicles in the U.S.?
2. How will EV Costs decrease in Future?
3. How are the public charging stations used?

1.5 *Dissertation Outline*

This dissertation is divided into five chapters in total. The introduction chapter explains the background and motivation of this study. Chapter 2 looks at developing a Marginal Abatement Cost Curve (MACC) for private transportation in the U.S. which accounts for geographical, behavioral, and stock heterogeneity. The MACC curve is used to understand how the heterogeneity in the consumer usage affects the economic and carbon benefits of Electric Technology Vehicle (ETVs). The chapter also attempts to understand the effects of including different heterogeneities on the share of population benefiting from the adoption of ETVs. The third chapter looks at the future costs of EVs through technological progress when demand-side heterogeneity is considered. The demand-side heterogeneity accounts for different driving and usage behavior of consumers which drives their choice of vehicle as well as the geographic variability in fuel prices which dictate the savings from the usage. The fourth chapter analyzes how the public charging stations are used and deals with the operational inefficiency—defined as the ratio of time spent in parking without charging to the total time the vehicle was parked at the public charging station using pattern analysis framework. The final chapter is a conclusion chapter, where major learnings and conclusions are enlisted along with future work.

2 CHAPTER 2

Heterogeneity in Economic and Carbon Benefits of Electric Technology Vehicles in the U.S.

Chapter Summary

To broadly contribute to sustainable mobility, electric technology vehicles (hybrid, electric and plug-in-hybrid) should become more price competitive with internal combustion vehicles. This study assesses the economic and carbon benefits of electric technology vehicles (electric, plug-in hybrid, and hybrid) in the U.S., accounting for household-by-household behavioral variability and geographical differences in fuel and electricity prices. This finer resolution provides insight into subsets of the population for whom adoption is economically or environmentally favorable, allowing us to construct Marginal Abatement Cost Curves for CO_2 that account for geographic, behavioral and stock heterogeneities. Currently, low gasoline prices and high initial expense means that, without subsidies, few consumers benefit financially from electric technology vehicles (1.9% of drivers). However, improved technology dramatically and non-linearly increases both the number of consumers that benefit and corresponding carbon emissions that could be abated without government subsidy. Our results clarify cost targets that electric vehicle technology must achieve in order to deliver net financial and subsidy-free environmental benefits.

2.2 *Background and Introduction*

Electric technology vehicles (ETV) are a leading solution for decarbonizing transportation(Sustainable Mobility for all 2017; Bloomberg New Energy Finance 2017; International Energy Agency 2018). In this paper, the term Electric Technology Vehicle (ETV) is used to include Hybrid Engine Vehicle (HEV), Battery Electric Vehicle (EV) and Plug-in Hybrid Vehicles (PHEV). An electric drivetrain, common to all three types, improves efficiency. Batteries provide flexibility to run vehicles on electricity derived from different fuel mixes, ideally low carbon ones. Governments around the world have been investing significantly to encourage consumers to adopt electric vehicles. In the U.S., for example, the federal government provides tax credits up to $7,500 for the purchase of BEVs and PHEVs(U.S.-EPA 2018b).

Despite considerable government investment and societal attention given to electric vehicles, there are critical unanswered questions. An important one is: what economic benefits do electric technology vehicles deliver to consumers? While this may seem a trivial question, there is as yet no analysis accounting for both the behavioral and spatial heterogeneity in the answer. There is substantial variability in driving patterns, preferred vehicle type, and gasoline and electricity prices. In the U.S., the average annual distance driven is 11,700 miles with a large standard deviation of 10,040 miles. Moreover, consumers own vehicle of different make, model and type of the vehicle from other consumers, e.g. 52% drive compact vehicles and 21% drive Sports Utility Vehicles (SUVs). Gasoline and electricity prices vary by location. In 2017, the average gasoline price in the U.S. was $2.53 per gallon with a standard deviation of $0.12 per gallon(U.S.-EIA 2018c). Texas had the lowest gasoline price of $2.29 per gallon, whereas California had the costliest gasoline at $3.08 per gallon. Similar variations can be seen in electricity prices. The average electricity price in the U.S. was 10.3 cents per kWh with a standard deviation of 3.3 cents. Residents of Louisiana paid 7.5 cents per kWh compared to those in Hawaii who paid 24 cents per kWh(U.S.-EIA 2018a). The above heterogeneities are expected to give rise to substantial variability in fuel savings from purchasing an electric technology vehicle.

2.3 *Literature Review*

Currently, the most resolved analysis of the economic benefits of electric vehicles is at the city level (Breetz and Salon 2018; Peterson, Whitacre, and Apt 2011; Hao et al. 2015). Results indicate that, in 3 of 14 U.S. cities with the highest subsidies, an average driver in these cities gets economic benefits from current electric vehicles (EV) (Breetz and Salon 2018). Other prior economic studies of benefits are at the state level(Parks, Denholm, and Markel 2007; Palmer et al. 2018). However, individual variations in driving patterns within cities and states must be accounted for. Also, as electric technology vehicles are part of national energy strategies, a national-level analysis of economic benefits to consumers is overdue. This work addresses this gap with a case study of the U.S. using individual responses regarding vehicle ownership and usage from the National Household Travel Survey (NHTS)(U.S.-DOT 2017). The NHTS includes annual miles driven on a particular vehicle which is calculated using one-day travel activity, odometer reading of the vehicle, user-reported annual miles driven and demographic information of the primary user of the vehicle(FHWA n.d.).

While a national analysis of the economic benefits of current electric technologies vehicles (with and without subsidy) is certainly useful, it is also important to consider technological progress. Motivations behind the U.S. EV subsidy include an expectation that the subsidy will support future cost reductions of the emerging technology. Recent price reductions in vehicle batteries support optimism that EV technology will continue to improve (U.S.-DOE 2017; UCS 2017; Chediak 2017). This work thus also analyzes how the population of U.S. consumers that benefit from electric technology vehicles grows as technology costs fall. In addition, the economic benefits from electric technology vehicles are sensitive to gasoline and electricity prices. Temporal variability in gasoline prices is particularly high due to volatility in the global market for crude oil.

The carbon benefits of Electric Technology Vehicles depend on the electrical grid they use to charge. Running an EV from coal-generated electricity can actually increase emissions(Graff-Zivin, Kotchen, and Mansur 2014; Nuri Cihat Onat, Kucukvar, and Tatari 2015). There is considerable geographical variability in grid mixes and ensuing carbon benefits in switching from gasoline to EVs. This dependence of EV carbon reductions on location has been studied in detail. Prior results for the U.S. have shown that the regional variation in grid mixes and average miles driven significantly affects the emissions from EV usage(Nuri Cihat Onat, Kucukvar, and Tatari 2015; Nuri C. Onat et al. 2017; Archsmith, Kendall, and Rapson 2015; Tamayao et al. 2015; Yuksel et al. 2016). For example, Graff-Zivin *et al* found substantial variation in the marginal emissions of electricity varying with respect to location and time-of-use(Graff-Zivin, Kotchen, and Mansur 2014), e.g. the upper Midwest region showing three times higher marginal emission rates compared to the western U.S. There are also studies investigating the life cycle impacts of electric vehicles(Hawkins et al. 2013; Manjunath and Gross 2017; Ma et al. 2012; Kim et al. 2016; Keshavarzmohammadian, Cook, and Milford 2018). These studies emphasize that if the EVs are compared to conventional vehicles in terms of GHG emissions then the context is very important. While most studies indicate that in the use phase in a relatively cleaner electricity grid mix, EVs prove to be a less polluting option. However, if the vehicle supply chain is considered, especially battery production from the production phase, the EVs can be significantly harmful in different ways such as human toxicity. Further, these life cycle impacts significantly depend upon what boundary of the system is considered, and hence the literature estimates vary significantly. Therefore, this study considers only the use phase of the vehicles where emissions are solely from the fuel used (gasoline for conventional vehicles and electricity for BEVs).

Using the usual aggregated approach, marginal abatement costs for carbon have been assessed in the transportation sector(City of New York 2013; Morisugi, Atsushi, and Atit 2011; Schroten, Warringa, and Bles 2012). For example, New York City projected marginal abatement costs for battery electric vehicles at \$80 per $MTCO_2e$ in 2020 and -\$10 per $MTCO_2e$ in 2030, and for PHEVs \$90 per $MTCO_2e$ in 2020 and -\$10 per MT CO_2e in 2030(City of New York 2013). The transition from positive to negative cost between 2020 and 2030 is due to assumptions about the cost reduction of electric technology vehicles. Morisugi *et al.* calculated the abatement costs in the U.S. for different CO_2 emission tax levels andto be \$234-399 per $MTCO_2e$ with a CO_2 emission tax of \$100 per $MTCO_2e$ for the transportation sector(Morisugi, Atsushi, and Atit 2011). The previous studies have not included behavioral heterogeneity in estimating carbon abatement costs.

2.4 *Contribution*

Our work also addresses another important question: What is the cost-effectiveness of electric technology vehicles as a carbon mitigation option considering that economic and grid emission benefits vary by behavior and location? This work addresses this question by modifying the usual Carbon Marginal Abatement Cost Curve (MACC) (\$/tCO_2e) to account for heterogeneity. The Marginal Abatement Cost Curve (MACC) is often used by policy analysts (McKinsey&Company 2007, 2009), and typically shows abatement cost (e.g. \$/tCO_2e) and total abatement potential (tCO_2e) for a given set of interventions. Interventions are ordered from least to highest cost of mitigation. Prior MACC analyses represent technology in terms of an average user, neglecting heterogeneity. This is reasonable when assessing 100% adoption of a technology. However, given observed behavioral heterogeneity (e.g. Sekar et al., 2016), it is important to consider mitigation paths in which technologies are adopted by subgroups that benefit most. Consider an example of a technology intervention with a net economic cost to the average consumer. It may be that the population divides into one group that saves money with the technology and another that does not. Considerable carbon savings with negative cost may be possible considering adoption by the first group. Segmenting the population according to relative benefits can thus upend the understanding of the carbon mitigation costs of a technology. This work will show that this is the case for electric technology vehicles in the U.S.

The model presented in this paper characterizes the economic and carbon implications of an electric technology vehicle purchase. While fuel and carbon savings motivate consumer choice, vehicles purchase decisions depend on many factors beyond net economic benefits. Personal vehicle choice is much studied, often using discrete choice models[40-50]. While understanding the conditions under which and the rate at which consumers would actually purchase electric technology vehicles is critical, this work considers a narrower question for a number of reasons. First, economic and carbon savings are important decision variables and, as described above, have not yet properly assessed. Second, public policies such as the federal tax subsidy for electric vehicles should be assessed for potential to deliver direct public and private benefits aside from the decision calculus of consumers (Zhou, Levin, and Plotkin 2016; Slowik et al. 2017; Cattaneo 2018). This is particularly true for electric vehicles as consumer decisions will depend on what fleet of electric technology vehicles is brought the market, the outcome of which is difficult to predict and depends partly on policy decisions. While decision science should be brought to bear to understand electric vehicle technology adoption, there is a complimentary role from a purely accounting economic perspective. Third, it is important to understand how technological progress and variations in fuel prices affect tradeoffs between conventional gasoline and electric technology vehicles. The marginal abatement curve framework explored here can deliver useful, if bounded, answers to this question.

To summarize the work, this research first develops a model accounting for *individual-level differences* in miles driven, *type of vehicle owned* (sedan, SUV, minivan and truck), and *lifetime ownership preferences* to estimate the economic benefits of electric technology vehicles (hybrid, plug-in hybrid, electric) in the U.S. The model also considers *the state-level differences* in gasoline and electricity prices. The National Household Travel Survey (NHTS) is used as the primary data source, which includes vehicle holdings characteristics for each surveyed household (a total of 309,000 households and 143,000 vehicles). Finally, the net economic benefits (or costs) are calculated to replace each existing internal combustion vehicle with a comparable electric technology vehicle. Consumers are assumed to choose a HEV, PHEV, or BEV depending on which provides the greatest private economic benefit. The economic analysis is combined with a state-by-state marginal emissions model to obtain a carbon abatement cost curve resolved consumer-by-consumer. This distinguishes subpopulations into groups that benefit economically from electric technology (and hence negative abatement costs) and those who do not. This work then considers how the economic benefits and MACC evolve with lower battery and related technology prices as well as higher gasoline prices. This is analyzed both with and without the current federal tax credit for electric and plug-in hybrid vehicles.

2.5 *Methodology*

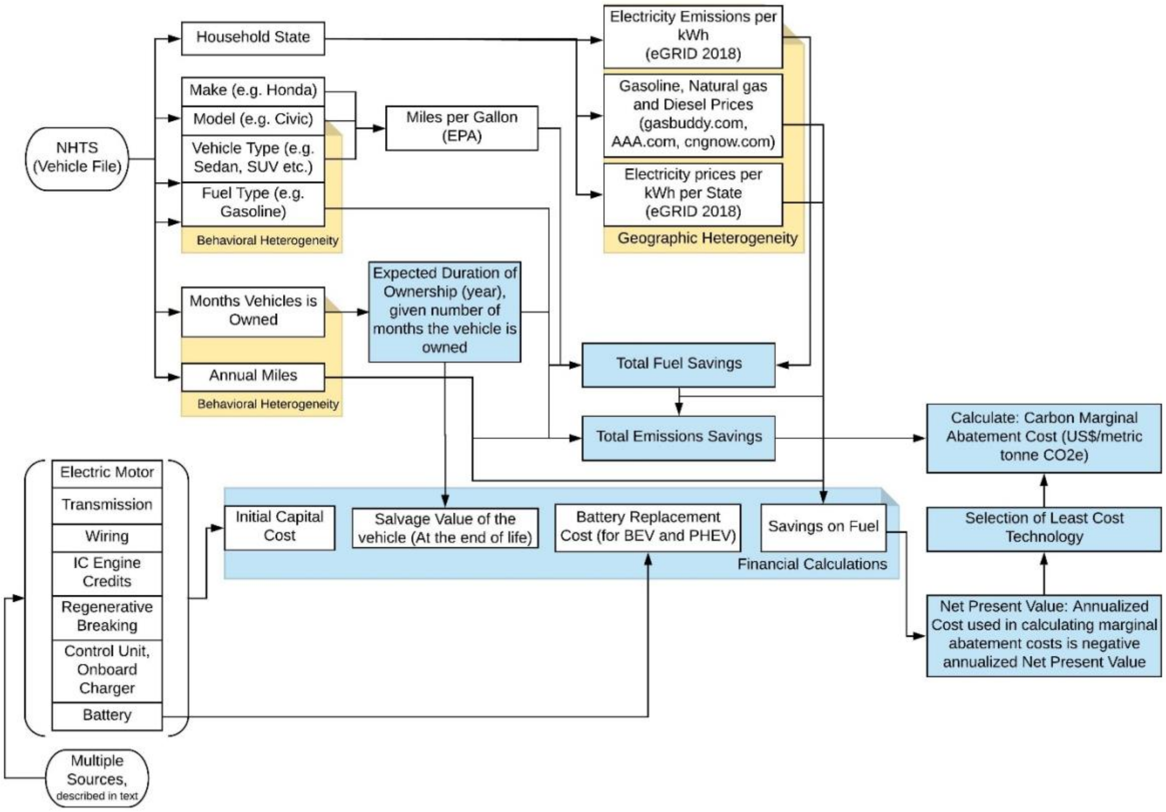


Figure 2-1: Methodological Framework. The diagram shows the flow of data and calculations and indicates data sources used, such as the National Household Travel Survey(U.S.-DOT 2017) *and others*(U.S.-EPA 2018c, 2018a; www.AAA.com 2018; CNG-Now 2018; GasBuddy.com 2017). *Blue backgrounds refer to model calculations, Yellow backgrounds show types of heterogeneity analyzed.*

Figure 2-1 shows the overall methodological framework. The National Household Travel Survey (NHTS) sample vehicle fleet is used as the main input for the vehicle-level analysis. NHTS includes the households' State of residence. This is used in modeling geographical heterogeneity to find state-specific electricity emissions, fuel and electricity prices. The NHTS dataset also reports make, model and type of the vehicle (used to estimate the initial capital cost and mileage), number of months the vehicle is currently owned (used to estimate the expected duration of ownership of the vehicle), and number of miles driven annually (behavioral heterogeneity) for each household vehicle. In evaluating purchase of an electric technology vehicle, this work assumes consumers keep the same make, model and type as their previous vehicle. Four technology options are considered: 1. Updated Conventional Vehicle, 2. Hybrid Engine Vehicle, 3. Battery Electric Vehicle and 4. Plug-in Hybrid Electric Vehicle. The meaning of *updated conventional vehicle* is the 2018 version of the model the consumers currently own. The economic and carbon implications of purchasing an ETV by comparing the ETV with the updated conventional vehicle are then assessed.

The NHTS collects vehicle attributes and use characteristics for households in the national sample. To calculate marginal abatement cost of each electric technology vehicle (HEV or BEV or PHEV), we need total cost of ownership (indicated by Equation 2-1 in the main text) of an ETV and the amount of emissions saved by a particular ETV. To determine the total cost of ownership we need initial capital cost. The calculations for initial capital costs are dependent on the vehicle's type of propulsion technology (electric vs. plug-in hybrid), class (Sedan vs SUV), make and model (Honda vs Toyota and Civic vs Camry). The dataset includes households' state of residence, used in indicating the resolution of geographical heterogeneity, i.e. determine state-specific electricity emissions, and fuel and electricity prices. The information about the intensity of vehicle use and the lifetime of a particular vehicle is a source of behavioral heterogeneity. The vehicles differ from each other in terms of make, model, and type of a vehicle (source of stock heterogeneity), which we have considered in our model. The following section explains how we generate the technology variants for each vehicle class.

2.5.1 Defining Consumer Vehicle Options for Internal Combustion Engine and Electric Technology Vehicles

The current vehicle market does not offer ETV analogues for every available model. With this said, the suite of available ETV models is expanding rapidly. For example, there were 11 new ETV models offered in 2018 compared to 2017(U.S.-EPA 2018c). This evolving market presents a challenge for modeling ETV adoption. Considering only currently available ETVs would properly reflect today's options but would misrepresent choices even a few years later. Thus, this work assumes a developed ETV market in which there is a reasonable analogue ETV option for any current vehicle model. Therefore, ETV choice is modeled as a differential technology "upgrade" to currently sold conventional vehicles. This leads to modeling incremental cost additions of each technology type (HEV or BEV or PHEV) for each vehicle class (compact, sedan, SUV, van and truck). Using prior models of ETV characteristics and costs(U.S.-EPA 2018a; www.AAA.com 2018; CNG-Now 2018; GasBuddy.com 2017), technical and performance specifications are designed and *additional costs* for ETVs are estimated based on a model conventional vehicle for each vehicle class.

The NHTS dataset contains information on the make, model and type of each vehicle in the sampled vehicle fleet. We use this information to estimate the initial capital cost and mileage. If consumers decide to switch and adopt a more energy efficient vehicle, assuming the consumers stay consistent, meaning the consumers stick to their current class type, make and model, they face four options: 1. Latest Conventional Vehicle, 2. Hybrid Engine Vehicle, 3. Battery Electric Vehicle and 4. Plug-in Hybrid Electric Vehicle. Currently, in the market, we do not have hybrid, battery electric and plug-in hybrid technology variants for every vehicle type, make and model in the NHTS vehicle fleet. For example, we do not have a battery electric truck or a battery electric Dodge Charger available in the real-world market. Therefore, we calculate the cost of the technology in addition to the price of its conventional variant. For example, in case of Dodge Charger, we calculate how much additional amount a particular consumer has to pay in get a HEV or BEV or PHEV variant which will have a comparable performance as that of a sedan (as Dodge Charger is a sedan).

We first identify make, model and fuel type of each vehicle in the dataset. For miles per gallon (or fuel efficiency), we have compiled a list of highest selling vehicles in the U.S. (added in the supplementary Excel sheet) with respect to vehicle types (Car, Van/Minivan, SUV, Truck) (GoodCarBadCar.net 2018). This list has the number of units sold for a particular vehicle make and model for 2017. The detailed vehicle list is attached in the supplementary information Excel sheet. The recent fuel efficiencies (miles per gallon) for each of these vehicles are taken from the U.S. Environmental Protection Agency (EPA) (U.S.-EPA 2018c). These mileages are for new Internal Combustion Engine (ICE) vehicles. We match each NHTS observation (i.e. make and model) with its corresponding U.S. EPA rated mileage. So that we can compare the electric technology vehicles with the latest conventional vehicles. For models which are not on this EPA list of highest-selling vehicles (for example, Jaguar XF), we have assigned a generic mileage for each vehicle type which is calculated as a weighted average of the number of units sold and mileage of highest sold vehicles.

For technical specifications and performance characteristics by vehicle type—sedan, SUV, van/minivan/station wagon, pickup truck, we have also generated non-existing technology variants. The power and performance characteristics of base conventional vehicles are assumed to be similar to vehicles with high market shares—for example, Toyota Camry (Toyota 2018a), Honda CRV (Honda 2018a), Toyota RAV4 (Toyota 2018b), Honda Odyssey (Honda 2018b), Ford 150 (Ford 2018). **Error! Reference source not found.** shows the technical specifications (power and battery capacity) and performance characteristics (miles per gallon or miles per charge) of the technology variants. The gasoline mileage (mpg) for hybrid and plug-in hybrid are assumed to be 27.5% more efficient than the conventional versions (Kromer and Heywood 2007b, 2007a). The electric mileages (miles per charge) are assumed and calculated as the average mileage for available electric (3.71 miles per kWh) and plug-in electric vehicles (3.14 miles per kWh) in the market (the calculations are shown in supplementary Excel sheet). For each vehicle class, we assume the battery efficiency drops as much as their conventional counterparts' fuel efficiency drops. For example, if the gasoline mileage drops by 21% from a sedan (32 miles per gallon i.e. mileage of a generic sedan) to an SUV (25.4 miles per gallon i.e. mileage of a generic SUV), then for electric variants the electric efficiency also drops by 21% from sedan (3.71 miles per kWh) to a SUV (2.95 miles per kWh). As the BEVs in the market have wide ranges (miles per charge or full battery capacity), we have modeled two BEV versions for each vehicle type with 100- and 150-mile ranges. The consumers who drive more than 150 miles daily—assumed maximum range of BEV—would have only HEV and PHEV technologies available to feasibly choose from.

Table 2-1 Technical Specifications and Performance Characteristics of Non-existing Technology Variants (Kromer and Heywood 2007b, 2007a; N.R.C. 2013b, 2013a).

		Technical Specifications				Performance	
Vehicle Type	**Technology**	**Battery Capacity (kWh)**	**ICE Power (kW)**	**Electric Motor (kW)**	**Total Power (kW)**	**Mileage (miles per gallon)**	**Range (miles per charge or full battery capacity)**
Sedan	CONVENTIONAL		131		131	34	
Sedan	HEV	1	102	29	131	43	
Sedan (Short Range)	BEV-100	27		131	131		100
Sedan (Long Range)	BEV-150	40		131	131		150
Sedan	PHEV-40	13	85	46	131	43	40
SUV	CONVENTIONAL		142		142	30	
SUV	HEV	1.5	111	31	142	38	
SUV (Short Range)	BEV-100	34		142	142		100
SUV (Long Range)	BEV-150	51		142	142		150
SUV	PHEV-40	16	92	50	142	38	40
Van/Minivan/ Station Wagon	CONVENTIONAL		209		209	22	
Van/Minivan/ Station Wagon	HEV	1.5	163	46	209	28	
Van/Minivan/ Station Wagon (Short Range)	BEV-100	40		209	209		100
Van/Minivan/ Station Wagon (Long Range)	BEV-150	60		209	209		150
Van/Minivan/ Station Wagon	PHEV-40	19	136	73	209	28	40
Truck	CONVENTIONAL		243		243	18	
Truck	HEV	1.5	190	53	243	23	
Truck (Short Range)	BEV-100	42		243	243		100
Truck (Long Range)	BEV-150	62		243	243		150
Truck	PHEV-40	20	158	85	243	23	40

2.5.2 Total Cost of Ownership

The current vehicle market does not offer ETV analogues for every available model. With this said, the suite of available ETV models is expanding rapidly. For example, there were 11 new ETV models offered in 2018 compared to 2017(U.S.-EPA 2018c). This evolving market presents a challenge for modeling ETV adoption. Considering only currently available ETVs would properly reflect today's options but would misrepresent choices even a few years later. Thus, this work assumes a developed ETV market in which there is a reasonable analogue ETV option for any current vehicle model. Therefore, ETV choice is modeled as a differential technology "upgrade" to currently sold conventional vehicles. This leads to modeling incremental cost additions of each technology type (HEV or BEV or PHEV) for each vehicle class (compact, sedan, SUV, van and truck). Using prior models of ETV characteristics and costs(U.S.-EPA 2018a; www.AAA.com 2018; CNG-Now 2018; GasBuddy.com 2017), technical and performance specifications are designed and *additional costs* for ETVs are estimated based on a model conventional vehicle for each vehicle class. The cost model accounts for batteries, other electric vehicle (EV) systems such as electric motor, transmission and integration, control unit, onboard charging unit, regenerative breaking, and wiring as well as credits for removing mechanical components of internal combustion engines for EVs. The battery cost and electric motor costs are scaled with respect to the battery size and power requirements for each vehicle type, and are based on the International Council on Clean Transportation (ICCT) report(Wolfram and Lutsey 2016). In addition to capital costs, an industry markup factor of 1.46 is assumed for all vehicle components (Rogozhin et al. 2010). BEV range is limited and must be accounted for in designing vehicles and their use by consumers. Given the wide ranges in miles per charge, two BEV versions are considered for each vehicle type, with 100 and 150 miles of range. Consumers who drive more than 150 miles daily may only choose HEV and PHEV technologies. For PHEVs, it is assumed that a consumer will first operate on electricity until the battery is drained and then switch to gasoline.

