Environmental and Policy Implications of Vehicle Automation and Electrification

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Avi Chaim Mersky

B.S., Civil & Environmental Engineering, Lafayette College

A.B., International Studies, Lafayette College

M.S., Civil & Environmental Engineering, Carnegie Mellon University

Carnegie Mellon University

Pittsburgh, Pennsylvania

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Thesis Committee Members

Constantine Samaras, Dissertation Chair

Assistant Professor

Civil and Environmental Engineering

Chris T. Hendrickson

Hamerschlag University Professor Emeritus

Director, Traffic 21 Institute

Civil & Environmental Engineering

Engineering & Public Policy

Heinz School of Public Policy

Zhen (Sean) Qian

Assistant Professor

Civil and Environmental Engineering

H. John Heinz III College

Jeremy Michalek

Professor

Director, Vehicle Electrification Group

Director, Design Decisions Laboratory

Engineering and Public Policy

Mechanical Engineering

Abstract

Mobility and transport underpin a society's economic and physical life. Travel, however, has significant external costs, not solely borne by those performing or requesting the service. In addition to the direct cost of building and maintaining the necessary infrastructure, an individual's decision to travel or transport goods affects the time others must travel, via congestion; injuries and fatalities; environmental health; and national energy security. When fueled by oil, for example, these costs add up to approximately $4.00 a gallon, depending on the specific vehicle. Two sets of technologies have the potential to drastically reduce the externalities associated with passenger travel: vehicle electrification and automation.

Ensuring a socially optimal outcome from changes in vehicle technology requires four components. The first is determining whether adopting a set of new technologies would provide a net social benefit. The second is knowing how to effectively encourage adoption of a technology that has been determined to provide a net social benefit. The third is knowing how to optimally construct necessary infrastructure for the technology, while considering how future changes in the technology or other technologies may affect this process. The fourth component is being able to effectively regulate a technology. This dissertation addresses each of these issues by focusing on specific novel applications and case studies. It then discusses the joint implications and questions raised by these chapters.

Chapter I introduces the environmental and safety externalities associated with passenger vehicle mobility. Chapter II focuses on the issue of determining the social value of implementing a new technology. A municipality evaluating a potential transition to an electrified vehicle fleet has its own set of decision criteria, which may be different than

other actors. Of the passenger vehicle models that the City of Pittsburgh is considering, battery electric vehicles (BEVs), but not plug-in hybrid electric vehicles, were found to have lower life-cycle GHG emissions than conventional vehicles in Pittsburgh. However, vehicle electrification was found likely to have higher total social emissions costs than conventional options. Chapter III focuses on technology adoption by investigating the statistical significance of demographics and incentives on electric vehicle sales in Norway. Chapter III shows that access to BEV charging infrastructure, being adjacent to major cities, and regional incomes have the greatest predictive power for the growth of BEV sales. While Chapter III does not test for causation, vehicle chargers are necessary for BEV adoption and the results show that charging infrastructure is significantly correlated with BEV adoption in Norway. This suggests the need to plan for charging infrastructure concurrently with BEV adoption.

Chapter IV focuses on how to optimally construct necessary infrastructure for electric vehicles when accounting for vehicle automation. For our simulation of about 2,000 trips in the greater Seattle, Washington area, moving from levels 0-3 to level 4 reduced peak electric load by about one-third and level 5 automation about two-thirds. Moving from no automation to level 4 automation nearly halved operator costs, while not having any significant effect on commuter costs. Moving to level 5 automation decreased operator costs by about 75% due to reduced number of charging stations, but shifted a portion of this reduction onto commuters. Chapter V focuses on how to effectively regulate technologies so that their future development increases social value, focusing on the specific problem of measuring the fuel economy of autonomous vehicles. The results showed that autonomous vehicles following algorithms designed without considering efficiency could degrade fuel economy by up to 3%, while efficiency-focused control strategies may equal or slightly exceed the existing EPA fuel economy test results by up to 5%, when compared to the base EPA cycles that they were simulated as following.

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Introduction

Research Motivation

Mobility and transport underpin a society's economic and physical life. The economy depends upon people being able to move goods and transport themselves from place to place. When people and firms decide to travel or move goods they mostly consider the cost to themselves: time, fuel, capital costs, tolls, vehicle maintenance, and transit fares, among others. These however are not the only costs that society bears from supporting travel. In addition to the direct costs of building and maintaining the necessary infrastructure, an individual's decision to travel or transport goods affects the time others must travel, via congestion; injuries and fatalities from crashes; environmental health; and national energy security.