The TCO contains initial capital cost, discounted fuel savings, discounted battery replacement cost (for BEV and PHEV), and discounted salvage value (shown in Equation 2-1). A discount rate of 7% is assumed for this work. It is common to use 7% as the discount rate in total cost of ownership calculations (Miotti et al. 2016; Gilmore and Lave 2013; Al-Alawi and Bradley 2013; O'Keefe, M; Brooker, A; Johnson, C; Mendelsohn, M; Neubauer, J; Pesaran 2010; Lipman and Delucchi 2006; Breetz and Salon 2018). Moreover, the discount rate of 7% is also suggested by the Office of Management and Budget (Weis, Jaramillo, and Michalek 2014; US-OMB (The Office of Managment and Budget) 2017). The duration of car ownership for each consumer is calculated. Note that the duration of car ownership varies (also shows the behavioral heterogeneity) by consumer (7 years average with standard deviation of 3.6 years). Duration determines the vehicle lifetimes used in calculating total cost of ownership and the salvage value.

$$\begin{aligned} &Total\ Cost\ of\ Ownership \\ &\quad = Initial\ Capital\ Cost\ - Discounted\ Fuel\ Savings \\ &\quad + Discounted\ Battery\ Replacement\ Cost \\ &\quad - Discounted\ Salvage\ Value \end{aligned}$$

Equation 2-1

Once the total cost of ownership is calculated for each ETV in comparison with a conventional vehicle, a *least total cost to the consumer* (i.e. the highest Net Present Value) option (preferred technology) is selected for a particular consumer.

2.5.2.1 Capital Cost

For BEVs and PHEVs, the initial capital cost includes battery price as well as other electric vehicle (EV) systems such as electric motor, transmission and integration, control unit, onboard charging unit, regenerative breaking, and wiring as well as credits for removing mechanical components of internal combustion engines. The battery cost and electric motor costs are scaled with respect to the battery size and power requirements for each vehicle type. The battery cell cost is calculated using the International Council on Clean Transportation (ICCT) report (Wolfram and Lutsey 2016), and is used to calculate the total battery cost (as shown in Equation 2-2).

$$Total\ Battery\ Cost\ (\$) = \$\ 2014 + Battery\ Capacity\ (kWh)\ \times \$\ 233\ per\ kWh \quad \text{Equation 2-2}$$

HEVs have similar components as that of PHEVs except for the onboard charging unit and the costs of battery and electric motor are lower. The initial capital costs are, thus, calculated as additional costs of the technology over a similar conventional internal combustion engine vehicle. The cost model is build using a Massachusetts Institute of Technology report (Kromer and Heywood 2007b, 2007a) and a National Research Council report (N.R.C. 2013b, 2013a). In addition to the costs of components, the industry markup factor of 1.46 is assumed for all vehicles (Rogozhin et al. 2010).

Table 2-2 Total Incremental Cost for the Non-existing Technology Variants with Technical Specifications as shown in Table 2-1

		Total Incremental Capital Cost ($)											
Vehicle Type	Technology	Total Battery Cost ($)	Battery Cell Costs ($)	Total Motor System Cost ($)	Other EV Systems ($)	Hybrid transmission and Integration ($)	Wiring ($)	EV Transmission ($)	ICE engine credit ($) for conventional starter and alternator	ICE Credit ($) for downsizing	ICE Credit ($)	Total Cost ($)	With Markup Factor ($)
Sedan	CONVENTIONAL												
Sedan	HEV	2248	233	1065	495	364	243		-121	-139		4155	6066
Sedan (Short Range)	BEV-100	8302	6287	3521	940		243	344			-3887	9462	13815
Sedan (Long Range)	BEV-150	11445	9431	3521	940		243	344			-3887	12606	18405
Sedan	PHEV-40	4989	2974	1319	940	364	243		-121	-277		7455	10885
SUV	CONVENTIONAL												
SUV	HEV	2364	350	1121	495	364	243		-121	-150		4316	6302
SUV (Short Range)	BEV-100	9930	7916	3790	940		243	344			-3887	11360	16586
SUV (Long Range)	BEV-150	13888	11874	3790	940		243	344			-3887	15318	22365
SUV	PHEV-40	5759	3745	1413	940	364	243		-121	-299		8298	12115
Van/Minivan/ Station Wagon	CONVENTIONAL												
Van/Minivan/ Station Wagon	HEV	2364	350	1479	495	364	243		-121	-220		4604	6722
Van/Minivan/ Station Wagon (Short Range)	BEV-100	11398	9383	5522	940		243	344			-3887	14560	21258
Van/Minivan/ Station Wagon (Long Range)	BEV-150	16090	14075	5522	940		243	344			-3887	19252	28108
Van/Minivan/ Station Wagon	PHEV-40	6453	4439	2019	940	364	243		-121	-441		9457	13807
Truck	CONVENTIONAL												
Truck	HEV	2364	350	1662	495	364	243		-121	-256		4750	6936
Truck (Short Range)	BEV-100	11700	9686	6405	940		243	344			-3887	15745	22988
Truck (Long Range)	BEV-150	16543	14529	6405	940		243	344			-3887	20588	30059
Truck	PHEV-40	6596	4582	2328	940	364	243		-121	-513		9837	14362

2.5.2.2 Calculation of Expected Duration of Ownership

After the initial capital cost, we calculate the expected duration of ownership. A lifetime of a vehicle differs from the expected duration of ownership because different consumers use their vehicles for a different number of years before switching and/or selling vehicles. The NHTS provides the number of months a vehicle owned. We use these observed durations to generate a distribution for how long owners have currently owned their vehicle. This duration differs from the actual duration of ownership before vehicle disposal or retirement.

The survival rate is calculated for each year i.e. the percentage of vehicles using their vehicle past the respective year, conditional upon the consumers have used their vehicles until that year (i.e. how long they have currently owned their vehicle).

The survivor function is shown in Equation 2-3, n_j is the number of consumers using their vehicles past duration t_j, and $h_j$is the number of consumers who sold their vehicles in the duration t_j. It is estimated by setting the estimated conditional probability of using the vehicle past t_j equal to the observed relative frequency of completion at t_j. The distribution is shown in **Error! Reference source not found.** and it depicts how frequently the consumers replace their vehicles.

$$\hat{S}(t_j) = \prod_{j=1}^{j} (n_j - h_j)/n_j \qquad \text{Equation 2-3}$$

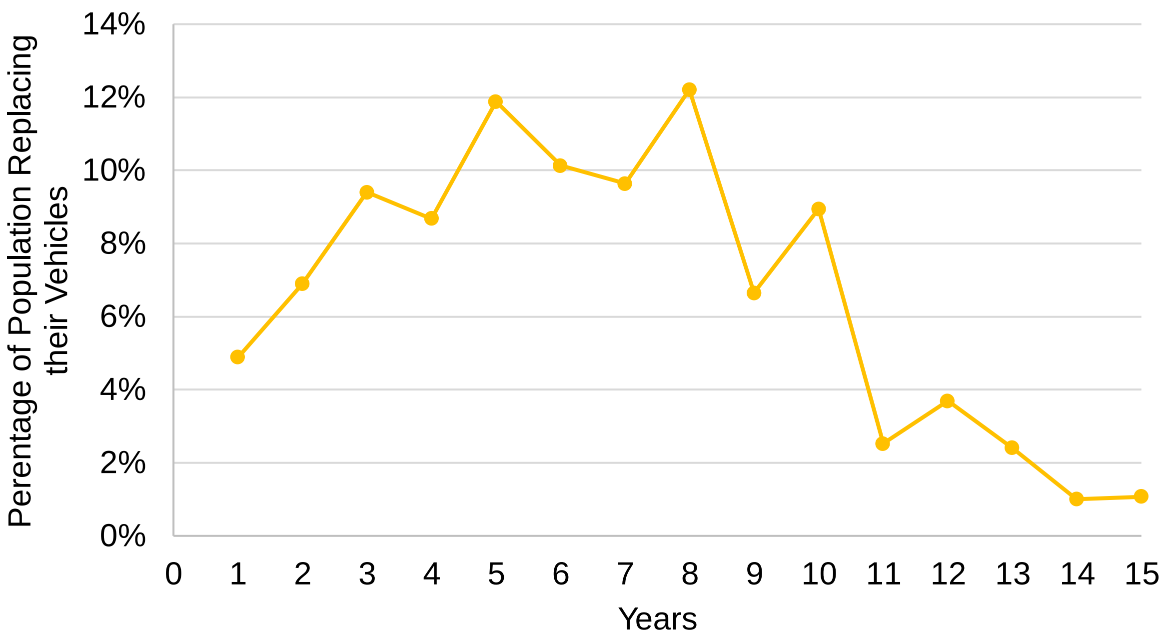


Figure 2-2: Distribution of Population Replacing their Vehicles after a given number of years

To calculate the expected duration of ownership (n), given a consumer has used their vehicle for 'x' number of years, we build the new distribution with the remaining probabilities by determining the conditional survival probability given that the vehicle own year (currently owned duration) is not complete, assuming the maximum lifetime is assumed to be fifteen years.

2.5.2.3 Salvage Value

The Salvage Value is a value of a vehicle in a used car market at the end of the expected duration of ownership. It is estimated as a function of years of ownership. Raustad has generated an equation to estimate depreciation percentage (is shown in Figure 2-3) as a function (With R^2=0.9997) of years of ownership of the vehicles (Raustad 2017). The author has collected data from Edmunds.com for several makes and models. The equation to calculate the depreciation percentage is as shown in Equation 2-4. The consumer receives the salvage value at the end of expected duration of ownership (n), therefore, we have accounted it as the present value of future money, as shown in Equation 2-6.

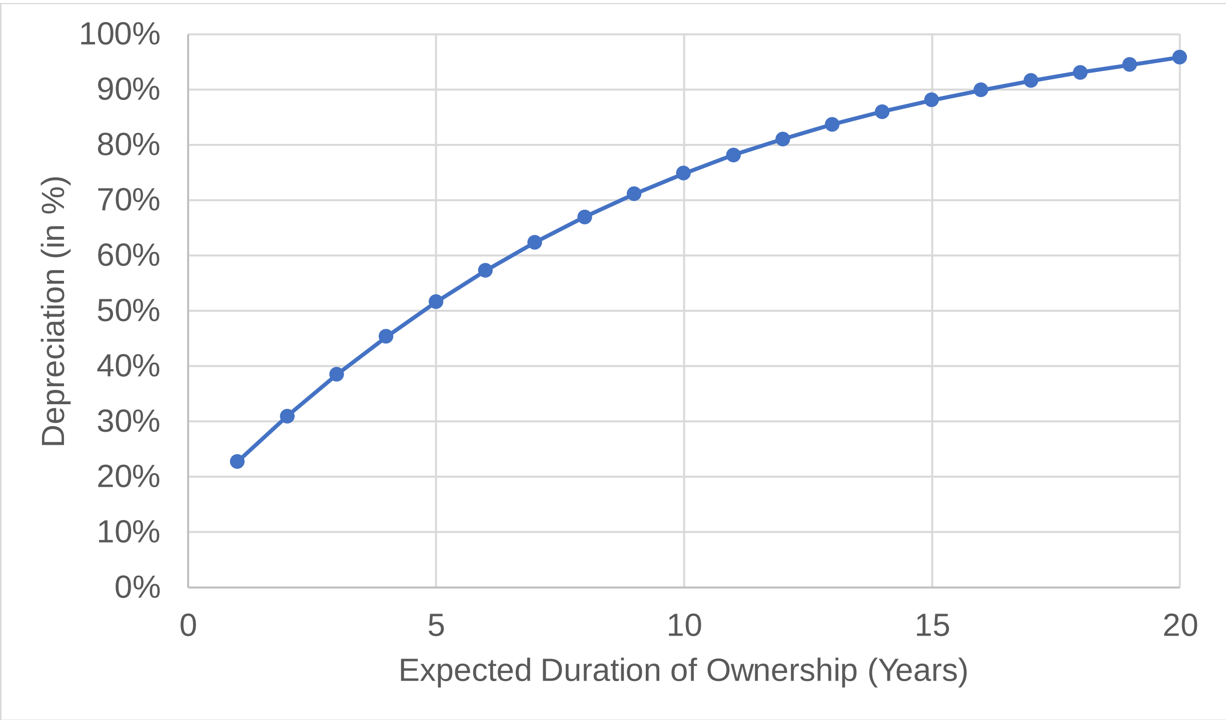


Figure 2-3: Depreciation Percentage at a function of Expected Duration of Ownership (Years)

$$\begin{aligned}&\mathit{Depreciation\ Percentage}\\&\quad = (6 \times 10^{-5})\, n^3 - (0.0038)n^2 + (0.093)\, n + 0.1384\end{aligned} \quad \text{Equation 2-4}$$

$$\begin{aligned}&\mathit{Salvage\ Value\ of\ a\ vehicle}\ (\$)\\&\quad = \mathit{Depreciation\ Percentage} \times \mathit{Initial\ Capital\ Cost}(\$)\end{aligned} \quad \text{Equation 2-5}$$

$$\begin{aligned}&\mathit{Discounted\ Salvage\ Value\ at\ the\ end\ of\ duration\ of\ ownership}\\&\quad = \mathit{Salvage\ Value\ of\ a\ vehicle} \times (1 + r)^{-n}\end{aligned} \quad \text{Equation 2-6}$$

2.5.2.4 Battery Replacement Cost

For BEVs and PHEVs, a battery replacement cost at the end of life, and life of the battery is estimated as a function of number of charging-discharging cycles and depth of discharge (Wood, Alexander, and Bradley 2011; Raustad 2017). The battery lifetime is calculated as shown in Equation 2-7 and Equation 2-8**Error! Reference source not found.**. E. Wood *et al.* calculated the power level of 70% of the peak power can be achieved with the depth of discharge of 80%

and charging-discharging cycles of 3,500 (Wood, Alexander, and Bradley 2011). Therefore, to calculate battery lifetime, we assume the depth of discharge 80%, and 3,500 charging-discharging cycles. Thus, for example, the battery of 27 kWh with efficiency 3.71 miles per kWh, depth of discharge 80%, and 3,500 charging-discharging cycles can provide 280,476 miles in its lifetime, and with 18,000 annual miles, the battery life would be 15.6 years. Using this battery lifetime, the discounted battery replacement cost is calculated. For the consumers who have battery lifetime more than the expected duration of ownership, and when these consumers sell their vehicles and the buyer of this used vehicle would need to replace the degraded battery shortly after. Therefore, to compensate for this battery use, we consider that the previous owner still pays for the battery replacement. To account for this cost, we reduce the discounted salvage value by the amount the consumer would have paid to replace the battery by saving annually until the end of the expected duration of ownership.

$$\begin{aligned} &Maximum\ Miles\ in\ battery's\ lifetime\ (miles) \\ &\quad = Battery\ Capacity\ (kWh) \\ &\quad \times Battery\ Efficiency\ (miles\ per\ kWh) \\ &\quad \times\ Depth\ of\ Discharge\ (80\%) \\ &\quad \times No.of\ Charging\ Discharging\ Cycles\ (3500) \end{aligned} \qquad \text{Equation 2-7}$$

$$Battery\ Lifetime\ (\ years) = \frac{Maximum\ Miles\ in\ battery's\ lifetime}{Annual\ Miles} \qquad \text{Equation 2-8}$$

Finally, we calculate the discounted fuel savings. The first step of calculating the fuel savings is to identify the fuel and electricity costs for each consumer. Using the household's State of residency, each observation is assigned electricity emissions per kWh (of generation) from the U.S. Energy Information Agency (U.S.-EIA 2018b) as well as the conventional fuel prices (www.AAA.com 2018; CNG-Now 2018; GasBuddy.com 2017). As all the calculations are done in comparison with the conventional vehicle, first annual fuel costs of conventional vehicles are calculated (Equation 2-9). Then the fuel costs of each of the technology variant are calculated for each vehicle type. The fuel costs for HEVs are calculated like that of a conventional vehicle (Equation 2-10). For BEVs, first the annual electricity consumption is calculated using the maximum range of the vehicle and then the cost of electricity consumption (i.e. the fuel cost) is calculated (Equation 2-11). For PHEVs, the fuel costs are calculated similar to that of BEVs, and it is assumed that the consumer first uses the electric energy and once the battery runs out (i.e. maximum range of PHEV) the vehicle is run on gasoline (Equation 2-12). The annual fuel savings are calculated for each of the technology variants (Equation 2-13) and then converted to discounted fuel savings (present value of annuity) for the total expected duration of ownership (Equation *2-14*). All these cost components are discounted at an assumed discount rate (r) of 7%. For each consumer, we select *the least total cost to the consumers* (i.e. the highest Net Present Value) electric technology vehicle. The annualized Costs are shown in Figure 2-5 as negative annualized Net Present Value.

$$\begin{aligned} &Fuel\ Cost\ for\ Conventional\ Vehicles\ (\$) \\ &\quad = \frac{Annual\ Miles}{Mileage\ (miles\ per\ gallon)} \times Fuel\ Price\ (\$/gallon) \end{aligned} \qquad \text{Equation 2-9}$$

$$Fuel\ Cost\ for\ HEVs\ (\$) = \frac{Annual\ Miles}{Mileage\ (miles\ per\ gallon)} \times Fuel\ Price\ (\$/gallon) \quad \text{Equation 2-10}$$

$$Fuel\ Cost\ for\ BEVs\ (\$) = \frac{Annual\ Miles}{Electric\ Mileage\ (miles\ per\ kWh)} \times Fuel\ Price\ (\$/kWh) \quad \text{Equation 2-11}$$

$$Fuel\ Cost\ for\ PHEVs\ (\$) = \left[\begin{array}{c} \frac{Range\ of\ PHEV\ (miles)}{Electric\ Mileage\ (miles\ per\ kWh)} \times Fuel\ Price\ (\$/kWh) \\ + \frac{(Annual\ Miles/365\ -\ Range\ of\ PHEV)}{Mileage\ (miles\ per\ gallon)} \times Fuel\ Price\ (\$/gallon) \end{array}\right] \times 365 \quad \text{Equation 2-12}$$

$$Annual\ Fuel\ Savings\ (\$) = Fuel\ Cost\ of\ conventional\ vehicles(\$) - Fuel\ Cost\ of\ Electric\ Technology\ Vehicle(\$) \quad \text{Equation 2-13}$$

$$Discounted\ Fuel\ Savings\ (\$) = Annual\ Fuel\ Savings\ \times \left[\frac{1-(1+r)^{-n}}{r}\right] \quad \text{Equation 2-14}$$

2.5.3 Emissions Savings

After selecting the least total cost to the consumer technology (or a preferred technology), we calculate the annual emissions saved by the respective electric technology vehicle. For conventional vehicles and HEVs, the emissions saved are calculated using the amount of fuel consumed (Equation 2-15-Equation 2-16).

$$Emissions\ for\ conventional\ vehicle\ (kgCO_2e) = \frac{Annual\ Miles}{Mileage\ (miles\ pergallon)} \times Emissions\ per\ gallon\ (kgCO_2e/gallon\ of\ fuel) \quad \text{Equation 2-15}$$

$$Emissions\ for\ HEV\ (kgCO_2e) = \frac{Annual\ Miles}{Mileage_{HEV}\ (miles\ pergallon)} \times Emissions\ per\ gallon\ (kgCO_2e/gallon\ of\ fuel) \quad \text{Equation 2-16}$$

To calculate emissions savings from BEVs and PHEVs, we first assign emissions for generating 1 kWh of electricity to each observation as per the household state. The electricity emissions are sourced from the Emissions & Generation Resource Integrated Database (eGRID) (U.S.-EPA 2018a). These emissions are average emission rates as specified by eGRID in the year 2014. For BEVs, the electric efficiency (miles per kWh) and annual miles driven are used to calculate the annual electricity consumption. Then using the electricity emissions (kgCO_2e per kWh) for generating 1 kWh in the respective state—assuming the consumers charge their vehicle in the state of their residence—are used to calculate the total annual emissions (Equation 2-17).

$$Emissions\ for\ BEV\ (kgCO_2e) = \frac{Annual\ Miles}{Electric\ Mileage\ (miles\ per\ kWh)} \times Emissions\ per\ kWh\ for\ the\ respective\ state\ (kgCO_2e/kWh)$$

Equation 2-17

For PHEVs, the emissions from electricity consumption are calculated in a similar fashion as that of BEVs. The emissions from gasoline consumption are calculated similar to that of HEVs, as shown in Equation 2-18. First using the battery range (as we assume consumers will use PHEVs on electricity first), we calculate the electricity consumption, followed by the emissions from electricity consumption. As the remaining daily miles are expected to be driven using gasoline, the rest of the emissions are calculated for consuming gasoline.

$$Emissions\ for\ PHEV\ (kgCO_2e) = \left[\frac{Range\ of\ PHEV\ (miles)}{Electric\ Mileage\ (miles\ per\ kWh)} \times \left(\frac{kgCO_2e}{kWh}\right)_{for\ respective\ state} + \frac{(Annual\ Miles/365\ -\ Range\ of\ PHEV)}{Mileage_{PHEV}\ (miles\ per\ gallon)} \times (kgCO_2e/gallon\ of\ fuel) \right] \times 365$$

Equation 2-18

The annual fuel savings are calculated using the emissions of conventional vehicle and emissions from an Electric Technology Vehicle. For the preferred technology then we calculate the total emissions saved over the expected duration of ownership.

$$Annual\ Emissions\ Savings\ (kgCO_2e) = Emissions\ for\ Conventional\ Vehicle - Emissions\ for\ Electric\ Technology\ Vehicle$$

Equation 2-19

To calculate carbon marginal abatement costs, we use the Total Cost of Ownership and the Total Emissions Saved over the expected duration of ownership.

The carbon marginal abatement costs (US$ per MTCO_2e, shown in Equation 2-20) are calculated for the preferred technology options.

$$Carbon\ Marginal\ Abatement\ Cost\ (US\$/MT\ CO_2e) = \frac{Total\ discounted\ cost\ of\ a\ technology\ (US\$)}{Total\ emissions\ savings\ by\ the\ respective\ technology\ (MT\ CO_2e)}$$

Equation 2-20

2.6 *Results and Discussion*

The first set of outputs produces distributions of economic and carbon implications of electric technology vehicle adoption. Summary results of this analysis are shown in Figure 2-4. Annualized cost includes amortized purchase cost, fuel expenses (gasoline and electricity), battery replacement and resale value when the vehicle is replaced. Annual emissions savings are calculated by assuming the vehicle is driven in the state of purchase, subtracting the emissions from gasoline used in a conventional vehicle from emissions due to electricity consumed by the electric technology vehicle (and gasoline for hybrid and PHEV models). The model assumes the consumer chooses between hybrid, electric or plug-in hybrid depending on which has the lowest annualized costs.

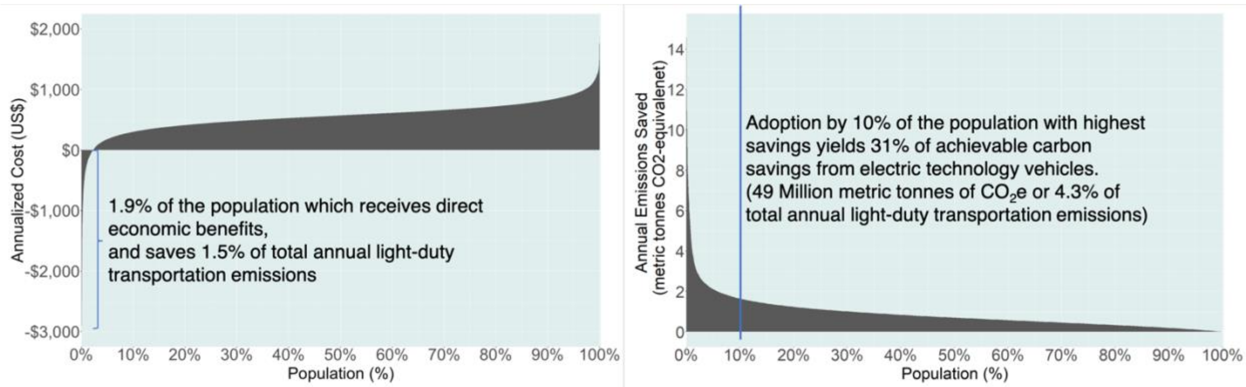


Figure 2-4: Unsubsidized Annualized Cost (US$/year) and Annual Emissions Saved (MT CO_2e) from switching from conventional to an electric technology vehicle, per vehicle owned by U.S. consumers, ordered from lowest to highest cost (highest to lowest emissions savings). The left figure shows that 1.9% of the population, having negative annualized costs, directly benefits financially. The right image shows how annual emissions savings vary by person, driven primarily by heterogeneity in annual mileage.

Following these results, this work calculates the Carbon Marginal Abatement Cost Curve, as shown in Figure 2-5. It shows the total amount of carbon mitigated (x-axis) if every consumer in the U.S. replaces their current vehicle with the electric technology vehicle (HEV, BEV, PHEV) that has the lowest discounted total cost to the consumer. It can be seen that most consumers currently prefer hybrids over BEV and PHEV if forced to switch from a conventional internal combustion vehicle. This work refers to the amount of carbon mitigated by the consumers with the negative carbon mitigation costs (and hence net emissions savings from the adoption of the preferred electric technology vehicle) as “Free Carbon”.

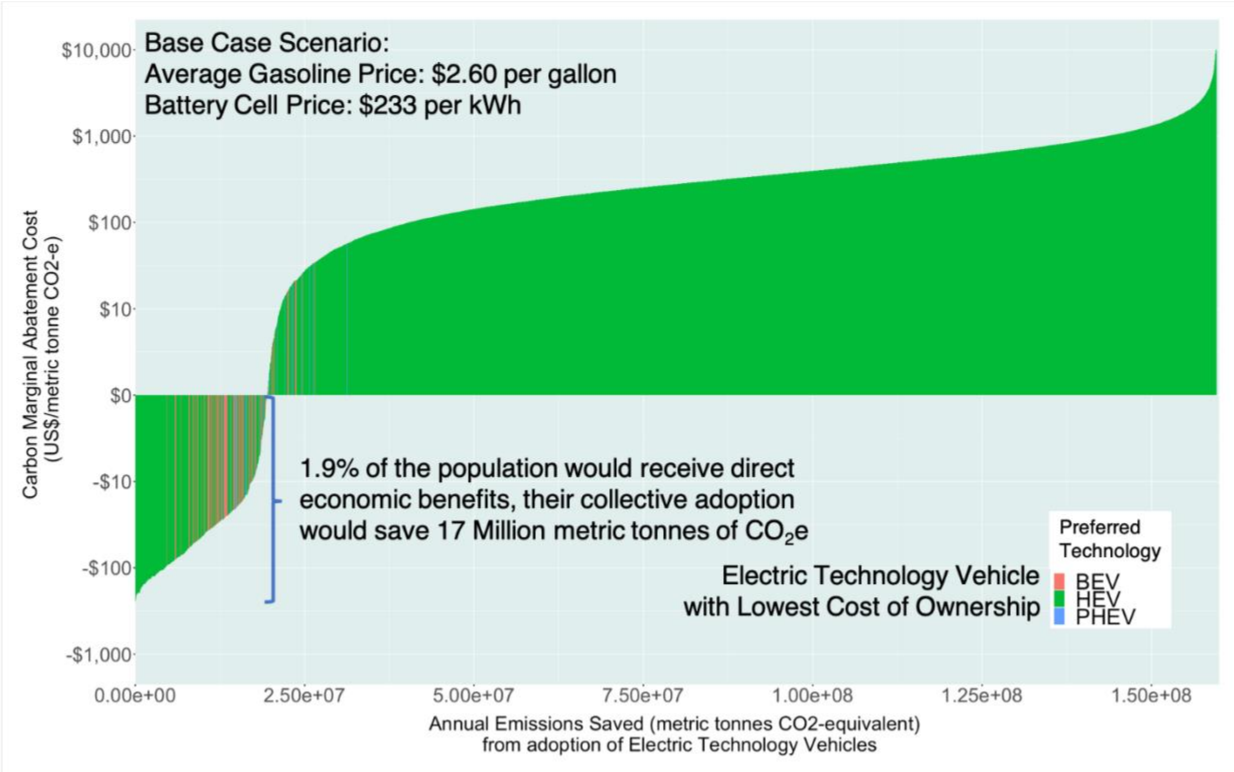


Figure 2-5: Carbon Marginal Abatement Cost Curve (MACC) for electric technology vehicles (ETV) with current prices and no subsidy (base case scenario). The figure shows a series of narrow rectangles, ordered from lowest to highest height, with log scale. Each rectangle height is the cost of abatement of one metric tonne (MT) of CO_2e for a response from the National Household Travel Survey (depends on household weight, typically 680). Negative marginal cost represents consumers who financially benefit (save money) from buying an electric technology vehicle. The width of each rectangle is the amount of carbon emissions saved in a year from this household class switching to its least cost electric technology vehicle, the total width reflects every personal vehicle in the U.S. being replaced by an ETV. Note that this base case scenario does not account for current federal tax credits for PHEV and EV of up to US$ 7,500 or state/local subsidies. (BEV: Battery Electric Vehicle, HEV: Hybrid Engine Vehicle, PHEV: Plug-in Hybrid Electric Vehicle).

A relatively small population, 1.9% of all drivers with very high annual mileage, benefits economically from electric technology vehicles, mainly hybrids. The estimated 'free carbon' in the base case scenario is 17 Million Metric Tonnes (MMT) CO_2e or 1.5% of the total light-duty transportation emissions in the U.S. To provide context for this figure, this work estimates that switching the entire U.S. vehicle fleet to BEVs and PHEVs would decrease light-duty vehicle emissions in the U.S. by 30%, assuming current electricity generation mixes around the country. Figure 2-5 shows the carbon abatement costs and corresponding annual emissions if the current fleet were replaced with a preferred electric technology vehicle with the least total cost of ownership. Only 1.9% of the population receives direct financial benefits and the 10% of the population in terms of emissions savings can potentially save over 49 MMT (i.e. 4.3% of the total light-duty transportation emissions) by moving to the cost-effective electric technology vehicle. As shown on x-axis Figure 2-5, if the entire U.S. fleet were replaced with the cost-effective electric technology vehicle, 159 MMT emissions can be saved (1.5% of total emissions).

The consumers who directly benefit financially have an average carbon abatement cost of -$49 per $MTCO_2e$ with an average annual mileage of 48,750 miles, compared to the consumers who do not save money, who have an average abatement cost of $5,130 per $MTCO_2e$ and drive an average of 10,856 miles annually. Large savings on fuel consumption by the first group enables these consumers to recover their high initial capital costs. Note that the average U.S. consumer drives 11,700 miles annually, thus consumers getting financial benefits from an ETV drive over four times the national average.

The MACC in Figure 2-5 is constructed with 2017 fuel and technology prices. However, these prices are expected to change with time. Therefore, two alternative scenarios are examined: (i) First, a doubled fuel price scenario, and (ii) a second scenario with 75% decrease in battery cell prices (i.e. \$58 per kWh, down from \$233 per kWh). Figure 2-6 shows the MACC with current technology prices, but fuel prices are doubled (average fuel price \$5.20 per gallon) compared to the base case scenario (average fuel price \$2.60 per gallon). As the fuel prices increase, the consumers are better off buying more expensive BEV or PHEV choices, as they recover these initial high capital costs through savings in fuel consumption. It can be seen that the technology of choice switches to BEV or PHEV instead of HEV (relative to base case scenario) due to electricity being a cheaper fuel. HEVs are still the best ETV choice for drivers with low mileage (lowest capital costs), who are generally on the right side of the figure. Abatement costs are as low as -\$10,000 per $MTCO_2e$. Note that abatement cost is a ratio, so large magnitudes can come from a large numerator, a small denominator, or both. For example, a consumer who saves \$2,870 annually by purchasing a BEV with a carbon reduction of only 0.28 $MTCO_2e$ has an abatement cost of -\$10,200 per $MTCO_2e$.

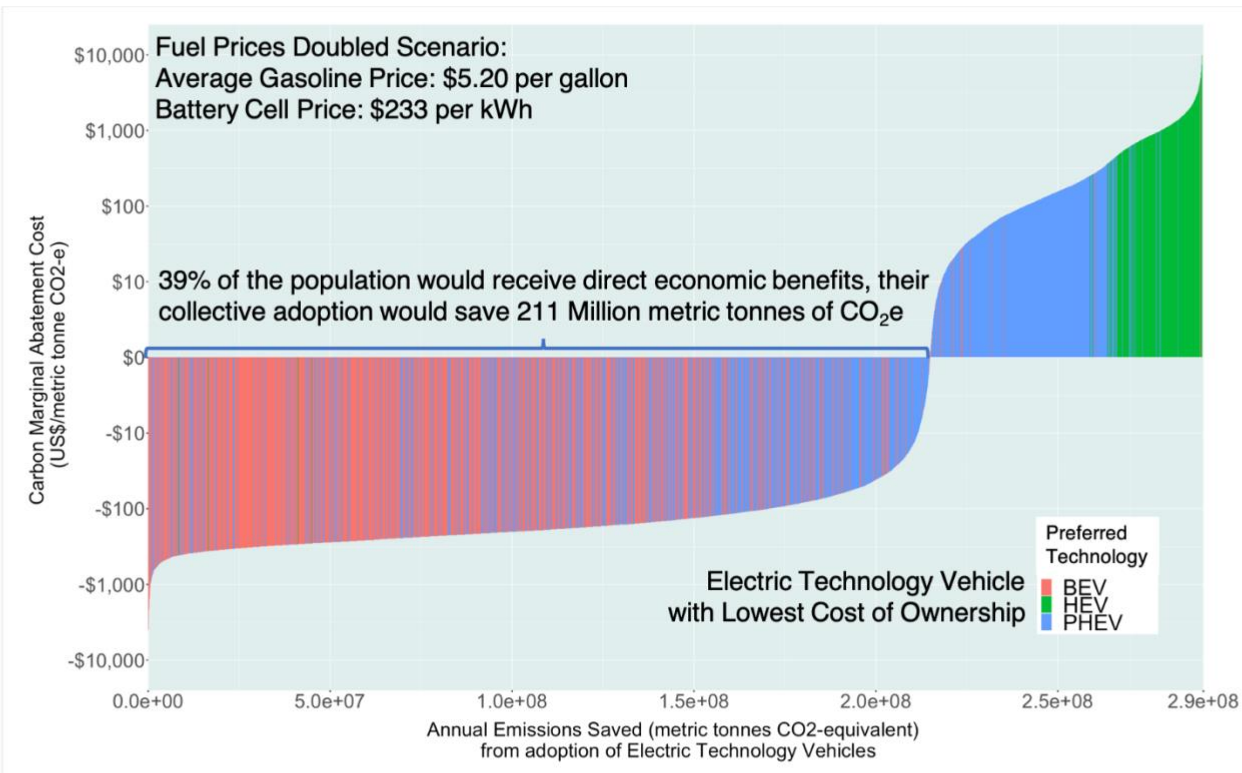


Figure 2-6: Carbon Marginal Abatement Cost Curve (MACC) for electric technology vehicles with doubled gasoline price (\$5.20 per gallon) and current electric technology vehicle prices. Adoption by the 39% of the population that saves money (negative abatement cost) yields 75% of achievable carbon savings from electric technology vehicles. Note that both axes have different ranges from Figure 2-5. With doubled fuel prices, some consumers save much more, resulting in a wider range on the negative y-axis. BEV and PHEV emerge as more often preferred compared to the base case (current fuel and technology prices, no subsidy), their adoption resulting in larger carbon savings (x-axis scale increase) compared to HEV dominated adoption in Figure 2-5. (BEV: Battery Electric Vehicle, HEV: Hybrid Engine Vehicle, PHEV: Plug-in Hybrid Electric Vehicle)

In the doubled fuel price scenario (average fuel price \$5.20 per gallon), the number of consumers benefitting from electric technology vehicles grows to a 39% share. The “free carbon” is 211 Million $MTCO_2e$ or 18.5 % of total light-duty transportation emissions. The consumers who benefit financially drive an average of 19,008 miles annually, and the consumers who do not benefit financially drive about 63% less (6,898 miles annually). The average mileage of consumers who benefit financially from ETVs (19,008 miles) is now much closer to the national annual average mileage of 11,700. This indicates that the pool of consumers that can benefit from these electric technology vehicles is broadened, from only extremely highly-used vehicles to those with slightly higher than average annual usage. The average carbon abatement costs also change to -$89 per $MTCO_2e$ (relative to -$49 in the base case) for financially benefitting consumers and for the rest of the population respectively.

Figure 2-7 shows the MACC for electric technology vehicles with current fuel price but lower costs for battery cells: $58 per kWh instead of the current $233 per kWh, which represent significant technological progress in battery production. Several estimates project rapidly declining battery cell prices, such as of $125 per kWh by 2022 as per U.S. Department of Energy (DOE)(U.S.-DOE 2017), $125 to $150 per kWh by 2030 as per Union of Concerned Scientists (UCS)(UCS 2017), and $100 per kWh by 2025 as per Bloomberg (Chediak 2017). The modeling here does not account for when these price targets will be achieved instead describes economic and carbon benefits given a future battery cell price. Similar to the fuel price change scenario, consumers move away from hybrid vehicles, but now with a stronger preference for battery electric vehicles (since batteries are cheaper) (Figure 2-6). With decreasing battery cell prices, consumers now save money with both initial capital investment of a pure electric vehicle as well as on fuel.

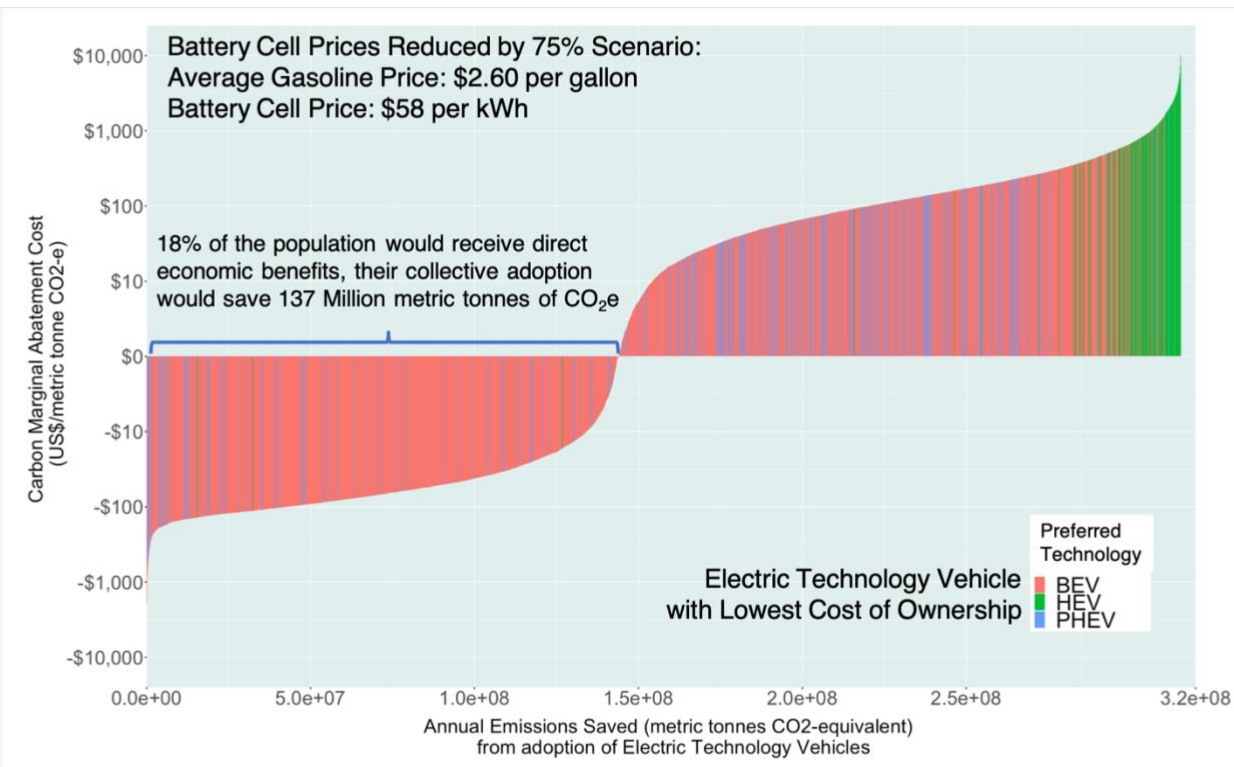


Figure 2-7: Carbon Marginal Abatement Cost Curve (MACC) for electric technology vehicles with current gasoline price and battery cell cost of $58 per kWh (75% of the current battery cell prices of $233 per kWh). Adoption by the 18% of population that benefits financially (negative abatement cost) yields 46% of achievable carbon savings from electric technology vehicles. Note that both axes have different ranges from the base in Figure 2-5 (current fuel and technology prices, no subsidy). Some consumers save much more with lower battery prices, resulting in a wider range on the negative y-axis. BEV and PHEV emerge as more often preferred compared to the base case, their adoption resulting in larger carbon savings (x-axis scale increase) compared to HEV dominated adoption in Figure 2-5. (BEV: Battery Electric Vehicle, HEV: Hybrid Engine Vehicle, PHEV: Plug-in Hybrid Electric Vehicle)

In the decreased battery cell price scenario, about 18% of the population benefits financially from ETVs, compared to 1.9% in the base case. The free carbon is 137 Million $MTCO_2e$ or 12% of total light-duty transportation emissions. The consumers who benefit financially drive 24,248 miles annually compared to the rest who do not benefit financially and drive 8,668 miles. The lower battery prices also affect the carbon abatement costs for financially benefitting consumers. In this case, the average carbon abatement costs are -\$55 per $MTCO_2e$ (relative to -\$49 in the base case) for financially benefitting consumers and \$6,800 per $MTCO_2e$ (relative to \$5,130 in the base case) for the rest of the population.

Figure 2-8 shows summary results for Free Carbon for scenarios with different gasoline prices (left side) and lower costs of batteries and other ETV systems (right side). EV systems refers to the electric motor, transmission and integration, control unit, onboard charging unit, regenerative breaking, and wiring. Notably, free carbon accelerates non-linearly with increasing gasoline price and decreasing gasoline price. This is due to an accelerating share of the population that benefits from ETVs with improved economics. To put the battery price scenarios in context, note that DOE reports a battery cell price target of battery cell price target for 2022 of \$125/kWh[20] and the Bloomberg forecasts a cost of \$100/kWh for 2025[22]. Achieving these targets results in substantial increases in free carbon, 55-80 MMT versus 17 MMT today, 3-4 times more carbon benefits compared to today. Note that full adoption of ETVs has potential to save 342 MMT of carbon, considering higher than savings shown in Figure 2-8. This is because the average consumer has yet to benefit economically from ETVs at these technology and gasoline prices.

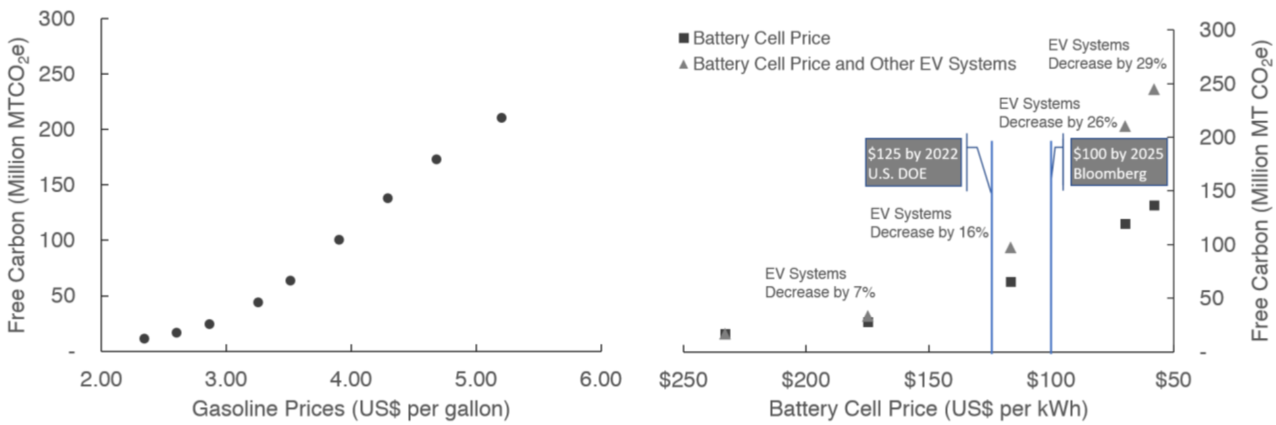


Figure 2-8: Impact of changes in price of gasoline, battery cells and other EV system on annual "free carbon". Free carbon is carbon reduction achieved if all consumers that benefit economically from electric technology vehicles adopt them. As the fuel prices increase, the amount of free carbon saved increases non-linearly. At lower gasoline prices, an increase of 50 cents per gallon saves 13 Million $MTCO_2e$ but the same increase at higher fuel prices saves 38 Million $MTCO_2e$ of emissions. Decreasing battery cell prices have a similar accelerating impact on free carbon. Moreover, if the prices of other EV systems (e.g. electric motors) decrease in step with battery cell prices (but at reduced rate), the amount of free carbon increases significantly and non-linearly. For example, with battery cell price at \$58 per kWh, the free carbon is 137 Million $MTCO_2e$, then combined with an EV systems price decrease of 29%, the free carbon amount increases to 245 Million $MTCO_2e$.

One conclusion to draw from this work is that behavioral and geographic heterogeneity must be included in a proper assessment of the potential of electric technology vehicles to deliver economic and carbon benefits. This work clarifies how accounting for heterogeneity affects results in Table 2-3, which shows the percentage of the population who get direct financial benefits from ETVs and the corresponding amount of free carbon saved if these consumers adopt. If consumer behavior is treated as average (11,700 miles driven year per year) and subsidies are removed, no consumer benefits from ETV purchase. If heterogeneous consumer behavior is considered but geographical heterogeneity is ignored, only 1.6% of the population benefits financially, saving 14 MMT (second row). If all heterogeneities are considered, the base case result returns to 1.9% of the population financially benefiting from ETVs and 17 MMT of free carbon. If current tax credits are included (up to $7,500 for PHEV and EVs) and, only geographical heterogeneity is considered, the percentage of population benefiting increases from 0% to 6%, with a free carbon potential of 33 MMT. Including the federal tax credit and both types of heterogeneity, the percentage of the population who benefits economically more than doubles to 13%, with the potential free carbon savings of 92 MMT. Note these 13% consumers save significantly high emissions compared to 10% population shown in Figure 2-4 as the subsidy provokes the shift in preferred electric technology vehicle (e.g. HEV to BEV or PHEV), and hence corresponding emissions savings are higher, even if considering the same consumer.

Table 2-3: Effect of including different heterogeneities on share of population benefiting from eletric technology vehicle adoption and free carbon. The first and second columns indicate what types of heterogeneity are considered, the third column indicates if federal tax credits are included. The fourth column shows the percent of the population which directly receives financial benefits and fifth column shows corresponding free carbon gains. The first row shows the case if every vehicle is driven the 11,700 annual miles of an average U.S. consumer, resulting in no consumers benefiting. The second includes individual variability in miles driven and vehicle types, but neglects geographic heterogeneiyt, i.e. all consumers pay national average gasoline and electricity prices.. The third row shows accounts for behavioal and geographic heterogentiy (the base case scenario), The fourth and fifth rows include federal tax subsidies.

Behavioral Heterogeneity	Geographic Heterogeneity	Federal Tax Credits	Share of Population Receiving Direct Financial Benefits from Cost-Effective Adoption of Electric Technology Vehicles	Free Carbon (Million $MTCO_2e$)
No	Yes	No	0%	0
Yes	No	No	1.6%	14
Yes	Yes	No	1.9%	17
No	Yes	Yes	6%	33
Yes	Yes	Yes	13%	92

Heterogeneity affects benefit-cost analyses of government policies to promote ETVs. For example, consider 10% of the population adopting ETVs. If this 10% comes from average consumers, carbon reductions would be 0.90 tonnes CO_2/vehicle (159 MMT are saved with 175 million ETVs). In contrast, if this 10% were individuals that benefit most economically from ETVs, annual carbon savings would 3.2 times higher, 2.84 tonnes/vehicle. Valuing the carbon benefit of emissions reduction at $40/ton (neglecting other societal benefits), emissions savings deliver $739 benefit per vehicle assuming average consumers benefit and $234 benefit per vehicle assuming most benefiting consumers adopt. Both assumptions (benefiting consumers and average consumers) are idealizations that do not capture the complexity of vehicle purchase decisions. Using highest benefiting consumers assumes sufficiently equivalent conventional and ETV models are available and that consumers view them so. Average consumers adoption assumes consumers ignore their individual use of a vehicle (i.e. driving a lot versus a little). The truth lies at an undiscovered point between adoption by those whose benefit and adoption by the average consumer. The critical policy point is this: the public benefits of promoting a technology depend on the heterogeneity of consumers' responses.

Note that neither beneficial adoption nor average adoption of ETVs leads to public benefits close to the $7,500 per vehicle currently spent on ETV subsidies. Viewed through the lens of current technology, the public cost of the ETV subsidy far exceeds its benefits (Michalek et al. 2011). However, much of the motivation for the subsidy presumably derives from expectations of it contributing to future cost reductions. Our results indicate the trajectory for growth in public benefits from lower technology costs. While this work does not undertake a longer-term benefit cost analysis of ETV subsidies, this work notes that it is conceivable to achieve benefits exceeding costs, depending how on much expenditure is needed to promote cost reductions. If the elasticity of cost reductions as a function of technology investment is sufficiently high (e.g. high learning rate in an experience/learning curve), there is potential for “cascading diffusion”, in which adoption by high-use subgroups enables cost reductions making the technology attractive to other consumer tiers (Herron and Williams 2013; Tsuchiya 1989). However, such an analysis would play out, accounting for behavioral and geographic heterogeneity is needed for a plausible estimate.

3 CHAPTER 3

Future Costs of Electric Vehicles: Effects of Technological Progress and Consumer Heterogeneity

3.1 *Chapter Summary*

Electric Technology Vehicles (ETV) can potentially transform the fuel and energy paradigm for transportation. Currently, ETVs are more expensive, primarily due to the high cost of the battery and electric drivetrain. This said, battery costs have been falling rapidly in recent years. This study explores the interaction between future cost reductions and adoption of ETVs using an experience curve. The least cost technology purchasing model developed for this study accounts for behavioral and geographical heterogeneities. Results show that the future market parity of ETVs depends on poorly understood factors: current costs and learning rates of non-battery EV technologies and future cost increases in conventional vehicles driven by stricter emissions requirements. Depending on which estimates are used, ETVs either become economically attractive for nearly 100% of the U.S. population or only for a relatively small share (18%) of high mileage drivers. These results suggest that a clearer resolution of cost trends in ETVs and conventional vehicles would dramatically increase confidence in the potential for ETVs to reach cost parity. Unsurprisingly, higher gasoline prices expand the parameter space in which ETVs bring economic benefits to consumers.

3.2 *Background and Introduction*

Decarbonization of transportation is critical to limit global warming to 1.5 degrees C (IPCC 2018a, 2018b) as well as to meet the 2 degrees C targets set in the Paris Accords (PPMC TRANSPORT 2018). From this point of view, the transport sector in the United States of America (U.S.) demands severe and immediate attention. The U.S. transport sector accounts for 28% of national emissions (i.e. 1,782 Million Metric Tons of CO_2e) 60% of which is from private transportation (U.S.-EPA 2018d, 2018c). Electric Technology Vehicles (ETV) can, therefore, play an important role in reducing these emissions. However, they are an emerging technology and have yet to attain cost parity with the incumbent and hence are not yet a significant market share. In this regard, it is important to understand how and when ETVs will be market competitive. This work uses the term Electric Technology Vehicle (ETV) to define Hybrid Engine Vehicle without plug (HEV), Battery Electric Vehicle (BEV) and Plug-in Hybrid Electric Vehicle (PHEV).

The higher cost is often a critical hurdle for an emerging technology to acquire market share. New technologies often evolve more rapidly than older incumbents, potentially reaching cost parity over time and overcoming the cost hurdle. For ETVs, the battery and the electric drivetrain are the two most significant components which make them more expensive to purchase than incumbent internal combustion vehicles. For some consumers, arguably, the lower operating costs of ETVs could be enticing enough to prefer ETV over a conventional vehicle. However, currently, the savings from operating a vehicle on electricity instead of gasoline over the duration of ownership may not be sufficient to overcome the additional initial capital costs of BEVs and PHEVs. Although it may be true in some cases because heterogeneity in consumers' behavior and their locations significantly dictate how much fuel savings a consumer is going to realize. Therefore, for the ETVs to be financially attractive to most consumers the initial capital costs need to reduce. One of the ways, these costs may decrease, is by reducing the manufacturing costs. When early adopters purchase a new technology the cumulative production of the said technology increases, and over a period of time the new technology becomes cheaper (or financially attractive). Therefore, it is important to understand how the initial adopters make the technology more affordable to the latter adopters.