Some of the costs of travel are associated with the use of petroleum or other fuel specifically, while others are associated with vehicle travel in general. Petroleum products are the dominant fuels of transportation, and result in environmental externalities, such as climate change and human health degradation. Vehicle use can also cause congestion, time delays, noise pollution, and safety concerns. The total external costs of a single gallon of gasoline for travel use by a single passenger vehicle is approximately $4.00 and is summarized in Figure 0-1. These numbers are based on a 3% discount rate; the fleet average of 35 mpg expected in 2020 (NHTSA and EPA 2012); the air-pollutant valuations; the costs of noise, accidents, congestion and oil security given in the CAFE impact assessment (NHTSA and EPA 2012); the E10 gasoline well-to-wheel pollution rates given in the GREET 2016 model (A. Elgowainy et al. 2016); and the cost of CO_2 equivalent emissions taken from the EPA based on 3% discounting 2020 average values (EPA 2016). Values were converted to 2016$ on the basis of the consumer price index (BLS n.d.).

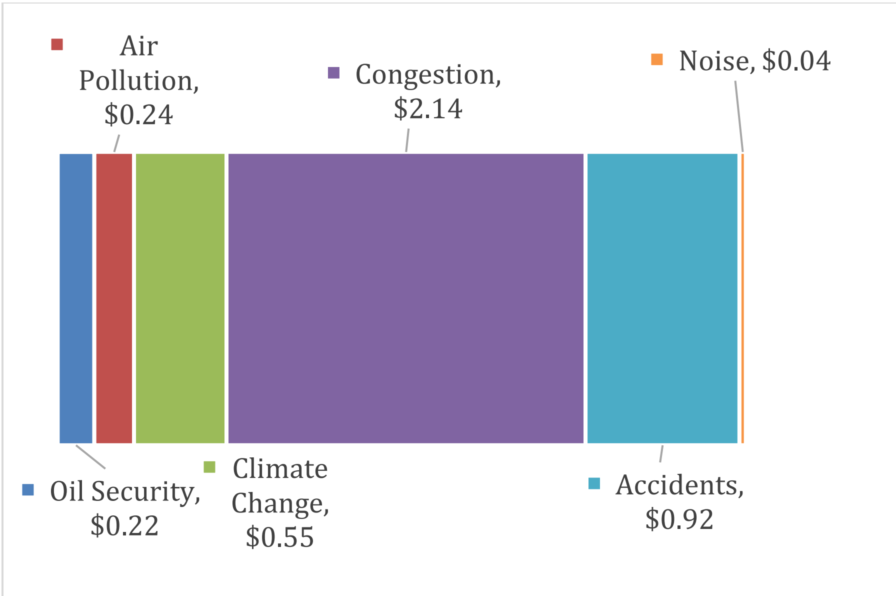

Figure 0-1: An Estimate of the External Costs of Gasoline, 4.09 2016$ per Gallon

Some of these externalities either have been decreasing over time or are expected to drop in the near future. As can be seen in Figure 0-2, passenger safety per mile travel has been steadily increasing since 1990 (US DOT 2017b). Accidents per mile, however, started increasing in 2011, even as personal damage decreased (US DOT 2017b). In addition, 2015 marked the first year in decades that total highway deaths increased (US DOT 2017b). While passenger safety has historically been increasing on U.S. roads, it appears to have recently plateaued.