In the U.S., currently, the total stock of the Battery Electric Vehicles (BEV) and Plug-in Hybrid Electric Vehicles (PHEV) is close to 4%; they accounted for 3.1 million vehicles globally by the end of 2017 (International and Agency 2018). This shows the significant market space the ETVs can capture if they are cheaper to adopt. However, a typical conventional vehicle still being cheaper than a comparable ETV option is a hurdle. The government, however, can play a key role by propelling the initial adoption through subsidies. These subsidies allow faster adoption and make the technologies cheaper for the latter adopters. Nonetheless, the current market share of ETVs and higher capital costs imply the potential for ETVs to reduce price and increase the market share. Although many economists have argued that the technology-specific subsidies may not be the most efficient method for more beneficial outcomes (Ballard and Medema 1993). Governments across the globe have indulged in heavy subsidies, at least with the one objective of making the technology lucrative to consumers and are likely to continue to do so. For example, the U.S. government has spent over $100 billion between 2006 and 2012 on various energy diffusion subsidies (Dinan and Webre 2012). Currently, a consumer in the U.S. can get $7,500 of federal tax credits for a purchase of a BEV and/or PHEV (U.S.-EPA 2018b). However, the BEVs and PHEVs have not reached cost parity and remain out of reach for most consumers.

Therefore, in this study, this work looks at how early adopters make the ETVs cheaper for the latter adopters using learning rates and the experience curve. The model—developed for this study—incorporates the inherent behavioral (individual differences in miles driven and vehicle type preferences) as well as the geographic heterogeneities (in fuel prices) of the U.S. consumers to calculate the financial benefits of ETVs. An important distinction to note is this model is a replacement of incumbent technology (i.e. the conventional vehicles) by an emerging technology (i.e. ETV) model, and not a diffusion or an adoption model.

This model shows how the adoption of ETVs (i.e. replacement of an incumbent conventional vehicle), now and in future, depends on the battery cell cost, the non-battery EV components cost, cost of evolving incumbent technology to accommodate the stricter emissions requirements (i.e. an Internal Combustion Engine Vehicle (ICEV) Cost Premium), and gasoline prices. This work further investigates if and how the federal tax credits (or subsidy) play a role for the consumers to move to the ETVs.

3.3 *Literature Review*

In previous studies, the learning rate and future cost have been analyzed in energy technologies (Azevedo et al. 2013; McNerney et al. 2010; Tsuchiya 1989). Wiesenthal *et al.* concluded that the learning rate can be used to explain the observed phenomena of adoption and cost reduction of technology as well as for better replication of historic cost data (Wiesenthal et al. 2012). Kahouli-Brahmi S. provided a critical analysis of the learning rate and energy-economics modeling. The survey conducted by the author of large-scale models showed that the incorporation of the learning rate with energy-economics models gives several new insights in understanding the cost reduction potential for a specific technology in bottom-up cost models (Kahouli-Brahmi 2008). Tran *et al.* analyzed the BEV adoption using an integrated approach and showed that it depends on the key interactions between the technology and consumer behavior (Tran et al. 2012). Edelenbosch *et al.* analyzed the interactions between social learning and technological learning for EVs. The authors have modeled both technological learning and social learning mutually and concluded that social learning stimulates diffusion for early adopters and this increased market share induced the technological learning (Edelenbosch et al. 2018). Thus, it is safe to say that the learning rate in energy-demand technology like ETVs is an acceptable modeling approach which incorporates the demand-side heterogeneity to understand and gain important insights into the auto market and its evolution in future.

3.4 *Contribution*

This study, however, does not look at technology diffusion; our model is a functional equivalent to the auto-market from the consumers' point of view. The main difference is in a typical diffusion model factors such as contagion diffusion, social influence, and social learning are included to study the penetration of a technology (Young 2009; Rao and Kishore 2010; Hall and Khan 2003; Rogers, n.d.; Huétink, der Vooren, and Alkemade 2010; Adner and Levinthal 2001). As we are looking at only the replacement of an incumbent technology, this work assumes an idealized future market in which consumers can choose from otherwise equivalent ETV and conventional models solely based on the least *Total Cost of Ownership* (TCO). While fuel savings motivate consumers to move to ETVs as modeled in this study, vehicles purchase decisions depend on many factors beyond net economic benefits. If the ETVs become cheaper in the future, the fuel savings from the ETVs become more important for a consumer. Although consumers choice of a technology does not always depend on cost such as driving experience, convenience of fueling (e.g., the locations where vehicles can be charged, the time that it takes to charge, and the frequency with which a vehicle must be charged), and the availability/familiarity of make/models. There are several studies which have studied the personal vehicle choice often using discrete choice models (Bunch et al. 1993; Brownstone, Bunch, and Train 2000; Ewing and Sarigöllü 2000; Jan Wassenaar et al. 2005; Potoglou and Kanaroglou 2007; Ahn, Jeong, and Kim 2008; Ziegler 2010; Hidrue et al. 2011; Andre Hackbarth and Reinhard 2013; Cirillo, Xu, and Bastin 2016; Liu and Cirillo 2017).

To address these questions, this work has an integrated model using demand-side heterogeneity which accounts for the *individual-level differences* in miles driven, *type of vehicle owned* (sedan, SUV, minivan and truck), and *lifetime ownership preferences* to estimate the economic benefits of electric technology vehicles (hybrid, plug-in hybrid, electric) in the U.S. The model also considers *the state-level differences* (i.e. the geographic heterogeneity) in gasoline and electricity prices. The National Household Travel Survey (NHTS) is used as the primary data source, which includes vehicle holdings characteristics for each surveyed household (a total of 309,000 households and 143,000 vehicles) (U.S.-DOT 2017). For every year, for the market going population to purchase a more efficient vehicle than their currently owned vehicle, the net economic benefits (or costs) are calculated to replace each existing internal combustion vehicle with a comparable Electric Technology Vehicle. Consumers are assumed to choose a HEV, PHEV, or BEV depending on which one of these provides the greatest private economic benefit. The addition of every ETV to the stock is used to calculate the reduction in technology cost using the learning rate. The learning rates are used for the battery as well as non-battery EV technologies such as an electric motor. The initial capital costs of ETVs are calculated using two different models—which account for two differing perspectives on bottom-up costs for non-battery EV technologies—to acknowledge the uncertainty about the additional costs of ETV technologies. This work has also undertaken additional analysis where the net economic benefits are calculated for different fuel prices and varying ICEV Cost Premium—which considers the conventional vehicles getting more expensive because of implementation of fuel efficiency rules such as CAFE standards (EPA and NHTSA 2012). This study also analyzed the effect of current federal tax credits for BEVs and PHEVs in inducing the ETV penetration. As explained earlier, this work does not look at the diffusion of ETVs but the replacement of incumbent technology by the more efficient and advanced technology because when the technology becomes cheaper the fuel savings from technology would motivate the consumers to move to ETVs.

3.5 *Methodology*

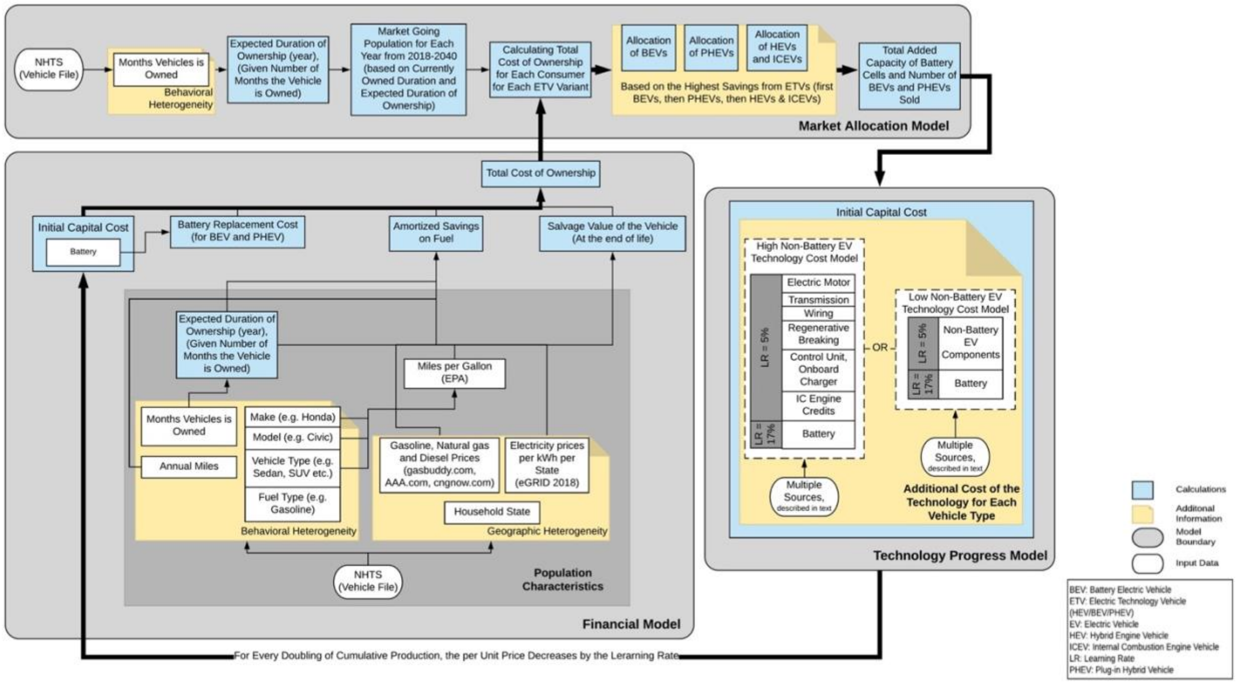


Figure 3-1 Methodological Framework of Integrated Incumbent Technology Replacement Model. The diagram shows the data sources such as the National Household Travel Survey (U.S.-DOT 2017) *and others* (U.S.-EPA 2018c, 2018a; www.AAA.com 2018; CNG-Now 2018; GasBuddy.com 2017) *as well as the flows of data. Blue background refers to calculations while yellow refers to additional information such as type of heterogeneity analyzed.*

Figure 3-1 shows the overall methodological framework. A detailed explanation appears in the annexure, here this work summarizes only main points. This work uses the National Household Travel Survey (NHTS) sample vehicle fleet as the main input for the vehicle-level analysis. NHTS includes the households' State of residence. This work uses this in modeling geographical heterogeneity to find state-specific fuel and electricity prices. The NHTS dataset also reports make, model, and type of the vehicle (used to estimate the initial capital cost and mileage in miles per gallon), number of months the vehicle is currently owned (used to estimate the expected duration of ownership of the vehicle), and number of miles driven annually (behavioral heterogeneity) for each household vehicle.

The integrated incumbent technology replacement model is divided into three parts: Market Allocation Model, Financial Model, and Technology Progress Model. All the calculations are repeated for each year from 2018 to 2040. In the Market Allocation Model, the consumer purchasing patterns are taken into account to recognize market going population every year to purchase (i.e. to replace) their current incumbent Internal Combustion Engine Vehicles (ICEVs), using the number of months the current vehicle is owned data from NHTS. After calculating the Total Costs of Ownership (explained in the Financial Model) for each technology option, the ETV technologies are allocated to the consumers based on the least TCOs (i.e. the highest savings). In the Financial Model, different components of TCOs are calculated. The TCO includes components such as initial capital cost, amortized fuel savings, battery replacement cost, and salvage value. The behavioral characteristics such as annual miles driven, type of vehicle, etc. from the NHTS are used in these calculations. The geographical variability in gasoline and electricity are also used in this model to estimate the fuel savings. The initial capital costs are calculated as additional costs of the technology (which includes battery and non-battery EV technologies such as electric motor, on-board charger, etc.) for each ETV variant compared to the latest ICEV. These additional costs reduce with time because of the experience curve. The reduction in the costs depends upon the cumulative production of the technology (for example, battery cells). The Technology Progress Model uses the number of BEVs, PHEVs, and HEVs allocated from the Market Allocation Model to estimate the cumulative production quantities for battery cells and non-battery EV technologies. Using the experience curve (i.e. the Learning Rate) and the cumulative production, the reduction in costs per unit is calculated to be used in the estimation of initial capital costs. This reduced capital costs because of experience curve make the ETVs financially attractive to the consumers for whom the ETVs could have been more expensive previously. The feedback loop of consumers adopting the ETVs and helping to reduce the costs of ETVs make the initial capital costs to reduce and hence the ETVs become cheaper in the subsequent years.

Nevertheless, the number of BEVs and PHEVs sold each year are constrained. In 2017, only 3% of cars sold in the U.S. were BEVs and PHEVs combined. Therefore, we think that it will be particularly difficult to significantly ramp up the production of these vehicles and hence assume that the total number of BEVs and PHEVs sold each year increase by 50% from the previous year as the production constraint. A recently published report by UBS Consulting also estimates the growth rate as 47% in their most optimistic penetration scenario, which is close to our assumption (Hummel et al. 2017). There is no production constraint for HEVs since they are very similar to ICEVs, except more fuel-efficient.

3.5.1 Market Allocation Model

Identifying Purchasing Consumers for Each Year: The first step of the model is to identify the consumers going to the market for the respective year. This work uses the observations of the number of months the vehicle is currently owned. The NHTS does not report the expected duration of ownership for a vehicle; this work derives it through random generation conditional upon the probability distribution of lifetime and survivor function given how long consumers have owned their current car, see Figure 2-2. The expected duration of ownership is the time period for which a particular consumer uses their vehicle. Duration determines the vehicle lifetimes used in calculating the total cost of ownership and the salvage value. Note that the duration of car ownership—explained in the annexure—varies by a consumer (7 years average with a standard deviation of 3.6 years).

For each consumer, this work finds out the purchase year and subsequent purchase year using the expected duration of ownership. For example, if a consumer has an expected duration of ownership of 7 years, and currently they have owned their vehicle for 3 years, then such a consumer will be in the market after 4 years (7 years – 3 years) i.e. in the year 2021 as the starting year is assumed to be 2018. The same consumer will be in the market to replace the vehicle in 2028, after 7 years (i.e. the expected duration of ownership) from 2021. This work follows the similar process for each consumer to find out their first purchase year and then subsequent purchase year. In short, this work finds out the population going to the market each year to purchase a vehicle. Once these market going consumers are recognized, the Financial Model is used to calculate the Total Cost of Ownership for each consumer.

For each year, the first step is to calculate the Total Cost of Ownerships (TCOs) for the total population going to the market for each ETV variant in comparison with an ICEV. The Financial Model explains the calculations for the TCO. Once the TCOs are calculated, all the consumers are arranged with respect to the *least total cost to the consumer* (i.e. the highest Net Present Value) for BEVs. This work assumes that the consumers who have the least TCO (i.e. saving maximum money) for the BEVs will move to the BEVs first. Once the consumers are allocated BEVs, the remaining consumers are again arranged with respect to the *least total cost to the consumer* for PHEV technology. The consumers saving the most (i.e. the least total cost) are then allocated PHEVs. Note that the number of BEVs and PHEVs possibly can be sold each year are constrained at 50% from the previous year. The allocation of BEVs and PHEVs have an impact on reducing technology prices for the consumers in the following year, which this work captures through the experience curve (or the learning rate). This work reports the estimated battery cell prices and number of ETVs added to the market for each year to be used as the starting point of the next year. The experience curve is applied to reduce the costs of both batteries as well as the non-battery EV components.

3.5.2 Financial Model

This work has assumed that the consumer's decision to purchase the vehicle solely depends upon the personal economics. The Total Cost of Ownership (TCO) is a useful method of calculating the direct and indirect costs associated with a purchase (Ellram 1995) (Hagman et al. 2016). In this case, the TCO constitutes initial capital costs, fuel savings in the duration of ownership, battery replacement costs, and the salvage value at the end of the duration of ownership as shown in Equation 3-1, is calculated to decide consumer's preference for an Electric Technology Vehicle (ETV).

$$\begin{aligned} &Total\ Cost\ of\ Ownership\ (TCO) \\ &\qquad = Initial\ Capital\ Cost\ - Discounted\ Fuel\ Savings \\ &\qquad + Discounted\ Battery\ Replacement\ Cost \\ &\qquad - Discounted\ Salvage\ Value \end{aligned} \tag{Equation 3-1}$$

In evaluating the purchase of an ETV, this work assumes consumers keep the same make, model, and type as their previous vehicle. This work models four technology options: 1. Updated Conventional Vehicle (Internal Combustion Engine Vehicle-ICEV), 2. Hybrid Engine Vehicle (HEV), 3. Battery Electric Vehicle (BEV) and 4. Plug-in Hybrid Electric Vehicle (PHEV). This work defines '*updated conventional vehicle*', as the 2018 version i.e. the latest of the model the consumers currently own. This work assesses the economic implications of purchasing an ETV by comparing the ETV with the updated conventional vehicle. A discount rate of 7% is assumed for this work as it is common to use 7% as the discount rate in TCO calculations (Miotti et al. 2016; Gilmore and Lave 2013; Al-Alawi and Bradley 2013; O'Keefe, M; Brooker, A; Johnson, C; Mendelsohn, M; Neubauer, J; Pesaran 2010; Lipman and Delucchi 2006; Breetz and Salon 2018). Moreover, the discount rate of 7% is also suggested by the Office of Management and Budget (Weis, Jaramillo, and Michalek 2014; US-OMB (The Office of Management and Budget) 2017). The salvage value is estimated as a function of years of ownership (Equation 2-4 to Equation 2-6) (Raustad 2017).

The current vehicle market does not offer ETV analogues for every available ICEV model. With this said, the suite of available ETV models is expanding rapidly. For example, there were 11 new ETV models offered in 2018 compared to 2017 (U.S.-EPA 2018c). This evolving market presents a challenge for modeling ETV adoption. Considering only currently available ETVs would properly reflect today's options but would misrepresent choices even a few years later. Thus, this work assumes a developed ETV market in which there is a reasonable analogous ETV option for any current vehicle model. Therefore, this work models ETV choice as a differential technology "upgrade" to currently sold conventional vehicles. This leads to modeling incremental cost additions of each technology type (HEV or BEV or PHEV) for each vehicle class (sedan, SUV, van, and truck). Using prior models (Kromer and Heywood 2007b, 2007a; N.R.C. 2013b, 2013a) of ETV characteristics and costs, this work has designed technical and performance specifications and cost estimates for ETVs based on a model conventional vehicle for each vehicle class. The technical and performance specifications of the designed vehicles are described in the annexure.

3.5.2.1 Initial Capital Costs

Prior to calculating the initial capital costs, this work defines the consumer vehicle options because the consumers do not have ETV analogues to their current conventional vehicle. This work defines the technical specifications such as power and performance characteristics, mileage (miles per kWh for BEVs and miles per gallon for HEVs and PHEVs) for each vehicle type (sedan, SUV, van/minivan/station wagon, pickup truck). These specifications are shown in Table 2-1.

The BEV range (total miles can be traveled using one completely charged battery) is limited and must be accounted for in designing vehicles and their use by consumers. Given the wide ranges in miles per charge, this work has modeled two BEV versions for each vehicle type with 100 and 150 miles of range. Consumers who drive more than 150 miles daily may only choose HEV and PHEV technologies. For PHEVs, this work assumes that a consumer will first operate on electricity until the battery is drained and then switch to gasoline.

Additional Cost of the Technology: The additional cost of an ETV includes the battery cell costs and the non-battery electric vehicle (EV) components costs. These non-battery components include systems such as electric motor, transmission and integration, control unit, onboard charging unit, regenerative breaking, and wiring as well as credits for removing mechanical components of internal combustion engines for EVs.

The cost of an ETV is calculated for each vehicle type based on the technical specifications (for example, battery size and power of the electric motor) which are designed using the characteristics of the conventional vehicles. The cost of the battery depends on the size of the battery and the type and size of the vehicle. The battery cost and electric motor costs are scaled with respect to the battery size and power requirements for each vehicle type. For example, a sedan with 100-mile range has a battery of 27 kWh and an electric motor of 131 kW power. This work uses the per kWh price of battery and per kW price of the electric motor along with other components such as onboard charger to estimate the additional cost of the technology. In addition to capital costs, an industry markup factor of 1.46 is assumed for all vehicle components (Rogozhin et al. 2010). The initial capital cost is one of the most important components to be accounted for while calculating the Total Cost of Ownership (TCO).

Battery Cell Price: Currently, there is a significant amount of literature present with a wide range of battery pack prices. Some of the literature estimates battery cell price and battery pack price separately. Along with lithium-ion (Li-ion) battery cells, there are components like battery management system (observes the output of each battery cell group), battery thermal management system (maintains operating temperature of the battery within desired range), and other pack assembly (such as module frames, steel pack case, covers, inside wiring and electronics etc.) which constitute a battery pack (Hummel et al. 2017; Curry 2017; Berckmans et al. 2017a). For this study, this work has assumed battery cell price per kilowatt-hour ($ per kWh). This work has considered $230 per kWh as the initial battery cell price. This price is in line with various estimates for the year 2018 from previous studies (Nykvist and Nilsson 2015a; Safari 2018; Nykvist, Sprei, and Nilsson 2019) and reports such as Bloomberg New Energy Finance (BNEF) (Curry 2017) and the Joint Technical Support Document from the U.S. Environmental Protection Agency (US-EPA) (EPA and NHTSA 2012). However, it is also important to note that there are other studies which have predicted the current battery cell prices to be much less, for example, $145 per kWh - $159 per kWh (BCG 2017; Kuhlmann et al. 2018; The Boston Consulting Group 2010).

3.5.2.2 Non-Battery EV Technology Costs

Although most published literature claims that the cost of the battery is the most significant additional cost component, this work believes that the non-battery components are also equally, if not more, important—and depending on the assumed cost model sometimes costlier than the battery in a vehicle. Importantly, the financial gains from BEVs considerably depend upon the cost model used to estimate the additional cost. However, there is a dearth of recent, updated and detailed bottom-up cost breakdowns for BEVs and PHEVs. Having said that, there are a few studies with bottom-up cost estimates for the cost of ETVs and/or the additional cost of the technology variants.

This work did not choose to follow the older and European market based studies like the National Renewable Energy Laboratory (NREL) model (Brooker, Thornton, and Rugh 2010) and the Geng Wu model (Wu, Inderbitzin, and Bening 2015), for our cost models. The National Research Council (NRC) has published comprehensive bottom-up cost models for BEVs and PHEVs (N.R.C. 2013b, 2013a). Nevertheless, these cost models are based on older consulting reports (Kromer and Heywood 2007a; Kolwich 2013). Although the recently published report from UBS Consulting produces a detailed teardown cost model of Chevrolet Bolt (Hummel et al. 2017), the report did not contain a similar analysis of PHEVs and HEVs.

Because of this uncertainty and lack of credible data sources, this work used two cost models which are at the two extremes of non-battery EV technologies costs. The High Non-Battery Cost Model is based on the International Council on the Clean Transportation (ICCT) report (Wolfram and Lutsey 2016) as the main source. The model has comparative cost models for BEVs, and PHEVs based on the bottom-up cost approach and contains component-wise costs. Secondly, the Low Non-Battery Cost Model is based on the BNEF (Soulopoulos 2017) model. The Low Non-Battery Cost Model does not contain a component-wise breakdown of the costs but is a highly referred model in the EV research community. These two models differ with respect to the method and cost of the components other than the battery, such as an electric motor.

High Non-Battery Cost Model: This model is a bottom-up cost estimation based on the ICCT report (Wolfram and Lutsey 2016) as well as the NRC report (N.R.C. 2013b, 2013a). The non-battery EV components considered in this model are an electric motor, EV transmission, power electronics wiring, regenerative breaking, control unit, and onboard charging unit as well as ICEV credits, which account for engine downsizing and replacing mechanical components in an

ICEV by an electric drivetrain. The size and cost of the electric motor are estimated with respect to the type of the vehicle (for example, a sedan Vs an SUV). For example, a sedan has a power rating of 131 kW versus an SUV has a power rating of 142 kW. The ICEV credits are also estimated based on the engine size. The additional cost calculated for a BEV sedan with a 100-mile range as per the High Non-Battery Cost Model is $10,745, including the battery, non-battery EV technologies, ICEV credits and markup factor. Similarly, a PHEV sedan with a 40-mile range would cost $7,883 extra than a comparable ICEV. Table 3-1 contains the specifications and the cost calculations for other vehicle types.

Low Non-Battery Cost Model: This model, as mentioned above, is based on the BNEF model (Soulopoulos 2017). The BNEF has developed the manufacturing cost of the BEV with three main components 1. Battery Pack, 2. Powertrain (includes electric motor, inverter, electronics, etc.) and 3. Vehicle chassis and assembly. As this work is considering only the additional costs, this work has excluded the vehicle chassis and assembly costs, although the BNEF has assumed them to be constant in the model. The powertrain costs and corresponding power ratings are extracted from the BNEF report and a straight-line equation is generated for powertrain costs ($) as a function of power ratings (kW) of EV technology variants. For PHEV variants, the powertrain costs are calculated using the ratio of power ratings of respective PHEV and ICEV engines.

For example, a 100-mile range sedan BEV would have additional costs of $7,437. This additional technology cost includes 27 kWh of battery, and the powertrain costs for 131 kW of power ratings (with $14.1 per kW and 935.1 constant costs) as well as markup factor and ICEV credits. Similarly, a PHEV sedan with a 40-mile range has an additional cost of $3,239. Both these costs are significantly lower than the High Non-Battery Cost Model estimates. Table 3-2 contains the additional cost estimations for other vehicle types.

The initial capital cost is a part of the Financial Model as well as the Technology Progress Model. In the Financial Model, it is a part of the Total Cost of Ownership. However, it is in the Technology Progress Model the per-unit price of the battery cell and the non-battery EV technology costs are decided. Therefore, the initial capital costs are dictated by the Technology Progress Model.