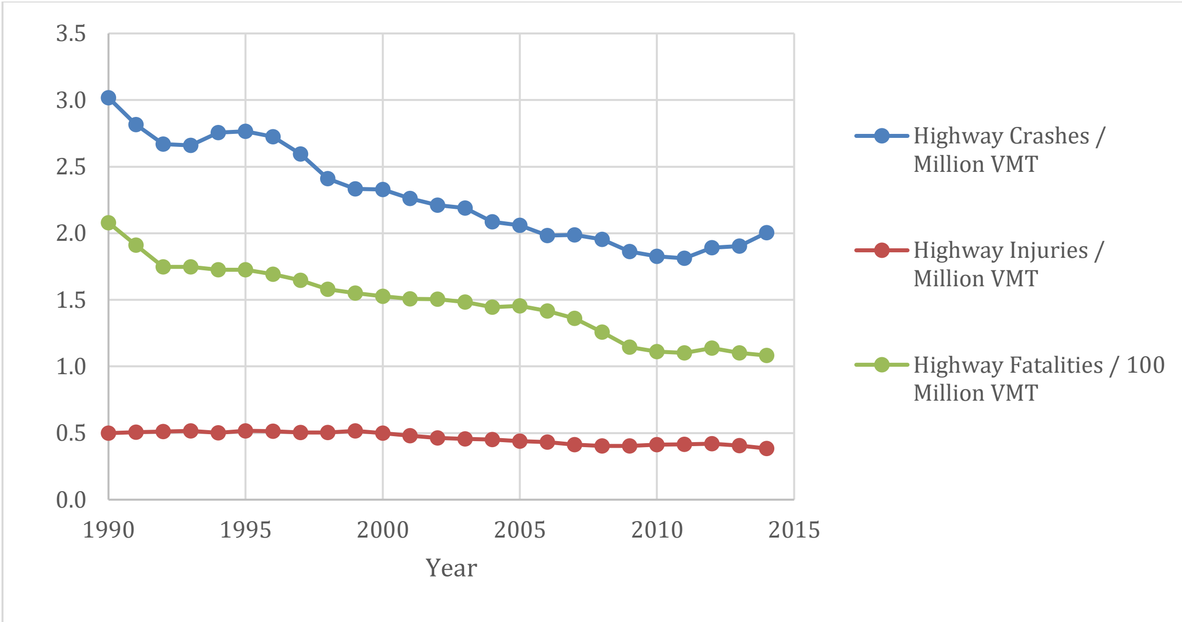

Figure 0-2: Highway Safety Trends (US DOT 2017b)

Oil consumption and its environmental externalities are also expected to continue to decline in the near future. Figure 0-3 and Figure 0-4 shows historical U.S. oil consumption and VMT trends, while Figure 0-5 shows the oil consumption per VMT trends. Starting in 2007, total U.S. oil consumption dropped, plateauing in 2009, even as VMT increased and then steadied (EIA n.d.; USDOT FHA 2017). This can be seen partly as an effect of the Corporate Average Fuel Economy rules (CAFE), which are designed to increase average passenger vehicle fuel economy by 60% between 2010 and 2021 (NHTSA 2012, 2017). In its 2017 Annual Energy Outlook, the EIA does not expect oil consumption to reach the 2005 peak in any scenario and in most scenarios sees oil consumption dropping through the 2030s (US EIA 2017). Other externalities such as congestion and time delays have increased over time. Between 2010 and 2014, hours of commuter delay in urban areas per year increased from 37 hours to 42 hours per person (Schrank et al. 2015).

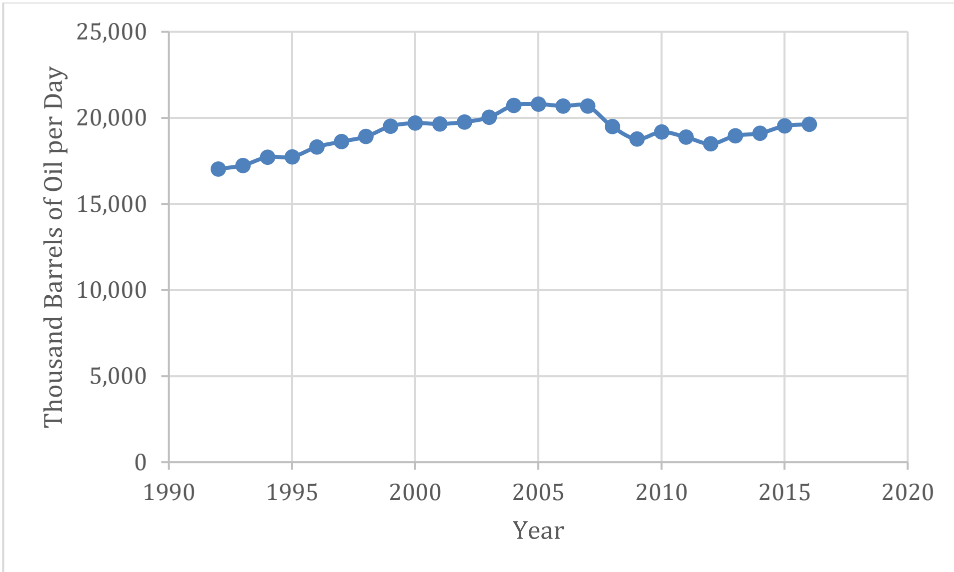

Figure 0-3: Oil Consumption Trends (EIA n.d.; USDOT FHA 2017)