Table 3-1 Additional Cost of Vehicles with High Non-Battery Cost Model

Vehicle Type	Technology	Total Battery Cost ($)	Battery Cell Costs ($)	Total Motor System Cost ($)	Other EV Systems ($)	Hybrid transmission and Integration ($)	Wiring ($)	EV Transmission ($)	ICE engine credit ($) for conventional starter and alternator	ICE Credit ($) for downsizing	ICE Credit ($)	Total Incremental Cost ($)	With Markup Factor ($)
Sedan	HEV	230	230	1065	495	364	243		-121	-139		2137	3120
Sedan (Short Range)	BEV-100	6199	6199	3521	940		243	344			-3887	7360	10745
Sedan (Long Range)	BEV-150	9299	9299	3521	940		243	344			-3887	10460	15271
Sedan	PHEV-40	2933	2933	1319	940	364	243		-121	-277		5399	7883
SUV	HEV	345	345	1121	495	364	243		-121	-150		2297	3354
SUV (Short Range)	BEV-100	7805	7805	3790	940		243	344			-4065	9057	13223
SUV (Long Range)	BEV-150	11708	11708	3790	940		243	344			-4065	12959	18920
SUV	PHEV-40	3692	3692	1413	940	364	243		-121	-299		6231	9098
Van/Minivan/ Station Wagon	HEV	345	345	1479	495	364	243		-121	-220		2585	3774
Van/Minivan/ Station Wagon (Short Range)	BEV-100	9252	9252	5522	940		243	344			-4937	11364	16592
Van/Minivan/ Station Wagon (Long Range)	BEV-150	13878	13878	5522	940		243	344			-4937	15990	23346
Van/Minivan/ Station Wagon	PHEV-40	4377	4377	2019	940	364	243		-121	-441		7380	10775
Truck	HEV	345	345	1662	495	364	243		-121	-256		2731	3988
Truck (Short Range)	BEV-100	9550	9550	6405	940		243	344			-6031	11451	16719
Truck (Long Range)	BEV-150	14325	14325	6405	940		243	344			-6031	16226	23690
Truck	PHEV-40	4518	4518	2328	940	364	243		-121	-513		7758	11327

Table 3-2 Additional Cost of Vehicles with Low Non-Battery Cost Model

Vehicle Type	Technology	Total Battery Cost ($)	Total Powertrain Cost ($)	ICE engine credit ($) for conventional starter and alternator	ICE Credit ($) for downsizing	ICE Credit ($)	Total Incremental Cost ($)	With Markup Factor ($)
Sedan	HEV	230	2167	-121	-139		2137	3120
Sedan (Short Range)	BEV-100	6199	2782			-3887	5094	7437
Sedan (Long Range)	BEV-150	9299	2782			-3887	8194	11963
Sedan	PHEV-40	2933	1808			-2522	2219	3239
SUV	HEV	345	2223	-121	-150		2297	3354
SUV (Short Range)	BEV-100	7805	2937			-4065	6676	9748
SUV (Long Range)	BEV-150	11708	2937			-4065	10579	15445
SUV	PHEV-40	3692	1909			-2638	2963	4326
Van/Minivan/ Station Wagon	HEV	345	2581	-121	-220		2585	3774
Van/Minivan/ Station Wagon (Short Range)	BEV-100	9252	3881			-4937	8197	11967
Van/Minivan/ Station Wagon (Long Range)	BEV-150	13878	3881			-4937	12823	18721
Van/Minivan/ Station Wagon	PHEV-40	4377	2523			-3203	3696	5397
Truck	HEV	345	2764	-121	-256		2731	3988
Truck (Short Range)	BEV-100	9550	4360			-6031	7880	11504
Truck (Long Range)	BEV-150	14325	4360			-6031	12655	18476
Truck	PHEV-40	4518	2834			-3913	3439	5020

3.5.2.3 Battery Replacement Costs

For HEVs, the battery replacement costs are not considered, as the battery typically lasts for the lifetime of the vehicle. For BEVs and PHEVs, the battery replacement costs are considered only if the expected battery life is less than 15 years—the assumed maximum duration of ownership of the vehicle. The life of the battery is estimated as a function of the number of charging-discharging cycles and depth of discharge (Wood, Alexander, and Bradley 2011; Raustad 2017) (Equation 2-7 and Equation 2-8).

3.5.2.4 Fuel Savings

Based on the state of residence, each vehicle is assigned average state electricity prices from the U.S. Energy Information Agency (U.S.-EIA 2018b). The fuel prices are also assigned with respect to the corresponding fuel type and U.S. State (www.AAA.com 2018; CNG-Now 2018; GasBuddy.com 2017). The fuel savings for each ETV is calculated and discounted for the expected duration of ownership as shown in Equation 2-9 and Equation 2-14.

3.5.3 Technology Progress Model

The experience curve was first used to describe the cost reductions in aircraft manufacturing (Wright 1936). It has been used in several energy technology studies (Harmon 2000; Weiss et al. 2010; Matteson and Williams 2015; Tsuchiya 1989; Neij et al. 2003). The experience curve says that every time the cumulative production capacity doubles, the cost per unit decreases by the learning rate (Matteson and Williams 2015; Tsuchiya 1989). The experience curve is shown in Equation 3-2.

$$C(P) = C_o(P/P_0)^{-\alpha} \qquad \text{Equation 3-2}$$

'P' represents the cumulative adoption of the said technology. For our study, 'P' denotes the total kilowatt-hour (kWh) capacity installed and/or adopted of the Li-ion battery cells. 'C' is the price per unit ($\$/kWh$), '$C_o$' and '$P_0$' are initial cost and production capacity, respectively. Finally, 'α' is known as the learning coefficient and is a positive empirical constant. The initial capacity of battery cells and the number of BEVs and PHEVs—used for the experience curve of non-battery EV component—are calculated and are shown in Table 3-3.

$$LR = 1 - 2^{\alpha} \qquad \text{Equation 3-3}$$

'LR' represents Learning Rate, and denotes the fractional reduction in the cost for every doubling of production as shown in Equation 3-3.

For this work, the experience curve has been implemented for two technologies 1. Battery Cells and 2. Non-battery EV Technologies. The ETVs encompass both Li-ion battery technology as well as non-battery EV components like the electric motor. With the increase in the number of ETVs allocated, these technologies go through the experience curve and collectively decrease the capital cost of the ETVs. The battery cell prices decrease with each installed battery cell and the non-battery EV technology prices decrease with each unit purchased of BEV or PHEV. However, the decrease in the prices is calculated using two different learning rates: Learning Rate for Battery (LR_B) and Learning Rate for Non-Battery EV components (LR_{NB}).

Table 3-3 Total Capacity Calculations (International and Agency 2018)

Model	**Type**	**2012**	**2013**	**2014**	**2015**	**2016**	**TOTAL**
Nissan LEAF	EV	9,819	22,610	30,200	17,269	14,006	103,578
Tesla Model S	EV	2,171	19,000	16,750	26,200	**29,156**	93,277
BMW i3	EV	0	0	6,092	11,004	*7,625*	24,721
Ford Focus EV	EV	683	1,738	1,964	1,582	872	6,839
Fiat 500E	EV	0	260	1,503	4,569	**3,897**	10,229
Smart forTwo EV	EV	137	923	2,594	1,387	657	5,698
VW e-Golf	EV	0	0	357	4,232	0	4,589
Chevrolet Spark	EV	0	560	1,145	2,629	3,035	7,369
Mercedes B-Class Electric	EV	0	0	774	1,906	632	3,312
Toyota RAV4 EV	EV	192	1,005	1,184	18	NA	2,399
Mitsubishi i-MiEV	EV	588	1,029	196	115	94	2,098
Kia Soul EV	EV	0	0	250	1,015	1,728	2,993
Honda Fit EV	EV	93	569	407	2	NA	1,071
BMW Active E	EV	965	0	0	0	0	965
Tesla Model X	EV	0	0	0	208	18,028	18,236
Average Battery Size (kWh)		*38*	*44*	*50*	*51*	*54*	
Average Battery Size (kWh)		*37*	*50*	*43*	*48*	*64*	
Chevrolet Volt PHEV	PHEV	23,461	23,094	18,805	15,393	24,739	113,163
Toyota Prius Prime Plug-in	PHEV	12,749	12,088	13,264	4,191	2,474	44,766
Ford Fusion Energi	PHEV	0	6,089	11,550	9,750	15,938	43,327
Ford C-MAX Energi PHEV	PHEV	2,374	7,154	8,433	7,591	7,957	33,509
BMW i8	PHEV	0	0	555	2,265	1,594	4,414
Cadillac ELR	PHEV	0	6	1,310	1,024	534	2,874
Porsche Panamera S E-Hybrid	PHEV	0	51	879	407	393	1,730

U.S. Stock Data (Units)			**Calculated Average Battery Capacity (kWh)**	
			BEV	**PHEV**
2005	1,120			
2006	1,120			
2007	1,120			
2008	2,580			
2009	2,580			
2010	3,770			
2011	13,520	7,980		
2012	28,170	46,570	37	13
2013	75,860	95,580	50	12
2014	139,280	150,940	43	10
2015	210,330	193,770	48	11
2016	297,060	266,650	64	12
2017	401,550	360,510	74	12
Total Vehicles (Units)	762,060			
Total Capacity (kWh)	29,714,700	4,214,632		
Total Capacity (kWh)	33,929,332			

Porsche Cayenne S E-Hybrid	PHEV	0	0	112	1,163	2,111	3,386
Honda Accord	PHEV	0	526	449	63	NA	1,038
BMW X5	PHEV	0	0	0	892	5,995	6,887
Smart ED	PHEV	2	0	0	0	NA	312
Mercedes S550 Plug in	PHEV	0	0	0	118	550	668
Volvo XC90	PHEV	0	0	0	86	2,020	2,106
Total		48,200	96,702	118,773	113,869	144,035	539,310

3.5.3.1 Learning Rates

There are two main learning rates (*LR*) used in this work 1. For Li-ion Battery (LR_B) and 2. For Non-Battery EV components (LR_{NB}).

Learning Rate for Battery *(LR_B)*: Nykvist *et al.* estimated the LR_B for Li-ion battery cell cost as 6-8% in 2015 using multiple sources of battery cell prices, but this work includes a significant amount of grey literature (Nykvist and Nilsson 2015b). However, Nykvist *et al.* have re-estimated the learning rate to be 17% (Nykvist, Sprei, and Nilsson 2019) in their latest work. The BNEF has reported the LR_B to be 19% and has used it in their reports, but the report does not provide a source of the LR_B (Curry 2017; Morsy 2017). Apart from these studies, a recently published estimate based on economies of scales by Kittner *et al.* shows the LR_B to be 17.31% (Kittner, Lill, and Kammen 2017). Moreover, another recently published study by Schmidt *et al.* have reported the LR_B to be 16% (Schmidt et al. 2017). Due to this wide variation and uncertainty about the LR_B, this work has assumed the LR_B as 17% for our model which is in line with these studies.

Learning Rate for Non-Battery EV Components *(LR_{NB})*: Similar to batteries, the literature has a wide variation for learning rate (LR_{NB}) for non-battery EV components for ETVs. Weiss *et al.* have shown that the experience curve and/or learning rate studies are still not conducted for several energy-related technologies including, but not limited to, electric motors and entire motor systems (Weiss et al. 2010; Gielen 2010). Therefore, this work looked at several studies about the LR_{NB} for the non-battery EV components. Most of these learning rates are for a particular component in the EV drivetrain and/or referenced from other studies as well as, in some cases, to personal communications. Most of these studies lack the data from the manufacturers. In addition, there is considerable variation in the LR_{NB} estimated and/or assumed by different studies. For example, Pasaoglu *et al.* have used 10% of LR_{NB} for EV components based on the experience curve for energy technologies, because the authors assume that the drivetrain technology is a matured technology (Pasaoglu, Honselaar, and Thiel 2012; Pasaoglu et al. 2016; McDonald and Schrattenholzer 2001). OPR van Vliet *et al.* and Contestabile *et al.* have assumed 5% *LR* for powertrains but this *LR* is calculated for the electric motors in the ICEVs (van Vliet et al. 2010; Contestabile et al. 2011). Weiss *et al.* have considered that the powertrain components have the same *LR* as that of the batteries and hence assumed that the LR_{NB} for the non-battery components to be 17% (Weiss et al. 2012). In a recent publication, Safari *et al.* estimated that the cost of electrification for mid-size BEVs has LR as 15+/-1% (Safari 2018). As can be seen, the LR_{NB} varies significantly in these studies and has uncertainty about the source. Therefore, for our study, this work has assumed 5% as the LR_{NB} for BEVs and PHEVs for non-battery EV components. It is based on the Ricardo-AEA report which was prepared by using a survey of manufacturers conducted by Delphi (Hill et al. 2016).

3.5.4 Efficiencies for Batteries and ICEVs

With the increasing demand for EVs and increase in EV penetration, the battery chemistry is improving which positively impacts the battery efficiency. The battery cells are getting dense and will be able to hold more charge in the future. This will enable the EV manufacturers to produce longer-range EVs as well as smaller batteries for shorter range EVs (Soulopoulos 2017; The Boston Consulting Group 2017; Kuhlmann et al. 2018; Berckmans et al. 2017b). In our model, this work has accounted for this EV technology development as a yearly 2% decrease in battery cell capacity for the new vehicles to achieve the assumed 100-mile and 150-mile ranges, irrespective of the type of the vehicle (Wolfram and Lutsey 2016).

This work also assumes that the fuel efficiency of the ICEVs is going to improve mainly due to the implementation of Corporate Average Fuel Economy (CAFE) standards as well as the introduction of new technologies. The University of Michigan Transportation Research Institute (UMTRI) has consolidated sales-weighted data about the fuel-economy rating (window sticker) of purchased new vehicles for October 2007 through December 2017 (UMTRI-(University of Michigan Transportation Research Institute) 2018). The dataset is added in the SI Excel sheet. This work has used this dataset to estimate the annual increase in the ICEV fuel efficiency in the future. This work has assumed that the battery efficiency (miles per kWh) also increases similar to that of the ICEVs' fuel efficiency (miles per gallon) because some technologies such as rolling resistance will be benefitting the ETVs as well.

ICEV Cost Premium: In the final rulemaking for the CAFE standards, the U.S. Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) analyzed the possible technologies which would benefit the ICEVs to increase the fuel efficiency (miles per gallon) and to achieve the CAFE standards for the manufacturers. These technologies include but are not limited to Engine Friction Reduction, Variable Valve Timing (VVT)-Intake Cam Phasing, VVT-Dual Cam Phasing, Discrete Variable Valve Lift (DVVL), Continuous Variable Valve Lift (CVVL), Electrical/Electro-hydraulic Power Steering, and Lower Rolling Resistance Tires Levels. Some of these technologies cannot be used simultaneously and some would have higher impacts depending on the size of the ICEVs. These technologies would impact the fuel efficiencies positively the manufacturing costs of the ICEVs are expected to increase (EPA and NHTSA 2012). However, there is significant uncertainty related to when these technologies will be part of the ICEVs as well as which of these technologies will be part of a particular vehicle, as it depends upon 1. Auto-manufacturers' choice 2. Size 3. Type and 4. Ignition system of the vehicle. Several analyses (for example, the ICCT (Wolfram and Lutsey 2016) and BNEF (Soulopoulos 2017)) looking at the future EV adoption outlooks have assumed cost increments for ICEVs with time. This work has used these published reports to estimate how expensive an ICEV will be in the future as a function of time (Brennan and Barder 2016; Kolwich 2013; Soulopoulos 2017; Wolfram and Lutsey 2016; EPA and NHTSA 2012). Our estimation is included in the SI Excel sheet. Henceforth, this work refers to it as '*ICEV Cost Premium*'. The BNEF report estimates the cumulative average growth rate (CAGR) for ICEV price increase to be 0.70% for sedans. As per Brennan JW et al. (Arthur D. Little report), the CAGR for ICEV price increase is 0.46% [92]. For this work, therefore, has averaged these two CAGRs and assumed that the price of ICEVs increase by 0.6% each year. For sedans, as this work has assumed the current price of a comparable ICEV to be $24,380, the annual price rise is $142. This price rise is in line with the other estimates published in various reports such as the ICCT and NRC (Brennan and Barder 2016; Kolwich 2013; Soulopoulos 2017; Wolfram and Lutsey 2016; EPA and NHTSA 2012). For other vehicle types, this annual price rise is scaled with respect to the ratio of power ratings. For example, for an SUV, the designed power rating (described in technical specifications) is 142 kW, and it is 1.08 times that of a sedan (131 kW). Therefore, the annual price increase for an SUV is $154. The estimates are shown in **Error! Reference source not found.** in the annexure.

In summary, this integrated model considers behavioral and geographic heterogeneity in the U.S. private transportation sector. The two different cost models are included to calculate the two extremes of the additional cost of the technology. The improvements in conventional technology considered as ‘ICEV Cost Premium’, making the ICEVs more expensive with time. every added ETV in the fleet helps to reduce the battery and non-battery EV components’ costs because of the experience curve. The reduced capital costs then make the ETVs more affordable for the latter adopters and increase ETV purchases. This analysis looks at how varying gasoline prices affect the finances of the ETVs. In addition, because of the uncertainty about the ‘ICEV Cost Premium’, this work also considers different percentages of annual price rise for ICEVs. The results highlight the impacts for these variations as well. Lastly, this work looks at how the federal tax credits affect the financial outlook of ETVs and how they induce the purchase of ETVs.

3.6 *Results and Discussions*

For the first set of results, this work conducted a scenario analysis where we considered both 1. High Non-Battery Cost Model and 2. Low Non-Battery Cost Model to estimate the additional technology costs. The results are shown in Figure 3-2. The figure shows the reducing battery cell price (in $ per kWh) for two cost models as well as for varying gasoline prices. For the High Non-Battery Cost Model with the gasoline price $1.95 per gallon, the ICEV Cost Premium makes a significant impact on battery cell price reductions. If the gasoline price stays low and the ICEVs do not get more expensive, the ETVs will not be financially attractive to most consumers. In this case, the replacement of incumbents with ETVs is not significant, and the battery cell price reduces only slightly from $230 per kWh to $213 per kWh. On the other hand, if it is assumed that the conventional vehicles get more expensive with time, and the battery cell price reduces from $230 per kWh to $96 per kWh even at the gasoline price of $1.95 per gallon. This signifies the impact of assuming the ICEVs get more expensive with time to accommodate more efficient technologies required to meet the stricter environmental regulations such as CAFE standards. Strictly from the consumers’ private financial benefits, if the gasoline prices are low, then the major drive towards ETVs will happen only if the conventional vehicles get more expensive and not otherwise.

For the High Non-Battery Cost Model with higher gasoline prices ($2.60 per gallon and $5.20 per gallon), the reduction in battery cell price is faster and substantial. The maximum reduction happens in the case of the High Non-Battery Cost Model and gasoline price $5.20 per gallon where the battery cell price reduces to $49 per kWh (reduction of 79%). This suggests that if the gasoline becomes more expensive, the majority of consumers will have more financial benefits from ETVs compared to the conventional vehicles and will lead to substantial replacement of the incumbent ICEVs by ETVs. In the Low Non-Battery Cost Model, the battery cell prices in 2040 are the same with or without ICEV Cost Premium scenarios, except when the gasoline price is at $1.95 per gallon. The Low Non-Battery Cost Model makes the ETVs more attractive financially compared to ICEVs at higher gasoline prices and even when the battery cell prices are high. Even in such a scenario, significant number of ETVs are adopted, and it leads to rapid reduction in battery cell prices as well as non-battery EV technology costs. When the gasoline price is $1.95 per gallon, the ICEV Cost Premium affects the consumers’ finances. It can be seen that, when the ICEV Cost Premium is not present the battery cell price decreases slower initially because of slower adoption versus when the ICEV Cost Premium is present. This trend highlights the impacts of assuming conventional vehicles get more expensive with time. However, it is important to note that there is significant uncertainty about these costs increments in conventional technology.

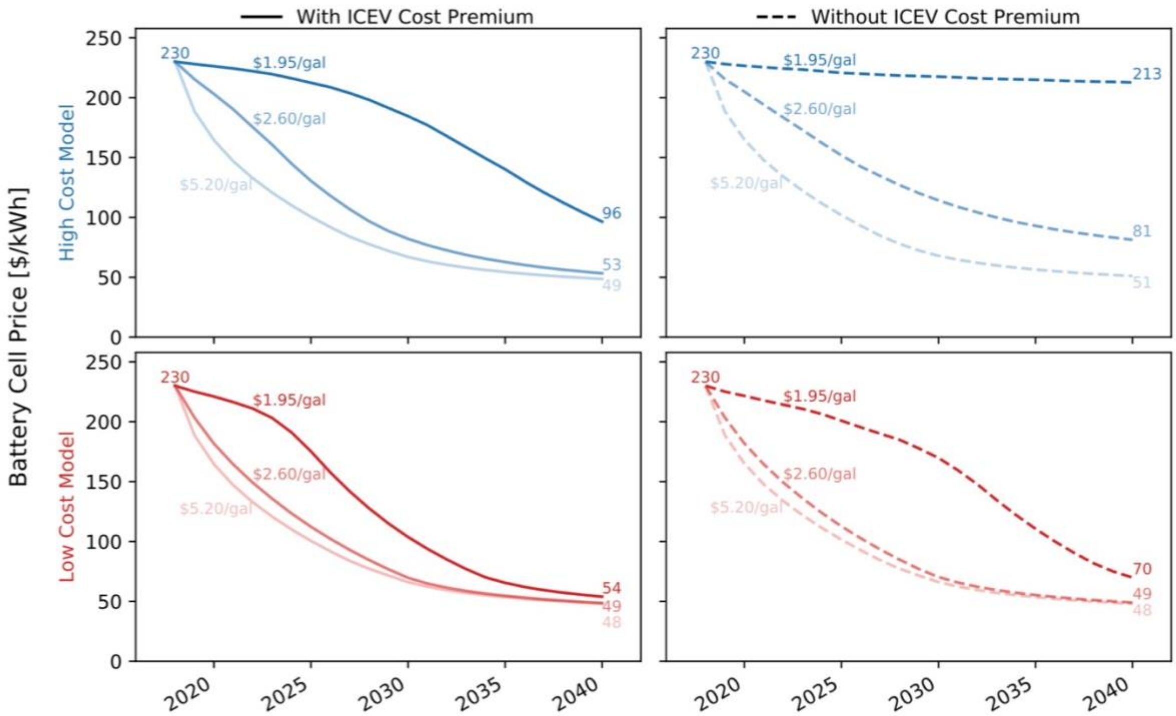


Figure 3-2 Reduction in battery cell price ($ per kWh) over time in different scenarios. The figure shows how the battery cell price reduces over time for High and Low Non-Battery Cost Models in presence and absence of ICEV Cost Premium with varying gasoline prices ($ per gallon). For the lower gasoline price, the battery cell price reduces slower initially and with the increased adoption the battery cell price reduces faster, except for the High Non-Battery Cost Model without ICEV Cost Premium. This shows the impact of ICEV Cost Premium on battery cell price reduction. At higher gasoline prices, for the High Non-Battery Cost Model the battery cell price reduces faster and significantly which is a result of higher and faster ETV adoption. For the Low Non-Battery Cost Model irrespective of the gasoline price and availability of ICEV Cost Premium the battery cell prices reduce significantly because of higher and faster ETV adoption.

Figure 3-3 shows how the additional cost of BEV-100 over the latest ICEV reduces with the High and Low Non-Battery Cost Models when ICEV Cost Premium is present or not. The figure highlights the gap between additional costs with different cost models and at a gasoline price $2.60 per gallon. In the Low Non-Battery Cost Model, the additional costs become zero significantly faster compared to the High Non-Battery Cost Model. However, the ICEV Cost Premium adds to the advantage of the Low Non-Battery Cost Model and bring the initial capital costs to parity with the conventional vehicles even faster. In the High Non-Battery Cost Model, the BEV-100 reach the cost parity faster when ICEV Cost Premium is considered. Nevertheless, it is important to note that if the ICEV Cost Premium is not available, the BEV-100 sedan does not reach cost parity until 2040 and stays more expensive than the conventional counterparts. The BEV-100 sedan reaching cost parity faster infers to the quicker adoption of ETVs, and as more ETVs are added to the fleet, the battery cell prices reduce faster and significantly (refer to Figure 3-2).

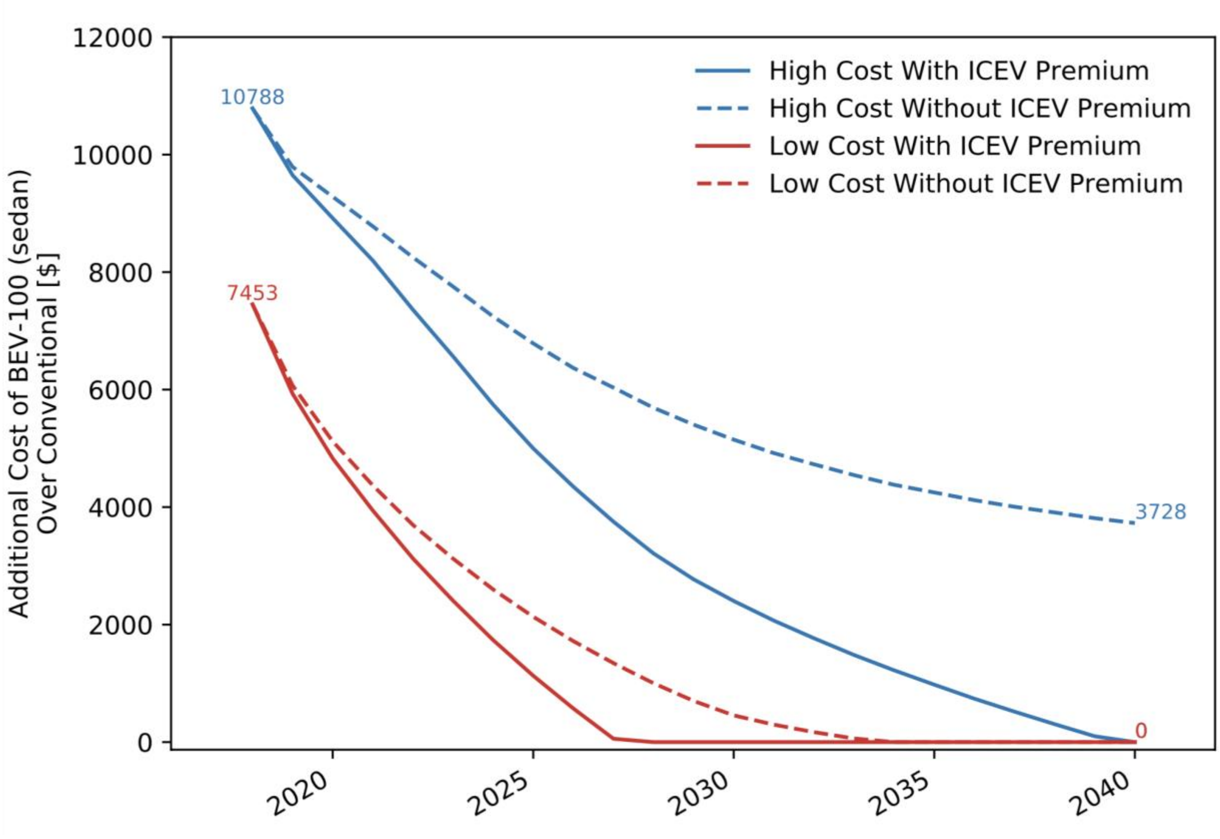


Figure 3-3 Reduction of the additional cost of BEV-100 sedan over the latest ICEV with time in different scenarios. The figure shows the initial difference between the High and Low Non-Battery Cost Models. The Low Non-Battery Cost Model of non-battery EV technologies make the BEV-100 significantly cheaper compared to the High Non-Battery Cost Model. Further, the impact of the ICEV Cost Premium can be seen in the trends of reducing additional costs of BEV-100. The Low Non-Battery Cost Model with ICEV Cost Premium is the fastest scenario to reduce the additional cost of BEV-100 technology to zero. The High Non-Battery Cost Model without ICEV Cost Premium is the slowest and it shows this additional cost will be a hindrance in higher ETV adoption by consumers.