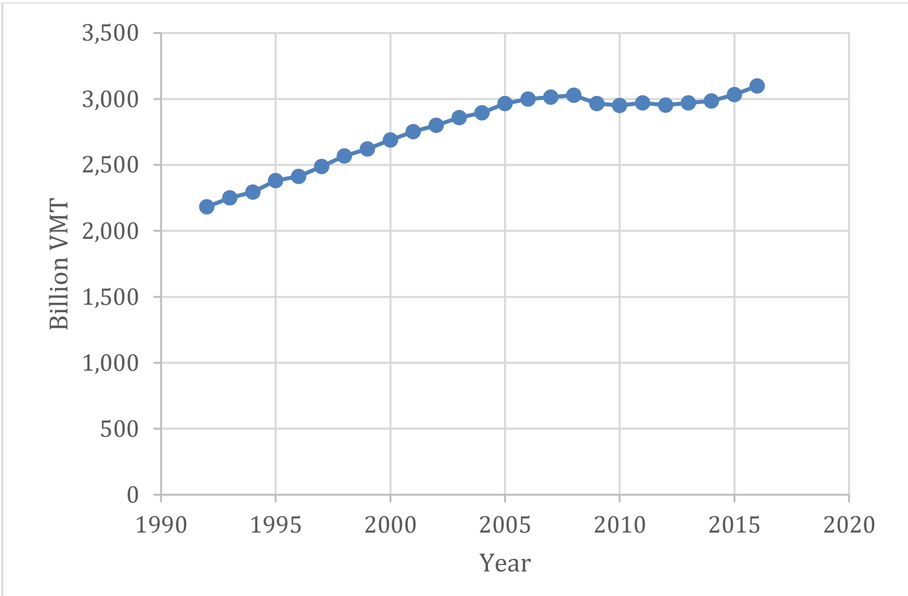

Figure 0-4: Highway VMT Trends (EIA n.d.; USDOT FHA 2017)

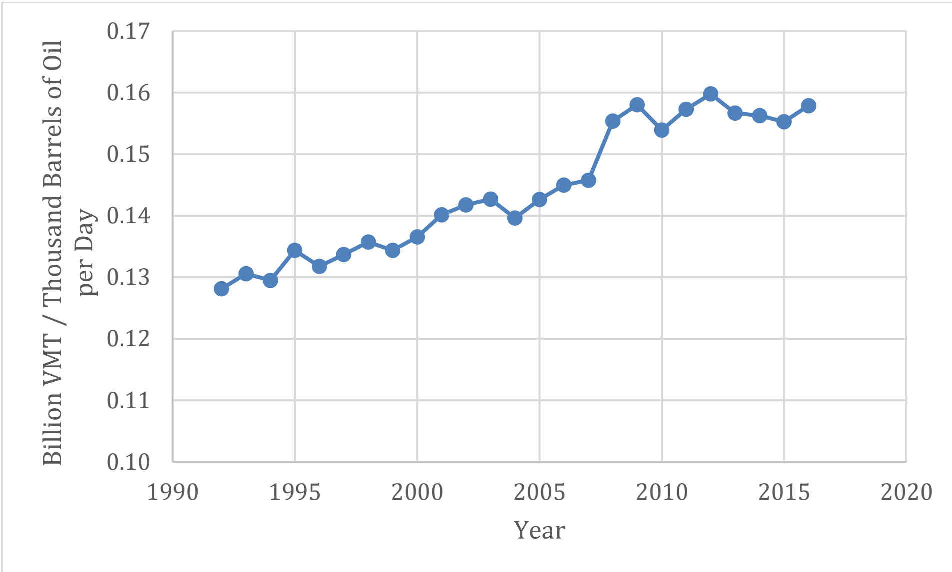

Figure 0-5: Oil Consumption per VMT Trends (EIA n.d.; USDOT FHA 2017). NOTE: Y-axis truncated to highlight changes

Two sets of technologies have the potential to drastically reduce the externalities associated with passenger travel: vehicle electrification and automation. For example, safety can be greatly increased with just current partially-autonomous technologies. Driver error and impairment are estimated to be factors in about 90% of all US roadway crashes (Dingus et al. 2016). Full deployment of just three automated technologies currently available on the market — blind-spot monitoring, lane-departure warning and forward-collision warning/crash-avoidance systems — could eliminate or mitigate up to 1.3 million motor vehicle crashes in the U.S. alone (Harper et al. 2016b). This is over one-third of all U.S. highway crashes (US DOT 2017b).

Environmental and energy security externalities are a function of fuel type, vehicle efficiency, performance, and total vehicle travel. These externalities and factors can be affected by both electrification and automation. Electrification would not only change the fuel type from petroleum to the electric grid mix, but would also increase the vehicle's individual efficiency. Electric vehicles (EVs) use about 60% of their stored energy compared to about 20% for conventional vehicles (Chae et al. 2011; Gautam et al. 2011; Miller et al. 2011; US DOE n.d.), though this doesn't include production and transmission losses which are present for both electricity and petroleum products. Electrification may also increase total vehicle travel, as the marginal cost of travel drops with price, though researchers disagree about this effect's magnitude and significance (Gillingham et al. 2016; Greene 1992; Greening et al. 2000; Small and Dender 2007; West et al. 2017). As electric vehicles are already available on the market, the magnitude of any of these changes is dependent primarily on adoption. Among the available levers of influence on consumer behavior, tax and monetary incentives, charging infrastructure, and parking and reserved lane benefits for EV owners are among the most common incentives tried, with direct monetary incentives having the greatest effects and charging infrastructure having a strong tracking and potentially causal effect (Bjerkan et al. 2016a; Diamond 2009; Håvard Vaggen Malvik et al. 2013; Hidrue, M. K. et al. 2011; Jenn et al. 2013; Martin et al. 2012; Mau et al. 2008; Mersky et al. 2016; Sánchez-Braza et al. 2014; Sierzchula et al. 2014; Skerlos and Winebrake 2010).

Automation has the potential to affect environmental externalities via changes in vehicle fuel type, vehicle efficiency, total vehicle travel, and performance. Autonomous vehicles (AVs) may make alternative fuels more attractive by decoupling the user from the need to actively seek out spatially limited refueling opportunities, or by decreasing the cost of building this infrastructure. Automation may also increase vehicle efficiency by accounting for future information on traffic conditions and routes, or by smoothing out acceleration patterns compared to humans (Asadi and Vahidi 2011; James M. Anderson et al. 2014; Mersky and Samaras 2016; Park et al. 2011; Rakha et al. 2011a). It is also possible that vehicle fuel economy will decrease if the control algorithms aren't specifically designed for efficiency (Mersky and Samaras 2016). Autonomous technology may also increase total vehicle travel if it decreases the actual marginal cost of travel or if it decreases the perceived loss of time traveling (Childress et al. 2015; Fagnant and Kockelman 2015; Harper et al. 2016a; James M. Anderson et al. 2014). Counteracting this, autonomous technology may help to enable ride sharing and dynamic carpooling, which would allow for increases in passenger travel, even as vehicle travel drops (Fagnant and Kockelman 2015; James M. Anderson et al. 2014; Martin et al. 2010). Finally, automation, when combined with vehicle-to-vehicle communication, can enable more effective usage of existing or upgraded right of way, increasing lane capacity, decreasing congestion, and increasing fuel economy (Bu et al. 2010; Fagnant and Kockelman 2015; Feng et al. 2015; Kesting et al. 2008; Rajamani and Shladover 2001; Shladover et al. 2012a).

Technological advances have the potential to decrease the cost of travel and greatly decrease the negative externalities associated with travel. However, this is not guaranteed. Without informed policy, vehicle automation and electrification could increase these externalities. Ensuring that these technologies provide a net social benefit requires technical analysis and an understanding of how these technologies change the costs, externalities and usage of vehicular travel and transport.

Research Topics

Ensuring a socially optimal outcome from potential changes in vehicle technology requires four components. The first component is determining whether adopting a set of new technologies would provide a net social benefit in a given locality and for a specific purpose. The second is knowing how to predict the adoption of a new technology by different groups and areas. The third is knowing how to optimally construct necessary infrastructure for the new technology, while considering how future changes in the technology or other new technologies may affect this process. The fourth component is regulating a technology effectively technology so that its future development is incentivized to provide a net social benefit.