To understand the impacts of the uncertainty about ICEV Cost Premium on the market share of BEVs and PHEVs in 2040, this model varies the percentage of annual price increase in ICEVs. We also study the impacts of different gasoline prices in conjunction with the varying ICEV Cost Premium. Figure 3-4 shows the collective market share of BEVs and PHEVs in 2040 in different criteria for the High Non-Battery Cost Model. An annual increase of 0.60% in the ICEV prices indicate the present situation (or the base-case scenario). At low gasoline prices and without an annual increase in ICEV prices, the market is conducive for ICEVs to be the dominant choice for the consumers, if solely their private financial benefits are considered. The consumers will replace their incumbent ICEVs by ETVs if they have favorable financial outlook. The favorable finances are possible if gasoline prices increase in the future. The fuel savings (electricity versus gasoline) from using BEVs and/or PHEVs help the consumers to save as much as the additional costs of ETVs over ICEVs, if not more. It can be seen from Figure 3-4 that as the gasoline price increases the share of BEVs and PHEVs increases substantially in the 2040 market, without any increase in ICEV Costs.

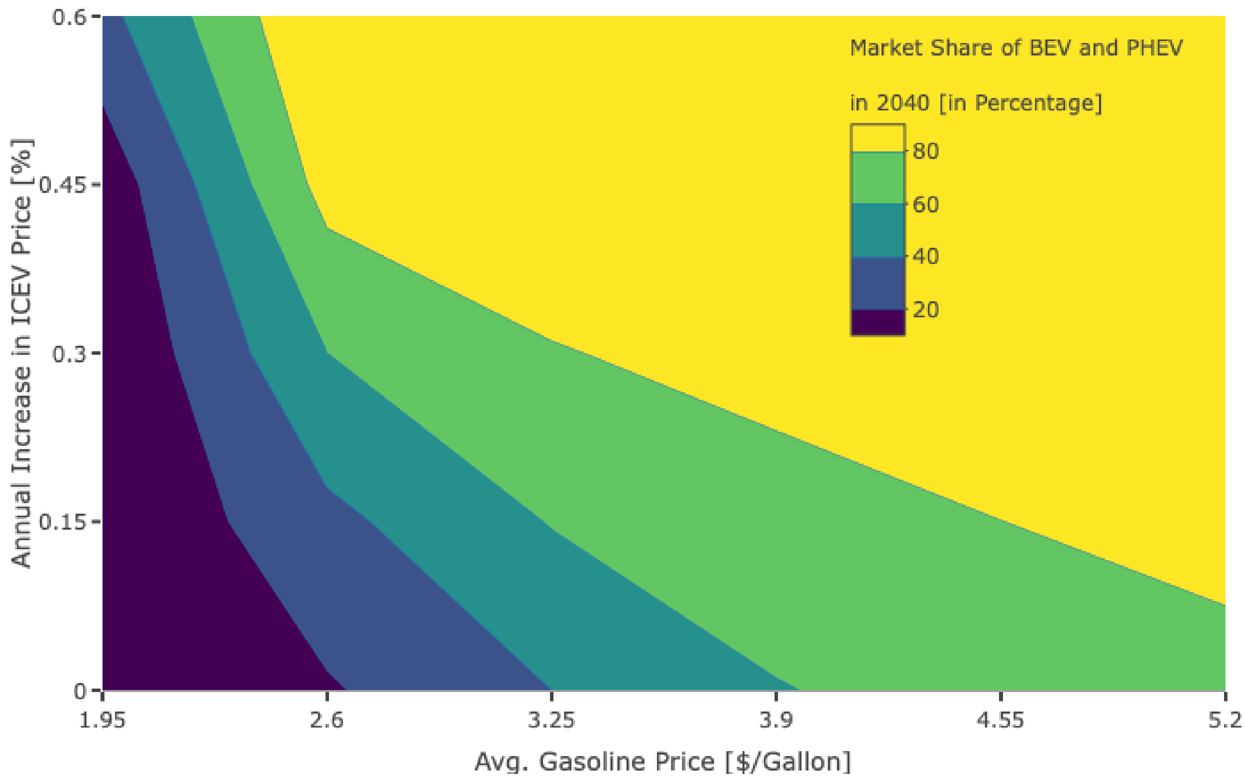


Figure 3-4 Market share of BEVs and PHEVs in 2040 for High Non-Battery Cost Model with varying gasoline price and varying annual increase in the conventional vehicles' price (i.e. ICEV Cost Premium). At lower gasoline prices and without ICEV Cost Premium, the BEVs and PHEVs stay more expensive compared to the conventional vehicles. On the other hand, expensive gasoline and ICEV Cost Premium act as agents to aid in getting a greater market share of BEVs and PHEVs in 2040. An annual increase of 0.60% in ICEV prices indicate the base case of this study. With this increase, if the gasoline price is $2.60 per gallon the BEVs and PHEVs achieve market share over 80% in 2040, and the battery cell prices reach $53 per kWh as shown in Figure 3-2.

Another mode of getting better financial prospects with ETVs is the ICEVs getting more expensive in the future to accommodate more efficient technologies. Even a small annual increase in ICEV prices makes a significant difference to the BEV and PHEV market share. If the gasoline price stays low ($1.95 per gallon), the ICEVs need to get more expensive by at least 0.50% annually for the BEVs and PHEVs to account for more than 20% of the market in 2040. It certainly corroborates that lower gasoline prices make the BEVs and PHEVs more financially attractive only to a few consumers who drive considerably more than the rest of the population. Once the gasoline prices are increased the effect of ICEV price rise on BEV and PHEV market share becomes more significant. The higher gasoline prices make it cheaper to use BEVs and PHEVs to drive. In addition to this, if the ICEV prices are increased annually, the gap between the initial capital costs of conventional and ETVs becomes smaller over a period of time. This reduced gap and better fuel savings make the BEVs and PHEVs financially more attractive to a greater number of consumers initially, leading to increased adoption of ETVs. With the higher initial adoption, the cumulative production of ETVs increases rapidly which reduces the battery cell prices and non-battery EV costs, compared to when gasoline prices are low and ICEVs do not get more expensive. Thus, the increased gasoline prices and an annual increase in ICEV prices act in conjunction to make the finances of BEVs and PHEVs better by allowing more savings on fuel and the reduced gap in initial capital costs. With the Low Non-Battery Cost

Model even with the lowest gasoline price of $1.95 per gallon and without ICEV Cost Premium, the BEVs and PHEVs achieve the market share over 95% in 2040, which is certainly a result of a smaller gap between initial capital costs of ETVs and ICEVs. Therefore, for the Low Non-Battery Cost Model with expensive gasoline and expensive ICEVs, it is a certainty that the BEVs and PHEVs achieve 100% market penetration.

Table 3-4 Impact of federal subsidies in inducing the sales of ETVs. The first column shows the cost model used to estimate the non-battery EV technology costs. The second column indicates how many years the federal subsidy was allowed for the market going population. The third and fourth columns show the total sales of BEVs and PHEVs, induced sales because of federal subsidies, and cost to the government per induced sale, when ICEV Cost Premium is present or otherwise. Note 'M' marks 'millions' in the table.

Cost Model	Federal Subsidy Time Limit	With ICEV Cost Premium				Without ICEV Cost Premium			
		Market Share of BEV and PHEV in 2040 (%)	Total Sales Until 2040	Induced Sales	Cost/Sales ($/Vehicle)	Market Share of BEV and PHEV in 2040 (%)	Total Sales Until 2040	Induced Sales	Cost/Sales ($/Vehicle)
High Cost Model	No Subsidy	100	359M			18	74M		
	3 Year	100	383M	24M	1,100	21	107M	33M	800
	5 Year	100	386M	27M	2,700	22	117M	43M	1,700
	10 Year	100	433M	74M	8,600	25	191M	117M	5,500
Low Cost Model	No Subsidy	100	524M			100	511M		
	3 Year	100	526M	2M	21,000	100	513M	2M	19,400
	5 Year	100	530M	6M	19,000	100	517M	6M	18,200
	10 Year	100	574M	50M	18,000	100	563M	52M	17,300

Table 3-4 shows how the federal subsidies (U.S.-EPA 2018b) in the form of tax credits induce the additional sales of BEVs and PHEVs if the federal subsidy is allowed for a specific time with different cost models. In the U.S., the federal government provides tax credits up to $7,500 for the purchase of BEVs and PHEVs (U.S.-EPA 2018b). The first evident results from the table are the number of vehicles sold for the Low Non-Battery Cost Model are higher than those in the High Non-Battery Cost Model. These high sales are the result of available tax credits making BEVs and PHEVs more financially attractive for a greater number of consumers. If the two scenarios (i.e. presence and absence of ICEV Cost Premium) of the Low Non-Battery Cost Model are considered, the cumulative sales in the absence of ICEV Cost Premium are less compared to the High Non-Battery Cost Model, as expected. The costs incurred by the government to induce a sale of a BEV and/or PHEV if the ICEV Cost Premium is present are higher than otherwise. Importantly, these costs per induced sale in the Low Non-Battery Cost

Model are significantly higher than those of the High Non-Battery Cost Model. More importantly, if we look at the cumulative sales when the tax credits are not available, the sales in the Low Non-Battery Cost Model are significantly higher. This suggests that the federal tax credits are not required if the Low Non-Battery Cost Model is used to estimate the additional cost of the technology.

In the High Non-Battery Cost Model, the total sales until 2040 with the ICEV Cost Premium are almost 5 times higher than otherwise. These high sales reiterate the impact of assuming more expensive ICEVs in the future. However, it also corroborates that the stricter environmental regulations are required for the conventional technologies to keep on improving, otherwise, the ETVs will have better fuel savings. The cumulative sales if the ICEV Cost Premium is available are always higher than when it is not, irrespective of the availability of the tax credits. Moreover, with ICEV Cost Premium when the tax credits are available, the sales are 2-3 times higher than otherwise. However, if only the induced sales are considered, they are higher when the ICEV Cost Premium is not present. This suggests that the federal tax credits had a greater impact on making BEVs and PHEVs financially more attractive when ICEV Cost Premium is absent. Note, the costs per induced sale are significantly lower than the actual tax credits of $7,500. However, these costs incurred to induce the sales of ETVs by the government do not make a substantial impact on long term sales. the induced sales, at least in the short term, allow the cumulative production to increase considerably. This reduces the battery cell price as well as the costs of non-battery EV technologies faster and rapidly closes the gap between initial capital costs of ETVs and ICEVs. This lower capital cost, however, can provide the necessary stimulus in making the ETVs financially more attractive to the latter adopters.

CHAPTER 4

A Pattern Analysis of Daily Electric Vehicle Charging Profiles: Operational Efficiency and Environmental Impacts[1]

4.1 *Chapter Summary*

Plug-in Electric Vehicles (PEVs) are considered one solution to reducing GHG emissions from private transport. Additionally, PEV adopters often have free access to public charging facilities. Through a pattern analysis, this study identifies five distinct clusters of daily PEV charging profiles observed at the public charging stations. Empirically observed patterns indicate a significant amount of operational inefficiency, where 54% of the total parking duration PEVs do not consume electricity, preventing other users from charging. This study identifies the opportunity cost in terms of GHG emissions savings if gasoline vehicles are replaced with potential PEV adopters. The time spent in parking without charging by current PEV users can be used by these potential PEV users to charge their PEVs, and replace the use of gasoline. The results suggest that reducing inefficient station use leads to significant reductions in emissions. Overall, there is significant variability in outcomes depending on the specific cluster membership.

[1] This chapter has been adapted from a manuscript published in the Advanced Journal of Transportation. To avoid a distracting degree of repetitive self-citation throughout the chapter, a blanket reference to the original publication is provided here: Desai, Ranjit R., Roger B. Chen, and William Armington. 2018. “A Pattern Analysis of Daily Electric Vehicle Charging Profiles: Operational Efficiency and Environmental Impacts.” Journal of Advanced Transportation 18; Article (January): 1–15. https://doi.org/10.1155/2018/6930932.

4.2 *Background and Introduction*

In the United States, the newly registered number of Battery Electric Vehicles (BEVs) and Plug-in Electric Vehicles (PEVs) increased by 159,616 in the year 2016 alone (Philip and Wiederer 2010). Though this is not a significant market share, the PEV penetration rate, BEVs and PEVs are considered together, is considerably high in the private transportation market. This has led policymakers to reconsider infrastructure planning to accommodate increasing PEVs, and assess sustainability implications of infrastructural development. Recently, a report prepared for the Clinton Climate Initiative (Philip and Wiederer 2010) outlined the incumbent and future issues of increasing penetration of PEVs. At the forefront is the adequacy and level-of-service (LOS) of charging stations; these issues are further underscored by the increasing need for out-of-home PEV charging opportunities. A critical component for management and decision-making regarding out-of-home charging decisions is the demand for these services, governed by drivers' charging behaviors. Understanding the timing and duration of PEV charging decisions supports making infrastructure and operational policies that meet economic, operational efficiency and environmental objectives.

The literature on assessing PEV charging has grown significantly in the past decade, generating studies that investigate both quantitative and qualitative issues. The literature can be roughly segmented into three areas: (i) consumer adoption and use; (ii) infrastructure performance and evaluation; and (iii) operational issues of stations.

4.3 *Literature Review*

4.3.1 Consumer PEV Adoption

The literature on consumer adoption and use has focused on identifying groups of PEV drivers with respect to their technology ownership and interaction with the infrastructure. One study (Woetzel, Sha, and Zhang 2010) (International Energy Agency 2014) identifies three groups based on adopters and potential PEV owners in China: (a) early adopters, (b) shapeable groups, and (c) late adopters, each consisting of two motivations that have their own set unique behaviors. For example, early adopters have behaviors labeled as trendy greens and running cost-sensitive. Another study (Franke and Krems 2013) assesses PEV charging behavior by applying a "user-battery interaction style" metric developed originally for small electronic devices to find out similarities in device use. In another study (Bunce, Harris, and Burgess 2014) PEV drivers were interviewed and found to generally manage without public infrastructure, with the battery still containing plenty of range when station recharging was initiated.

Although PEV range is typically adequate for completing most daily home-based tours without intermediate charging (Pearre et al. 2011), continued PEV adoption, as technological forecasts indicate, can benefit from continued installation and planning of out-of-home charging (Bailey, Miele, and Axsen 2015), in addition to further considering PEV driver's perceptions and experiences at stations. Although consumer interviews and analogous insights from the literature are helpful for describing charging behaviors, a study defining user groups or "market segments" based on a pattern analysis of empirical time-dependent charging data from out-of-home charging stations is absent in the literature. Such a study could contribute greatly to help effective policy implementation from both an operational and sustainability impact perspective.

4.3.2 Infrastructure Performance and Evaluation

PEV adoption will also impact the electric grid and shift environmental impact from point-source vehicle to electricity generator emissions due to increasing electricity demand. The literature has produced work on network optimization models that quantify and assess infrastructure and environmental impacts at the network level. These studies consider developing public charging infrastructure (He et al. 2013; He, Yin, and Zhou 2015) by optimizing social welfare relative to impacts on the electrical grid. Other studies assess the electric grid impacts from widespread charging through conventional travel surveys, where travel logs of PEV drivers (Kelly, MacDonald, and Keoleian 2012) from the NHTS are used to predict electricity consumption and load profiles. Other studies further expand on these by applying network charging scheduling (Gan and Low 2007) and time-of-use rates (Davis and Bradley 2012) to optimize and assess electrical loads on the infrastructure. In another study, large-scale vehicle survey data (Shahraki et al. 2015) are used to model charging location decisions by maximizing PEV driving miles to jointly maximum environmental benefit. An activity-based modeling approach (Kang and Recker 2009) was used in another study to assess PEV environmental impacts, suggesting that public charging facilities allow charging during the daytime and can potentially reduce emissions. Although observed travel data is used in these studies, the effects of individual charging behaviors at the stations themselves have not been examined and operational inefficiencies in station turnaround are not considered.

4.3.3 Operational Issues at Charging Stations

Operational issues have also been considered in the literature. Interviews (Caperello, Kurani, and TyreeHageman 2013) of PEV owners conducted assessed perceptions of charging etiquette at public and workplace charging locations, concluding that no common charging guidelines evolved unless a pathway of communication between users exists, which ultimately leads to inefficiency in infrastructure use. Another study (Faria, Baptista, and Farias 2014) addresses these inefficiencies by considering occupancy rates, infrastructure costs, and parking premiums to assess the economic feasibility of deploying charging stations using an economic model. This study also finds that policies that promote more infrastructure development and increased station usage are beneficial to decrease range-anxiety issues and charging premiums from the user perspective (Faria, Baptista, and Farias 2014), however, no empirical data was used. It is important to note that the PEV charging behavior at the public charging stations is not studied before, and therefore the uniqueness of this analysis is, this study brings into light the insights to charging behavior characteristics using pattern analysis of daily charging profiles observed at public charging stations and are supported by the dataset.

4.4 *Contribution*

The overarching goal of this study is to characterize the observed PEV daily charging patterns and assess the environmental impacts. One main task is to identify potential market segments based on the observed patterns of actual PEV adopters at existing charging stations. The focus of this study is to analyze the charging behavior of PEV users at the public charging stations. However, the fundamental unit of this analysis is not a PEV user but a charging profile observed in a single day (as shown later in Figure 4-2). A second task is to calculate the opportunity cost for improving operational efficiency and environmental impacts. The identified segments are used as a basis to accomplish this scenario analysis. The efficient operations scenario calculates the GHG emissions savings from reducing the duration of parking without charging, allowing other potential PEV drivers and adopters to charge. This displaces gasoline miles these potential PEV drivers might have incurred since they could not use their PEVs. The dataset lacks information about the PEV users who could not get the access to charging stations if they were occupied (denoting latent demand); the smart charging stations do not have a mechanism to keep track of this parameter. Furthermore, determining latent demand for public infrastructure, such as roads, is in its own right a difficult problem (Faria, Baptista, and Farias 2014). Similarly, the demand for public charging stations is difficult to determine. In case of the City of Rochester Authorities have confirmed in the personal discussion that there have been instances when PEV users could not get access to public charging stations because all the charging stations at the particular location were occupied. Furthermore, the authors have noted that for extended periods the data shows stations occupied continuously, where a following PEV occupies the station just a previous PEV departs. Further investigations into this queueing phenomena is underway by the authors.

In the City of Rochester, for a population of 208,880 (City of Rochester 2016)—as of July1,2016—has 28 level-2 (City of Rochester 2016) (with J1772 connector) public charging stations installed and operating through ChargePoint network (City of Rochester 2016)[22]. Each level-2 charging station can accommodate two PEVs at a time. Therefore, if all the charging stations in the City of Rochester are occupied at a time, there should be 56 PEVs plugged-in to charging stations. In the upstate New York region, Buffalo, NY (population 256,902 (City of Rochester 2016)) has 29 (City of Rochester 2016) level-2, and Syracuse, NY (population 143,378 (City of Rochester 2016)) has 27 public charging stations through ChargePoint network. The data used for this analysis is collected from charging event logs collected at these 28 (City of Rochester 2016) level-2 smart public charging stations installed in the City of Rochester. The charging stations were installed as part of a New York State Energy Research and Development Authority (NYSERDA) grant to the City of Rochester and are managed by ChargePoint Inc. (City of Rochester 2016). For this work, these charging stations are heuristically grouped—explained in the next section—into three main locations (Figure 4-1).

4.5 *Dataset*

The City of Rochester currently owns and maintains seven public smart charging stations that log the charging activities of vehicles using the stations. Types of data collected through these stations include (i) timestamps of charging events, such as the time PEVs plug-in at the stations; (ii) computed performance metrics, such as energy consumed (kWh); and (iii) other station information. The data used in the analysis were collected over a period of more than two years between March 2014 and May 2016. Charging station location coordinates were extracted and charging stations were grouped heuristically into three distinct areas: (i) Rochester Downtown (RDT), (ii) Marketview Heights (MVH), and iii) Ontario Beach Park (OBP). The RDT extent is defined by the area outlined by the Rochester Downtown Development Corporation (Rochester Downtown Development Corporation 2016), and can be considered as a business district with 58% (Table 4-1) of the land use around the charging stations is occupied for commercial use. The MVH is defined by the area defined in the Rochester Public Market Master Plan Report prepared by Market Ventures Inc. for the City of Rochester in February 2012 (Market Ventures Inc. 2012). The MVH area has 31% occupancy for commercial use and 38% for residential use. Further, the OBP encompasses the areas as defined by Monroe County Parks Department (Monroe County New York 2015), and 34% of properties around the area is occupied for residential use. Given these guidelines, five stations are located within the RDT area, and one station is located at each of the MVH and OBP extents. The following Figure 4-1 shows the locations of charging stations and Table 4-1 shows the land use of the neighborhood around these public charging stations. The figure marks the locations of charging stations, and not actual number of charging stations. For example, a map of parking lots marks locations parking lots, and not the capacity of total number of vehicles the lots can accommodate. Similarly, the Figure 4-1 depicts the seven locations of charging stations. Therefore, each location may contain more than one charging station and can accommodate at least two vehicles at a time. Further, the Table 4-2 summarizes data from the charging stations at these locations.

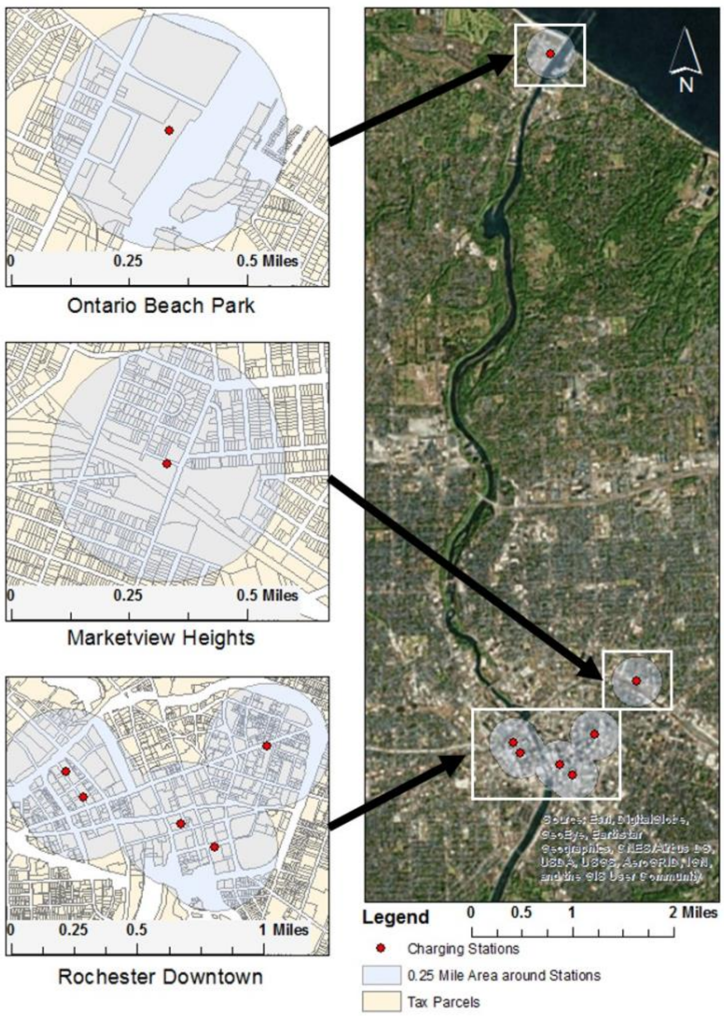


Figure 4-1: Location of charging Stations in the City of Rochester (with ¼ mile radius)

Table 4-1 Land Use Around Public Charging Stations (Monroe County New York 2015) (Monroe County New York 2015) *(for ¼ mile radius)*

	Rochester Downtown (RDT)	Marketview Heights (MVH)	Ontario Beach Park (OBP)
Population Density	6200	7700	3500

(per sq. mile)			
Unemployment Rate	11%	26%	7%
Residential Land Use	4%	38%	34%
Commercial Land Use	58%	31%	7%

4.5.1 Data Processing

The unit for this pattern analysis was *one daily PEV charging pattern for a single vehicle observed at public charging stations*. Consequently, drivers who used the stations on multiple days had multiple daily patterns in the sample considered for analysis. PEVs reside in one of three states: (i) not parked (no activity); (ii) parked with charging; and (iii) parked without charging, each assigned a numerical value of 0, 1, or 2 respectively. Since only a nominal scale for activities is required for pattern analysis and classification, the actual values of each state are inconsequential. Examples of observed charging patterns are shown below in Figure 4-2. The resulting daily pattern was further discretized into 256 data points taken at 5.625-minute intervals. The final resolution (number of points) is bounded by the requirements of the Walsh-Hadamard Transform (Theodoridis and Koutroumbas 2008a) used in the pattern analysis, which requires the number of data points (n) to be of the order of 2^n.

Errors in the logged data led to incomplete observations which were omitted from analysis. Charging events that contained total parking durations of two minutes or less were also omitted as these events are from the user (a) opening a charging session without inserting the plug into their car, then the system automatically closes the session to allow other users to use the station, or (b) the original user opens a session and decides to switch charging to an alternate port at the station (These causes were confirmed by the ChargePoint help desk staff). Events with missing or zero station user ID's were also omitted. The original dataset contained a total of 9,680 unique charging events between March 2014 and May 2016. After omitting these events based on previously stated criteria, 8,929 unique charging events were used for subsequent analysis. Using these 8,929 unique charging events, 7,554 unique daily charging patterns were generated by "stitching them together" for a particular vehicle and day for the pattern analysis.

4.6 *Methodology*

In order to characterize the daily PEV charging patterns of drivers, a pattern analysis is applied to identify homogenous segments or clusters of patterns. Charging patterns are quite complex, varying over time and geography. Example patterns observed in the sample are given in Figure 4-2. Each of these patterns represents a daily profile that starts at 12:00 AM and ends at 11:59 PM (24-hour period) for a particular PEV driver. For example, the first pattern (A) (User-ID: 137113) shows, the driver started his/her activity around 7:30 AM and used the facility for charging until 10 AM, and continued to park without charging until 3:30 PM. This PEV driver, thus, used the facility for 8 hours, but charged the PEV for only 2.5 hours. Daily patterns can also consist of multiple charging events. Pattern D shows a PEV driver using the station twice (two plug-in events) in a single day. In the case of multiple plug-in events within a single day (24 hours) for the same PEV driver, events were stitched together into a single daily charging pattern. In pattern D, the driver used the station for charging for a total 5.5 hours out of 7.25 hours of parking.