This dissertation addresses each of these issues by focusing on specific novel applications and case studies. First, in Chapter II, the issue of determining the social value of implementing a new technology is investigated using a case study of the social value of electrifying part of the City of Pittsburgh's municipal fleet. Valuing private and social costs and benefits of fleet electrification is a well-investigated field, with several papers jointly investigating private and external costs along part or all of the vehicle/fleet life cycle (Emery et al. 2017; Tamayao et al. 2015; Weis et al. 2015, 2016; Yuksel et al. 2016; Yuksel and Michalek 2015). Of the 36 papers reviewed for this chapter, however, only Holland et al's (Holland et al. 2015) looks into the specific spatial dispersion effects of air pollutants. This is important when investigating local actor and government motivations. Also important is how government agencies account for their emissions. Chapter II adds to the literature by combining the social and private costs with an investigation into the motivations and scopes of concerns and accounting methods of municipal governments.

Chapter III investigates the predictive power of Norway's national EV incentives on adoption, as well as regional demographics. The question of the effectiveness and predictive power of incentives on driving EV adoption is mature, with many studies on EV preference and incentives based on stated preferences (Axsen, J. et al. 2009; Bolduc et al. 2008; Brownstone et al. 2000), models of the vehicle market demand (Eppstein et al. 2011; Mau et al. 2008; Mueller and de Haan 2009), and international comparisons of consumer preferences as they relate to EVs, (Helveston et al. 2015; Peter Mock and Zifei Yang 2014; Sierzchula et al. 2014; Sprei and Bauner 2011). Norway has had one of the largest, earliest, and most comprehensive EV incentive programs in Europe (Eppstein et al. 2011; Erik Figenbaum and Marika Kolbenstvedt 2013; Peter Mock and Zifei Yang 2014; Sprei and Bauner 2011). This chapter contributes to the literature by providing one of the first statistical analyses of the full vehicles sales data of Norway as it pertains to EV incentives and regional demographics.

Chapter IV investigates optimal investments in electric vehicle infrastructure given differing scenarios of vehicle automation. As discussed in Chapter IV, Section 2.2, literature review, the question of optimal placement and quantity of electric vehicle infrastructure for charging, both along a route (Bae and Kwasinski 2012; Ghamami et al. 2016; Huang et al. 2015; Knapen et al. 2012; Nie and Ghamami 2013; Sathaye and Kelley 2013) and while parked (Chen et al. 2013; Frade et al. 2011; He et al. 2013; Xi et al. 2013; Zhu et al. 2016), is well investigated. The literature is also split among those investigating optimization from the infrastructure, operator, driver, or electric grid perspective, as well as those that investigate some combination of these. I was unable, however, to find any literature investigating how electric vehicle charging infrastructure might be optimized for parked commuters when considering differing scenarios of vehicle automation. This chapter adds to the literature by investigation how a municipality can optimize its electric vehicle charging infrastructure, given different scenarios of automation, from the joint perspective of the operator and drivers. The chapter also investigates how taking advantage of autonomous technology may change the electrical demand on the grid from EVs.

Chapter V investigates how to design regulations for developing technologies to help ensure socially optimum outcomes. As discussed in Chapter V, Section 1.1, while much research has been done on the problems of and potential solutions to fuel-economy testing for conventionally driven vehicles (Bhavsar et al. 2014; Gonder and Simpson 2006) and how autonomous features may change fuel consumption (Bhavsar et al. 2014; Grumert et al. 2015; Rajamani and Shladover 2001; Wu et al. 2014; Zlocki and Themann 2014), little has been done to answer the question of how to evaluate autonomous fuel economy, and no papers found suggested a program to integrate current autonomous technology into current fuel-economy tests. Currently the only basis to account for this are the "off-cycle technology credits" available for CAFE compliance (EPA and NHTSA 2010). However, these are non-standardized and only available for "new and innovative technologies" (EPA and NHTSA 2010), decreasing their predictability and limiting the temporal scope of their use. Chapter V contributes to the literature by developing and testing a framework for evaluating the fuel economy of vehicles with autonomous features, using a simulated car following framework.

Chapter VI will first summarize the joint conclusions that can be made from the interior four chapters. Chapter VI will then explore the policy implications of these conclusions. Chapter VI will then summarize the novel unique contributions to the field's literature that this dissertation provides. Finally, Chapter VI will investigate and discuss the questions that this dissertation develops and its implications for future research.