Table 4-2 Dataset Characteristics based on observed Plug-in Events.

	Sample Size: 8929 Plug-in events (Different from Daily patterns)											
	Total Parking Duration (hours)				Parking With Charging (hours)				Parking Without Charging (hours)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Whole Network	3.9	3.1	0.0	64.1	1.8	1.1	0.0	12.1	2.1	2.8	0.0	61.7
RDT (n = 7051)	4.5	3.2	0.0	64.1	1.9	1.2	0.0	12.1	2.6	2.9	0.0	61.7
OBP (n = 1316)	2.3	1.8	0.0	17.4	1.5	0.9	0.0	4.7	0.7	1.4	0.0	14.4
MVH (n = 562)	1.5	1.3	0.0	9.1	1.3	1.1	0.0	5.4	0.2	0.6	0.0	7.2
Seasons												
Winter (Dec, Jan, Feb) (n = 2250)	4.3	3.1	0.0	26.8	2.0	1.2	0.0	10.6	2.3	2.7	0.0	17.8
Spring (Mar, Apr, May) (n = 2410)	3.9	2.9	0.0	23.3	1.8	1.1	0.0	10.5	2.1	2.6	0.0	22.2
Summer (Jun, Jul, Aug) (n = 2086)	3.8	3.1	0.0	33.5	1.6	1.0	0.0	12.1	2.2	2.9	0.0	33.0
Autumn (Sep, Oct, Nov) (n = 2183)	3.7	3.2	0.0	64.1	1.7	1.1	0.0	11.4	2.0	2.9	0.0	61.7

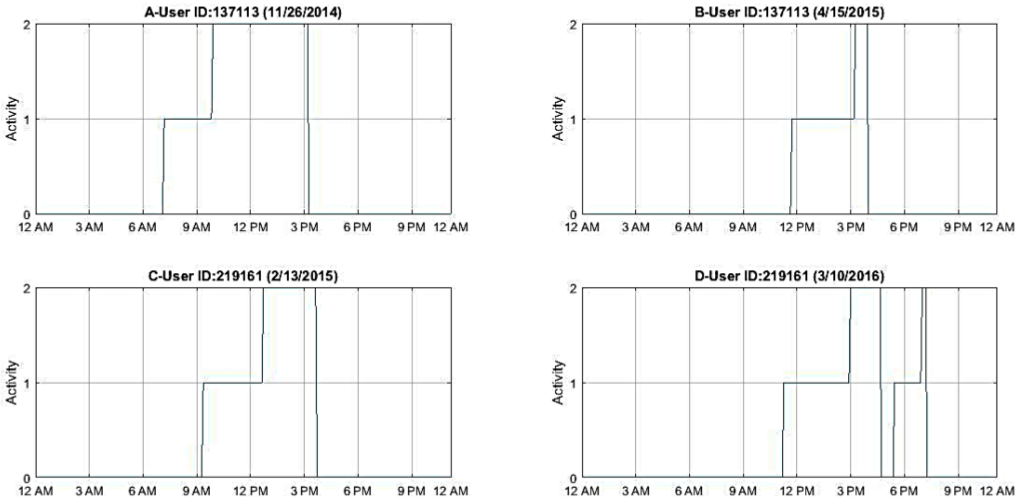


Figure 4-2: Observed charging patterns of PEV drivers in the sample ('0' – No Activity, '1' – Charging, '2' – Parking Without Charging)

Given the complexity and time-varying nature of PEV charging patterns, a pattern analysis helps identify clusters of similar patterns to facilitate discussion and subsequent analysis. Apart from uncovering similarities across patterns, this approach can also simplify and summarize a large sample of pattern data. Past studies use pattern analysis to classify travel patterns (Recker, McNally, and Root 1985) and characterize vehicle travel patterns and to examine the feasibility of PEV operation (Chen, Clifton, and MacArthur 2014). This study adopts a similar approach towards classifying daily charging patterns of PEV drivers into homogenous segments with respect to their daily patterns.

Pattern analysis has been applied to a wide range fields from voice recognition to image analysis, all of which aim to classify patterns into sensible segments. The clusters do not group the PEV users but the daily charging profiles of the PEV users observed at the public charging stations. The same PEV user can have multiple patterns of usage as well as can be observed to use the charging stations at different locations. Importantly, pattern analysis can provide different and a few in number clusters of homogeneous daily charging profiles, and the identified clusters can be used for policy making where a particular charging behavior can be targeted. Furthermore, the observed operational inefficiency depends upon the patterns of charging behavior, and along with the total parking without charging time, it is important to understand how this inefficiency is distributed. The pattern analysis provides the specific number of clusters of daily profiles which can be further understand the causes of the operational inefficiency.

The overall methodological framework is shown below in Figure 4-3. Conventionally, a sequential three stage process of pattern analysis consists of (i) pattern specification; (ii) feature extraction and (iii) clustering. First, plug-in event data is taken from the sample and stitched together to form daily patterns. The process for this was described previously in section 4.5. Given the resulting sample of daily charging patterns, features are extracted from these daily patterns for the subsequent clustering stage. The output of clustering and consequently the entire pattern analysis process is a set of homogenous segments of patterns, with patterns within the same segment are similar to each other, while patterns in different segments are dissimilar to patterns in other segments. These identified segments serve as the basis for subsequent scenario analysis to investigate the potential of policy interventions and technology options. The next section describes the pattern analysis process and discusses the clusters that are an outcome of this process.

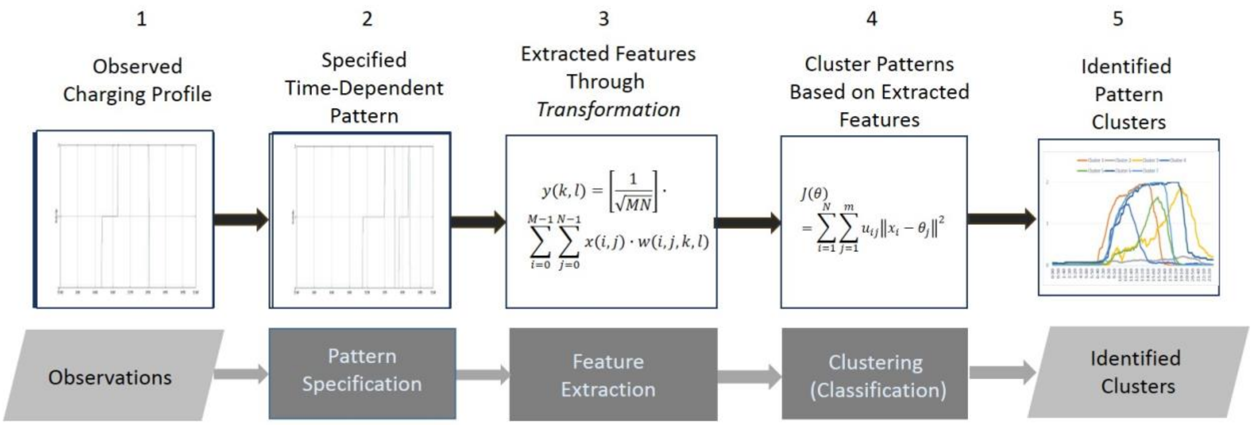


Figure 4-3: Methodological Framework

4.7 *Pattern Analysis Process*

Conventionally, pattern analysis consists of a sequential three stage process: (i) pattern specification; (ii) feature extraction and (iii) clustering. These stages and the overall methodological framework are described further in the next section. Pattern Specification

First, plug-in event data are taken from the sample and stitched together to form daily patterns. In this stage, all the plug-in events are converted into a "signal" consisting of three possible states that refer to three activities, '0' for no activity, '1' for charging activity and '2' for parking without charging activity, as explained in the previous section. Daily time-varying EV charging patterns are generated or "stitched" together in chronological order based on the timestamp of charging events logged by the smart charging stations. Examples of patterns specified and outputted in this stage were shown in Figure 4-2.

4.7.2 Feature Extraction

In this stage, features are extracted from the specified patterns for subsequent clustering. Observed events such as charging (state=1) and parking without charging (state=2) are time dependent. The main goal of feature extraction is to extract statistically independent "features" from the observed patterns that are best suited for subsequent cluster analysis in the classification stage. These features serve to summarize the patterns and capture the most important pattern characteristics. The feature extractor used is the Walsh-Hadamard Transformation (WHT), though others such as the Karhunen-Loeve or Haar could also have been used (Theodoridis and Koutroumbas 2008b). The WHT extracts features referred to as Walsh coefficients (Walsh 2016), that are used in the cluster analysis. These extracted features can conceptually be considered as "building blocks" of the observed patterns. An analogous process would be a principle components analysis on a digital image. In pattern analysis, a feature extraction allows identifying separate orthogonal features from the image, or in this case time-dependent pattern. These features, in this case Walsh coefficients, are used in subsequent clustering of patterns as "attributes" of this observed pattern.

4.7.3 Pattern Classification

The extracted features from the previous stage are used in a clustering algorithm to identify homogenous segments of patterns. The output of clustering and consequently the entire pattern analysis process is a set pattern segments, with patterns within the same segment being similar or homogenous to each other, while patterns in different clusters are dissimilar each other. Conceptually, each cluster contains patterns (which are time dependent) that have similar "features." In the literature, several clustering algorithms exist; this study uses the k-means clustering algorithm.

The K-means algorithm is a cost-based algorithm (MacQueen 1967), in which the cost function $J(\theta)$ given by:

$$J(\theta) = \sum_{i=1}^{N} \sum_{j=1}^{k} u_{ij} \left\| x_i - \theta_j \right\|^2 \qquad \text{Equation 4-1}$$

where θ_j is the centroid of cluster j, u_{ij} is a binary indicator that equals 1 if point x_i is nearest to θ_j, N is the total number of points and k is the number of clusters. For the k-means algorithm, the number of clusters is specified a-priori. As the number of clusters increases the marginal reduction in the cost function decreases until a negligible value, indicating the correct number of clusters is specified. A plot of the cost function ($J(\theta)$) as a function of number of clusters (k) is given below in Figure 4-4. It shows the variation of cost function with respect to increasing number of clusters. The final number of clusters for a particular sample of patterns is determined based on identifying the point of marginal return on the cost function.

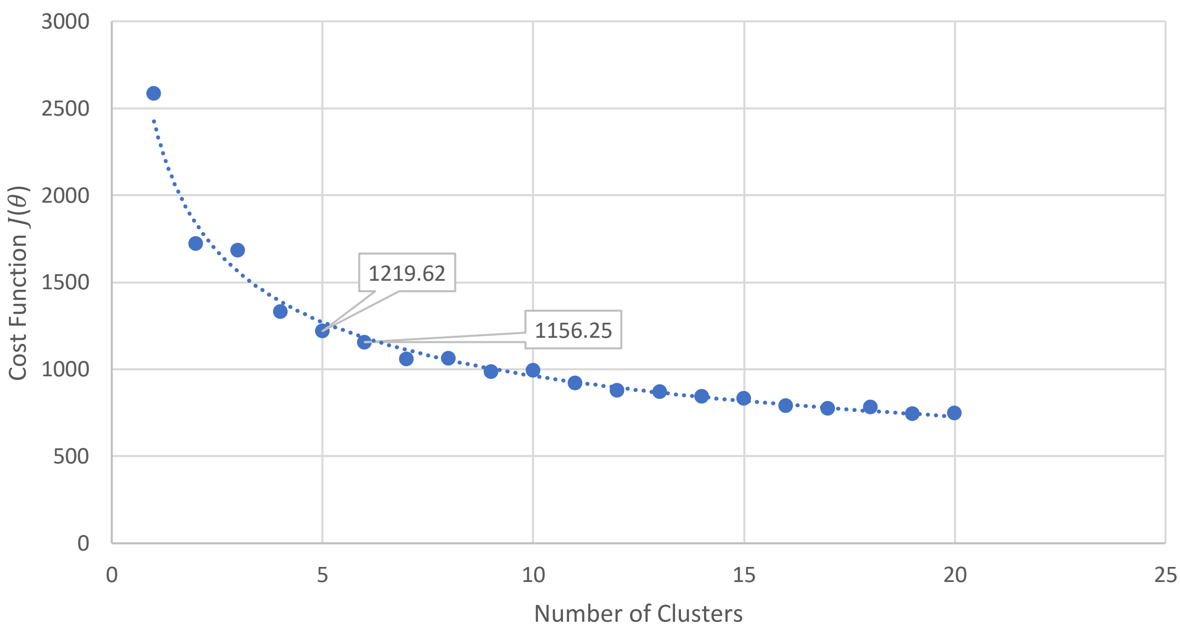


Figure 4-4: Cost Function value vs. Number of Clusters assumed a priori

4.8 *Identified Clusters of daily Charging profiles*

The pattern analysis approach described in the previous section identified 5 distinct clusters of daily charging profiles from the sample. This section examines the clusters and their members with respect to (i) charging; (ii) parking without charging and (iii) parking durations. Additionally, inverse Walsh-Hadamard Transform on the feature centroids of each cluster is used to reconstruct a composite image for each cluster and to facilitate interpretation. These images are shown below in Figure 4-5.

4.9 *Characterization of Identified Clusters*

Each identified cluster is characterized with respect to charging and parking activities. Figure 4-5 shows the reconstructed profiles from the inverse Walsh-Hadamard for each cluster. Note that the profile represents a composite of all activities at a specific time. For example, only if all events at a specific time were charging (state = 1) would the profile distinctly indicate "charging". For this reason, the distribution of patterns within each cluster residing in the three different states considered are also plotted over the one-day period.

Cluster 1 (CL-1, 772 patterns; 10 % of the sample of patterns): The reconstructed composite profile of CL-1 indicates that most charging activities start at 6:30 AM and peak (60% of patterns) at 8:45 AM. The daily profiles in this cluster are observed to have a peak (90% patterns) of parking without charging activity at about 1:45 PM. The patterns from CL-1 are mostly (85%) observed at RDT on weekdays (95%).

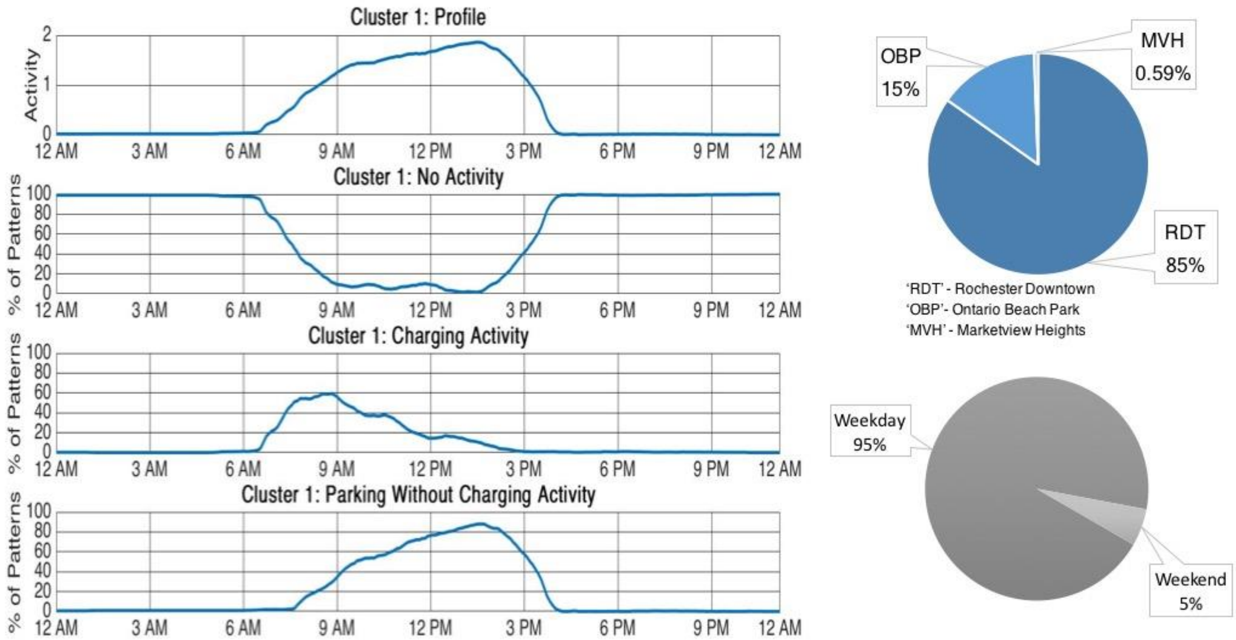
Cluster 2 (CL-2, 3,438 patterns; 46% of the sample of patterns): The composite profile of CL-2 has a distribution characterized by a low peak (20% of events) at 2:15 PM. Note again that the profile represents a composite of all activities at a specific time, making it difficult to tease out specific activities. The peak of parking without charging activity is observed at 3:30 PM with only 12% of patterns. Unlike CL-1, the patterns from CL-2 are observed at all the locations and has highest (30%) contribution of patterns observed on weekends. The patterns observed at MVH have highest contribution of 14% in CL-2 compared to the rest of the clusters. As CL-2 is largely comprised of shorter plug-in events, and MVH being the location near a public market, it can be inferred that the PEV drivers who access the public charging stations at the MVH and have charging profiles belonging to the CL-2 tend to use the charging stations for shorter durations.

Cluster 3 (CL-3, 1,355 daily patterns; 18% of the sample of patterns): These patterns show a peak (68%) of charging activity at 8:45 AM and a very level of parking without charging activity with a peak (98.45% of patterns) at 4:15 PM. The patterns in this cluster indicate more parking without charging than parking with charging. CL-3 is constituted of 98% patterns observed at RDT, and 97% patterns observed on weekdays. Similar to CL-1, the charging activity of such patterns coincides with a typical working day schedule around the business district of Rochester.

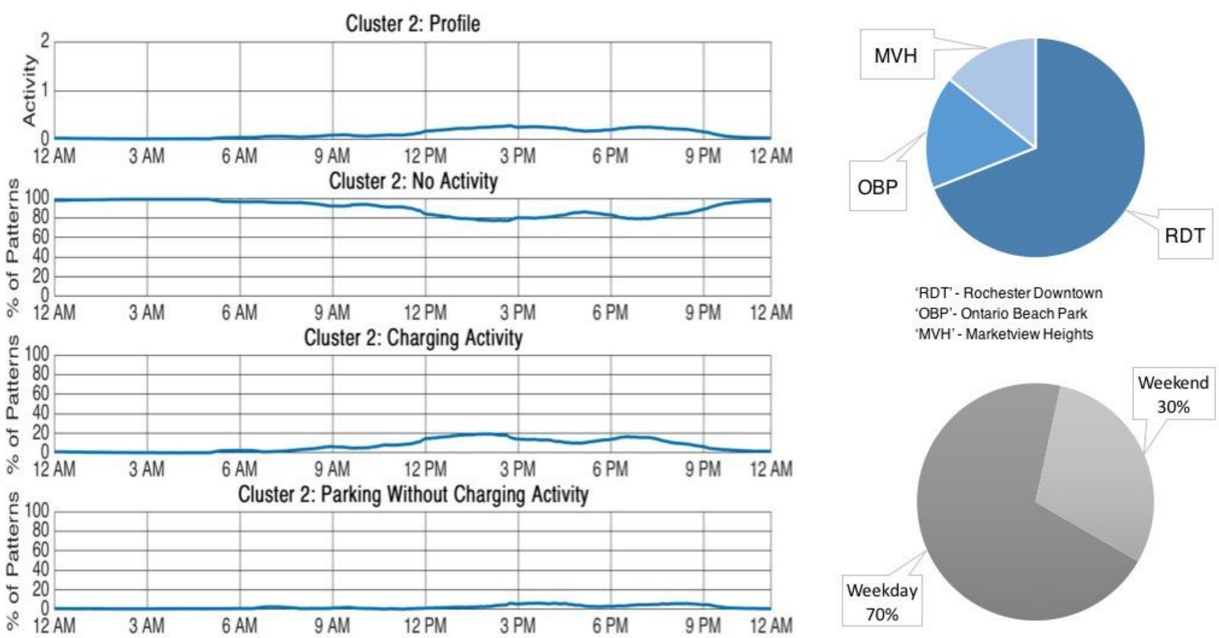
Cluster 4 (CL-4, 1,500 patterns; 20% of the sample of patterns): The parking with charging activity for these patterns peak (70% of patterns) at 9:00 AM. The parking without charging activities peak (60 % of patterns) at 11:30 AM. CL-4 does not have higher peak of parking without charging activity than parking with charging activity. Further, the patterns observed at RDT are 84% and 92% are observed on weekdays.

Cluster 5 (CL-5, 489 patterns; 6% of the sample of patterns): The parking with charging of these patterns peak (55% of patterns) at 9:00 AM. The parking without charging peaks (90% of patterns) at 5:30 PM. The patterns observed at OBP have highest contribution of 27% in CL-5 compared to rest of the clusters. As OBP can be considered as a leisure place, a typical PEV driver may stay at OBP for the entire day, which can be inferred with the charging activity ranging from 7:30AM to 6:20PM.

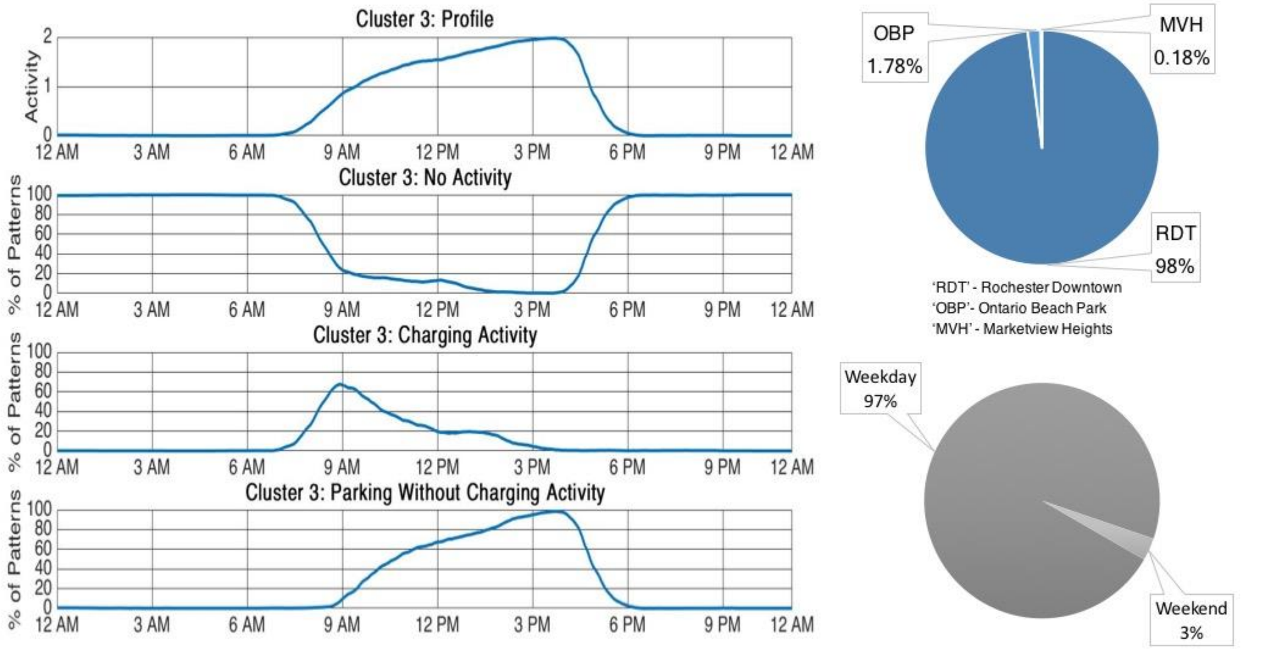
Importantly, the charging profiles observed in CL-3, CL-1 and CL-5 show charging behavior characteristics which are likely to be observed on a working day at a public charging station located in business district, in this case RDT.



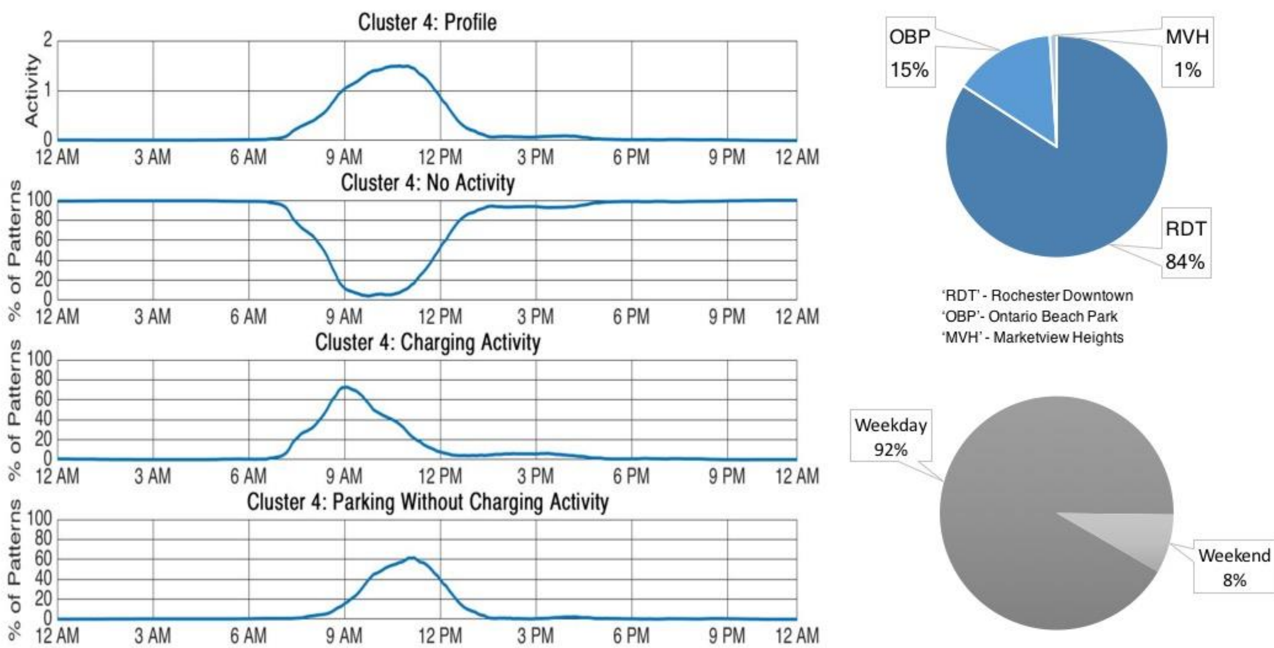
(a) Cluster 1



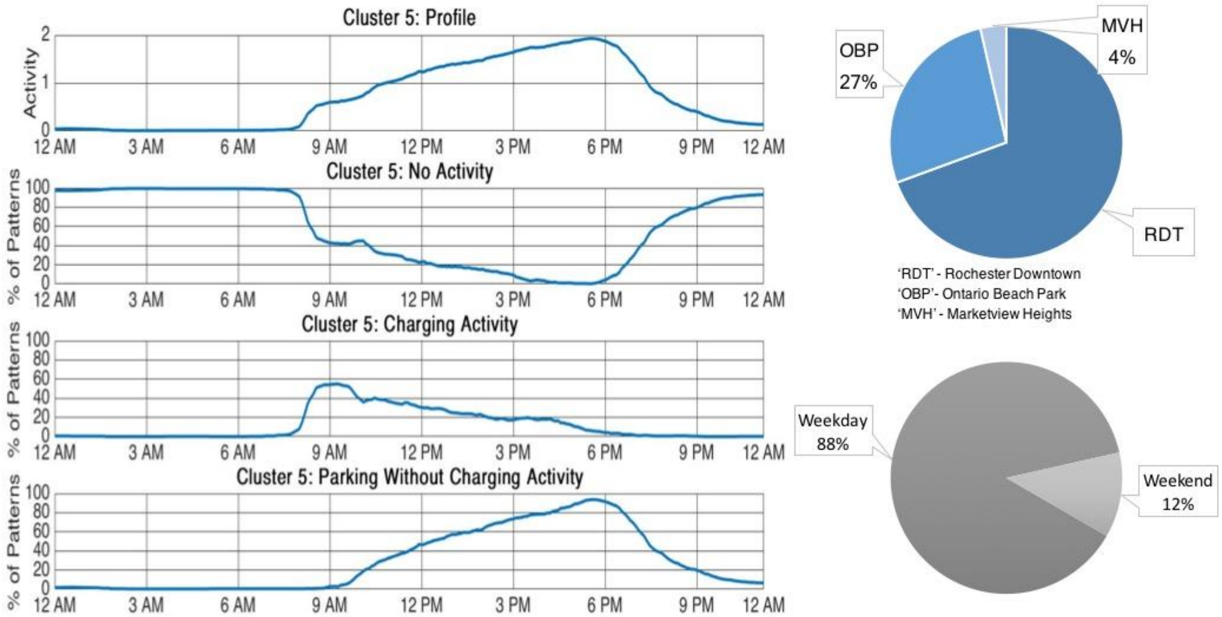
(b) Cluster 2



(c) Cluster 3



(d) Cluster 4



(e) Cluster 5

Figure 4-5: Cluster Profiles and Distribution of Patterns in Activities '0'-No Activity, '1'-Parking with Charging, '2'-Parking without Charging along with distribution of patterns with respect to location and type of day the pattern was observed (for example, weekday of weekend) (a) Cluster 1, (b) Cluster 2, (c) Cluster 3, (d) Cluster 4, and (e) Cluster 5

4.10 *Comparison of Identified Clusters*

Figure 4-6 shows distribution of three dimensions, across patterns within each identified cluster: (a) parking duration (PD), (b) parking duration with charging (PDWC), (c) parking duration without charging (PDWOC) and (d) total sum of parking without charging durations of all patterns across different clusters. For PD, CL-5 while being the smallest cluster with only 489 daily patterns, had the highest median PD (more than 10 hours). However, CL-2, the largest cluster with 3,438 daily patterns, has the lowest median PD (2 hours). Irrespective of the cluster sizes, the median for PD varies from 2 hours to 10 hours. In contrast, the PDWC does not vary significantly across clusters. The median for PDWC varies from 1.5 hours to 2.5 hours across clusters. Figure 4-6c also shows the distribution of PDWOC for all clusters. CL-5 has the highest median around 7.5 hours and CL-2 has the lowest (almost negligible) median. This characteristic of a charging behavior indicates efficient (or inefficient) operation of charging stations. Furthermore, Figure 4-6d shows that CL-3 has the highest total sum duration of hours spent parking without charging, followed by CL-1 and CL-5. These total hours spent parking without charging activity indicates the inefficiency of user turnaround at stations, likely due to the currently cost-free situation. Figure 4-6 also shows that, except for CL-2 and CL-4, the remaining clusters exhibit a higher median for PDWOC, relative to PDWC. However, due to their membership sizes, CL-2 and CL-4 still show a significant *total sum duration* of parking without charging.

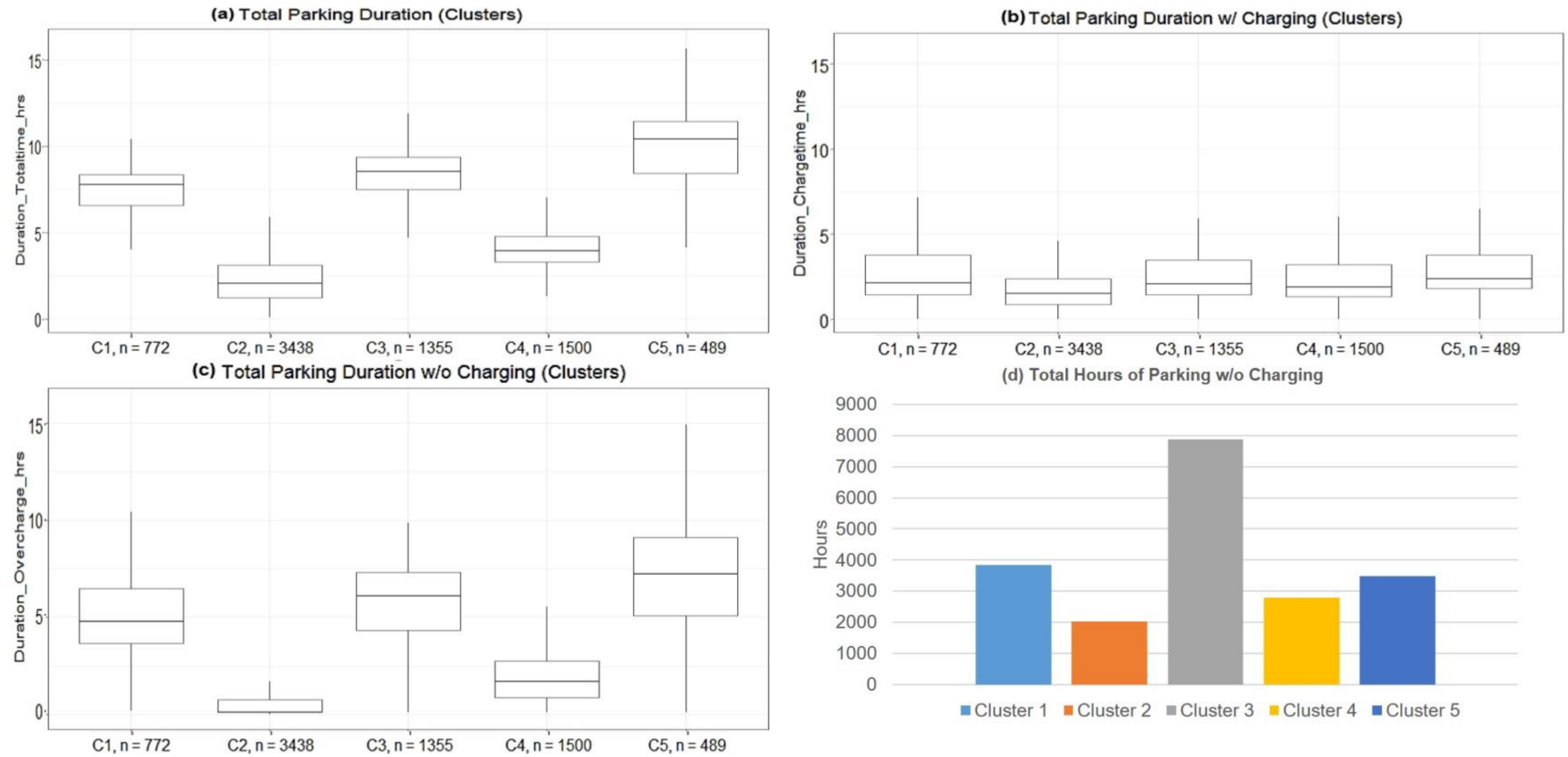


Figure 4-6: Variation of activities across clusters (a) Parking Duration (hours), (b) Parking Duration with Charging (hours), (c) Parking Duration Without Charging (hours) and (d) Total (i.e. sum of all the daily patterns in the respective cluster) Hours of Parking Without Charging across clusters

4.11 *GHG Emissions Analysis*

The pattern analysis in the previous section uncovered five distinct clusters of daily charging profiles, each with a large frequency and total sum duration of parking without charging across daily profiles of PEV drivers. User operational inefficiency at charging stations is an issue that needs to be addressed to efficiently allocate institutional resources. Additionally, this inefficiency may demotivate potential PEV adopters who see out-of-home charging locations constantly occupied. The efficient user operations scenario is explained in detail in the following section.

This scenario examines the impact of reducing inefficient station use through reducing the parking without charging duration. By allowing more efficient use and turnaround of charging stations, more PEV drivers can use the stations, thus potentially displacing gasoline miles incurred otherwise with electricity. These drivers could be potential PEV adopters or current PEV drivers who see the occupied station and turn away discouraged. The main assumption is that 100% time spent in parking without charging can be replaced with PEV drivers who need to charge. The GHG emissions savings from this displacement of inefficient station sue is determined as follows:

$$\begin{aligned} &GHG\ Emissions\ Savings = Emissions\ displaced\ by\ replacing\ gasoline \\ &= \left\{\frac{\{Avg._{PWOC} \times P_{avg.} \times \eta_e\}}{\eta_{gas}} \times \left(\begin{matrix} Emissions\ per\ gallon\ of\ gasoline \\ (MT\ CO2\ eq./gallon) \end{matrix}\right)\right\} \\ &- \left\{E \times \left(\begin{matrix} Emissions\ per\ 1\ kWh\ of\ electricity\ generation\ in\ NYUP \\ (MT\ CO2\ eq./kWh) \end{matrix}\right)\right\} \end{aligned}$$

Equation 4-2

where $Avg._{PWOC}$ is the average time spent in parking without charging in hours per daily profile in respective cluster, $P_{avg.}$ is the assumed average charging rate of 3 kW, which is averaged rate across all the individual plug-in events in the observed sample in (kW), η_e is the electrical efficiency of PEVs in $(miles/kWh)$ and is assumed based on the literature: 3 miles/kWh (Idaho National Laboratory 2010)—for increase and decrease in electrical efficiency the GHG emissions savings vary in proportion, E is electricity consumed per average profile of respective cluster in (kWh). Given that consumption of 1 gallon of gasoline emits 8.887×10^{-3} metric tons (MT) of CO_2 eq. (US-EPA 2016)—for gasoline, CO_2 and CO_2 equivalent are same because gasoline combustion results in only CO_2 and H_2O, the total GHG emissions displaced by allowing more station charging can be calculated. The analysis was carried out for each individual cluster identified.

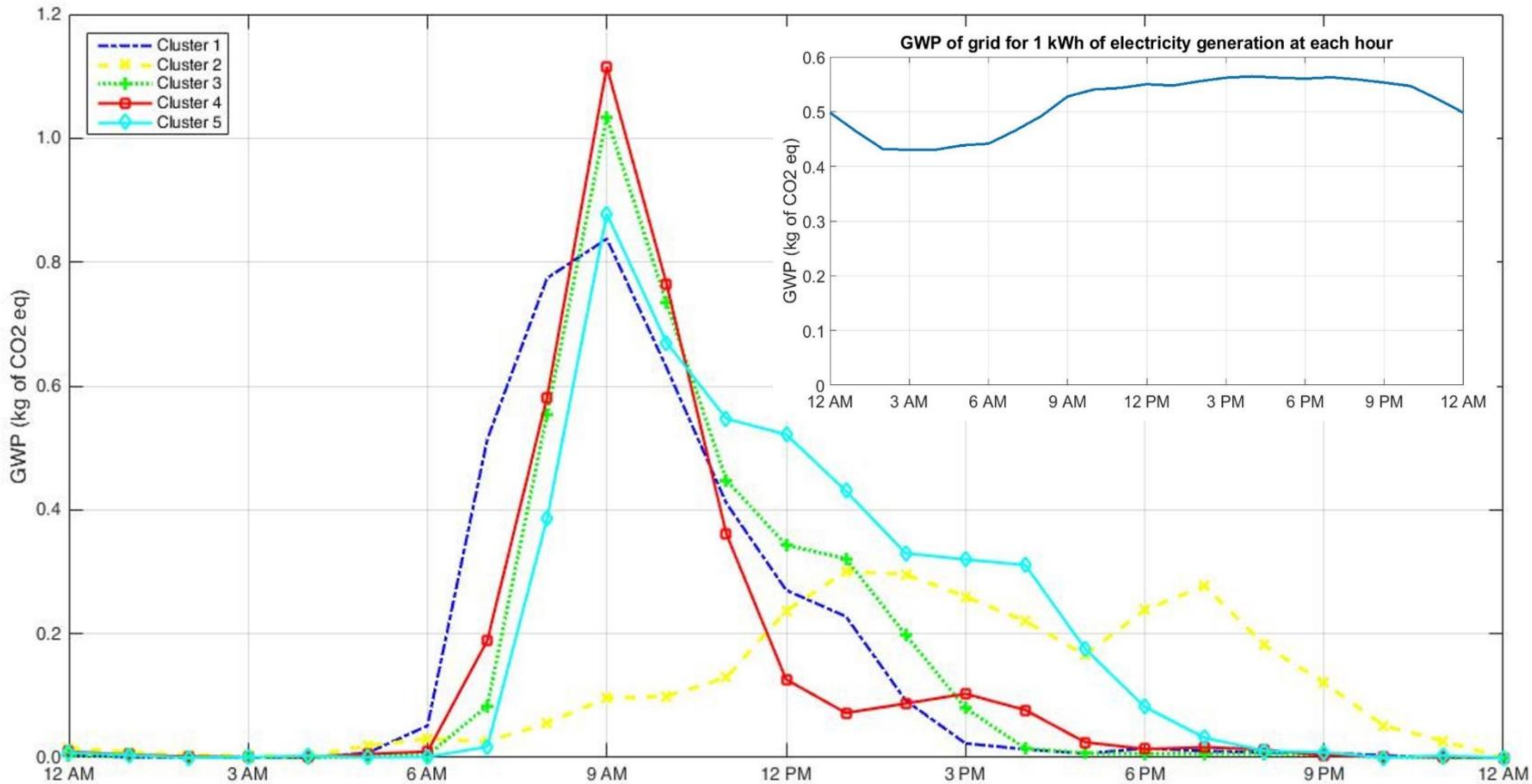


Figure 4-7: Global Warming Potential (GWP) in terms of kg of CO2 eq. for electricity consumed by an average daily profile of respective cluster at each hour and emissions from grid for generation of 1 kWh at each hour

To determine the GHG emissions from the electricity consumed, hourly electricity consumption is assumed to correspond to the number of PEV drivers using the facility for charging at that particular hour. Additionally, for upstate New York, the electricity production mix changes at each hour depending upon the demand for electricity (www.NYISO.com 2016), resulting in varying environmental impact each hour per kW-hr of charge. Figure 4-7 depicts the global warming potential (GWP) in terms of kg of CO_2 equivalent for one unit (1 kWh) of electricity production for a varying grid mix of upstate New York (www.NYISO.com 2016) for a typical day.

The Figure 4-7 shows that every 1 kWh of electricity produced from 12:00 AM until 8:00 AM is cleaner compared to the rest of the day and the GWP stays below 0.5 kg of CO_2 equivalent. However, after 8:00 AM, the GWP of electricity production starts increasing and around 6:00 PM it has the highest GWP of 0.56 kg of CO_2 eq. because at this hour the electricity grid mix has most of the supply from fossil fuel power plants to meet the additional peak demand. Therefore, every 1 kWh of electricity consumed by the PEV drivers during a day has GWP directly proportional to the GWP shown in Figure 4-7 at that hour. Figure 4-7 further shows the GHG emissions for an average profile belonging to each cluster. CL-4 at 9:00 AM shows the highest GHG emissions, followed by CL-3 and CL-5 respectively. Note this peak occurs at a specific time

Looking at average daily profiles for each cluster and their GHG emissions savings indicate opportunities for significant emissions savings. Overall, if efficiency in PEV user operations is improved i.e. the PDWOC is reduced, significant GHG emissions savings can be realized. For an average daily profile, CL-5 has the maximum total GHG emissions savings potential across the day, largely because profiles in this cluster have highest average parking without charging time over the day. CL-3 and CL-1, have the second and the third largest GHG emissions savings potential for similar reasons based on the entire daily GHG savings. Finally, CL-2 has the least GHG emission savings, due to low PDWOC, over the day, relative to the other clusters (Figure 4-6c). Overall, the results suggest that displacing inefficient parking at charging stations with PEV charging from additional PEVs can lead to significant GHG emission savings, even in the case of CL-2 which has a lower median of PDWOC relative to the other clusters.

As stated earlier, in section 4.2, the CL-3 has the highest PDWOC (Figure 4-6d), with respect to the sum of all the daily charging profile in the cluster; proportionately this cluster has 7880 hours of total parking without charging duration, which is the highest among all five clusters. However, a daily charging profile belonging to CL-5 exhibits longest PWOC activity (starting at 9:00 AM until 12:00 AM, shown in Figure 4-5e). This can also be referred to Figure 4-5c, CL-5 has highest median of PDWOC per daily profile, followed by CL-1 and CL-3 respectively. If all the clusters were of the same membership size, the CL-5 would have had largest total parking duration without charging, and hence the maximum GHG emissions savings potential. If the hour-specific electricity consumption is considered as a criterion, a CL-4 profile has the highest GHG emissions at 9:00 AM (Figure 4-7), followed by CL-3 and CL-5 respectively, which corresponds to the charging activity of an average profile belonging to a particular cluster at 9:00 AM.

As this dataset sample may not represent the actual population of charging events, we cannot draw inferences at the population level. However, based on this sample, for realizing GHG emissions savings, we can target the daily profile represented in CL-5, as they exhibit highest PDWOC on a typical day, or we can target the daily profile represented in CL-3, as the CL-3 has the highest total parking without charging duration (in total hours). If the calculations of GHG savings are performed considering efficiency of gasoline vehicles, with respect to the projections of expected improvements in miles per gallon (mpg) as per CAFE standards (U.S.-EPA 2011), the amount of GHG emissions displaced varies in proportion to the gasoline vehicle efficiencies. For higher gasoline engine efficiency, the emission savings are less and vice versa.

4.12 *Conclusion*

Our results indicate that the daily charging profiles of PEV drivers observed at the public charging stations can be clustered into five different groups based on their charging behavior. The five identified patterns display distinct PEV charging behaviors with respect to parking with charging activity, and parking without charging activity. These five clusters indicate that though the PEV drivers have variability in their charging profiles, the median for charging durations are similar (1.5 hours to 2.5 hours). However, they have significant durations of parking without charging, which can be conceptualized as '*inefficient operation of charging stations*'. This inefficiency is about 54% of the total usage time of the charging stations. The GHG emissions analysis suggests this inefficiency if reduced, can have a positive environmental impact (in terms of GHG emissions savings) resulting from an assumed displacement of gasoline vehicles.

Several extensions to this work are envisioned. First, the analysis precluded consideration of behavioral changes. To address this, a queueing simulation model of station operations could be implemented based on this data, providing insights into shifts in station turnaround under different policies. The queueing simulation can further be used to analyze a policy of maximum allowed time to use public charging stations to reduce this inefficiency. Second, empirical data on charging prior to reaching the stations could be collected providing a clearer picture of charging needs at the station and subsequently could be used to reduce the duration of parking without charging.

5 CHAPTER 5: CONCLUSION

5.1 *Systemic Modeling Uncertainties*

The models in this study are developed around the core idea of variability in consumers' vehicle use. Implicit in this modeling is the assumption that consumers are purchasing a new vehicle to replace their current ones. However, ride-hailing services are fundamentally changing how consumers ownership and vehicle use in the future, bringing in potential systematic shifts. This can potentially propel consumers to move away from using their own private vehicles and public transportation in favor of shared mobility. In 2018, 36% of the U.S. population used ride-hailing services such as Uber or Lyft, increasing from just 15% in 2015 (JIANG 2019). Vehicles used for ride-hailing are expected to accumulate more travel miles than private vehicles, and consumers with vehicles that travel more miles have been found to receive larger direct financial gains from switching to ETVs. Therefore, if a consumer wants to use their vehicle for ride-hailing services, then they should switch to an ETV, which would also result in GHG emissions reductions for society. Since early adopters propel reductions in prices for latter adopters, if ETV-based shared mobility increases, ETV prices will drop. Reduced ETV prices would make them cheaper to adopt for consumers who would not financially benefit from ETV adoption initially. More consumers moving towards ETVs would significantly gain market share for ETVs and replace incumbent conventional vehicles. Thus, a fundamental change in consumer behavior may potentially push the market towards electrified private transport.

Along with modeling uncertainties, the results of the analyses depend on critical assumptions of key parameters like learning rate. Along with learning rate, there are other parameters such as battery cell price and cost of non-battery EV technologies, which affect the results. In this section the effect of uncertainty in learning rates is explained. A learning rate defines the actual cost reduction as a result of doubling of cumulative production. This assumption brings in the parameter uncertainty in this work. Learning rates affect the outlook of future costs of technology. This work used 17% and 5% as the learning rates for the battery cells and non-battery EV technology. Learning rates are estimated by using reported prices, however, there is a significant lack of reliable battery cell prices as well as non-battery EV technologies. In the future, as new literature with dependable data sources becomes available, these estimates would need to be updated. The learning rates for battery cells are also contingent on developments in other sectors such as energy storage. In future estimations of learning rates, battery technologies should be considered as a whole and developments in battery technologies across different sectors should be used to estimate learning rates. Thus, if the uncertainty in learning rates is properly addressed and new learning rates are estimated, then price reductions due to adoption would differ from the projections presented in this dissertation. Higher learning rates would project faster reductions in per-unit prices and faster adoption of ETVs, and vice versa. A faster adoption would mean the ETVs will become financially more attractive for most consumers. No public data is available to better resolve learning rates, future research can address this situation.

5.2 *Implications for Decision Making*

This work deals with the adoption of ETVs and estimating their carbon and financial benefits. ETVs and charging infrastructure are already subsidized and thus a target of government interventions, this study can support policy decision making. With the increase in ETV-based shared mobility as well as the market-share of PEVs, the demand for public charging stations will rise. Therefore, governments will need to install additional charging stations to meet demand. However, installing additional charging stations could be costly as it entails purchase of installation of electric vehicle supply equipment, extending electricity lines, and real-estate costs. Moreover, with the improving battery technology, battery cells are expected to become more energy dense and facilitate longer range of driving with a fully charged vehicles. As greater number of automakers are likely to follow the suit and manufacture longer range vehicles, the consumers who are concerned about the 'range anxiety' could become the prospective electric vehicle owners and add to the market share of PEVs. This added fleet will also increase the demand to use the public charging stations. Additionally, in the areas with multi-dwelling unit (MDU) households, consumers would be faced with a challenge of unable to install private changing units. And if the consumers residing in these MDU facilities switch to the plug-in electric vehicles, there will be additional demand to use the public charging stations. Therefore, prior to an installation decision, decision-makers should consider analyzing consumers' behavior at public charging stations. The City of Rochester case study revealed that public charging stations are used for parking instead of charging more than 50% of the time (Desai, Chen, and Armington 2017). The PEV users using the charging stations mostly for parking instead of charging could hinder the other PEV users from using the charging stations. As the governments, mainly, install the public charging stations to attract more consumers to adopt a plug-in electric vehicle, for a such a potential PEV adopter it could be demotivating to witness public charging stations occupied and not available to use for other PEV user. As such, governments should consider implementing policies to disincentivize the use of public charging stations as long-term parking. Therefore, the use of public resources like the public charging stations should be monitored and analyzed. So, that the inefficiencies in the operation could be recognized and addressed by implementing efficient use-oriented policies.

This work takes into account demand-side heterogeneity of vehicle use to recognize the potential economic and carbon benefits of ETVs. However, the purchase decision of these vehicles is affected by the federal subsidies, therefore, the implications of the results of this study on technology subsidy policies are critical to understand. Current federal tax credits are available to all the consumer alike to purchase a BEV/PHEV. This work highlighted that the consumers who would financially benefit the most drive significantly higher than the national average in the U.S. Therefore, offering federal subsidies to all the consumers is not an ideal situation. However, this dissertation can help in recognizing the subpopulation who does not financially benefit from ETVs now, but if the federal subsidy is offered to this subpopulation, it can make the ETVs financially attractive. The consumers who have net cost (meaning 'consumers pay from their pocket') positive but lower than the current federal subsidy (i.e. $7,500). In Figure 2-5, this subpopulation would have positive abatement cost. These consumers should be recognized and should be offered the federal tax credits. For this key subpopulation, the net cost of adopting to an ETV can this be changes to net financial gains.

If this subpopulation, therefore, is offered federal subsidies, can become the part of early adopters along with the consumers who receive direct financial benefits because of their heavy use and add to the cumulative production of ETVs inducing greater price reductions. Table 3-4 shows the money spent by the government per induced adoption. Although, the cost incurred by the government to induce an adoption are high, the federal tax credits can make the ETVs look financially more attractive. Therefore, these subsidies can be used as a tool to induce higher early ETV adoption. This early ETV adoption can then result in future price reductions and making ETVs financially more attractive to consumers who currently face high technology prices. Along with subsidies, this work also looked at sensitivity of results for different oil prices. Although it effects of varying oil prices are dealt in previous chapters specifically, it is important to reiterate the emphasis of future oil prices on the ETV outlook. At high oil prices, the financial gains turn substantially in favor of ETVs compared to the incumbent internal combustion vehicles. The oil prices are—and may always stay—highly volatile, however, if the government decides to provide an aggressive support to the electric vehicles, new laws and additional tax imposition (for example carbon tax) can be used as viable policies options to make the ETV financial look more attractive. Private transportation in the U.S. presents significant variability from consumer-to-consumer preferences as well as vehicle-to-vehicle performances. Therefore, while conducting analyses or estimations of potential sustainability gains of new technology, attention should be paid to the inherent variability in the system.

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