Chapter I Environmental and Economic Tradeoffs of Municipal Fleet Electrification and Photovoltaic Installation in PJM

The previous chapter discussed this dissertations motivation and structure. This chapter investigates how a municipality can evaluate the net social value of electrifying a portion of their vehicle fleet.

A municipality evaluating a potential transition to an electrified vehicle fleet has its own set of decision criteria, which differ from other actors. National governments are accountable to the whole of their citizens, municipal government only their constituents, and a corporation only to its shareholders. In addition, several cities are exploring ways to simultaneously increase both distributed solar photovoltaic (PV) generation and electric vehicle (EV) charging infrastructure. While most PV installations would not directly charge an electric vehicle, PV would start to change the emissions from electricity purchased by municipalities. This chapter conducts a life cycle assessment and cost-benefit analysis for municipal fleet electrification decisions, using Pittsburgh, PA in the PJM Regional Transmission Organization as a case study. The analysis includes Pittsburgh's municipal parking, licensing, and inspection vehicle fleet over several electricity grid scenarios, and assesses the use of PV installations at city-owned parking facilities. Costs were included while comparing vehicle options, as were the emissions and externality costs of GHGs, SO2, and NOx from both direct and upstream effects. For the municipal vehicles under consideration for Pittsburgh's fleet, BEVs, but not PHEVs, were found to have lower life cycle GHG emissions than HEVs. However, vehicle electrification was found likely to have higher total social emissions costs than conventional options. As the electricity grid transitions to lower-polluting sources, EVs have clear advantages over conventional vehicles. A peak capacity of about 6,000 kW of PV is possible on Pittsburgh parking facilities. While the nuances of emissions allocation between PV and EVs are important, this capacity would produce an amount of electricity equivalent to greater than 30 times the yearly travel of the municipal vehicle fleet. The necessary structures to preserve parking spaces while providing PV, potentially make this system cost prohibitive. By providing a life cycle assessment and analysis this study provides a method for municipalities, counties, states, and other stakeholders to evaluate the potential benefits and costs of vehicle electrification.

2.1. Introduction

In the absence of larger Federal efforts, cities and states are increasingly undertaking initiatives to reduce greenhouse gas emissions and air pollutants from their operations. Many cities have responded to the US withdrawal from the Paris climate change agreement by joining it individually (Hidalgo and Peduto 2017; Medium 2017). As part of these efforts, many cities are evaluating strategies to electrify their municipal vehicle fleets, as well as increase penetration of low-polluting electricity sources such as photovoltaic (PV) solar power (City of Pittsburgh 2017; Lambert 2017; Lawrence 2017; Nootbaar 2017). A municipality evaluating a potential transition to an electrified vehicle fleet has a different set of decision criteria than other actors, which include the social costs of air emissions, and municipal climate change mitigation goals. The federal government operates a passenger vehicle fleet of more than 92,000 vehicles (US DOT 2017a) and states, counties and municipalities operate more than 1.3 million fleet automobiles, providing a large opportunity to reduce emissions. Realizing this opportunity however, requires careful consideration by fleet operators about location and usage conditions. Previous research has indicated that the current fuel composition of some power grids may degrade air quality via vehicle electrification (Tamayao et al. 2015), which is why simultaneous consideration of transitioning to electric vehicles (EVs) and improving the environmental attributes of the power system is warranted.

Recent work on life cycle assessment (LCA) of regional vehicle electrification include Weis et al. (Weis et al. 2016), who looked at the air emission externalities associated with charging in the PJM region and Yuksel et al. (Yuksel et al. 2016) who looked at how regional differences in grids, climate and driving patterns affected GHG emissions from vehicle electrification. Both of these primarily assessed impacts using the emissions from estimated marginal electricity generating units. Choi et al. (Choi et al. 2013) and Freire and Marques (Freire and Marques 2012) both estimated impacts with either marginal or average grid greenhouse gas (GHG) emissions combined with private costs. Marginal considerations are important because EV charging represents new demand, has temporal characteristics, and average grid emissions could underestimate emissions because of the likelihood of fossil generation as load following units. Holland et al. (Holland et al. 2015) performed a similar analysis to Yuksel et al. (Yuksel et al. 2016), without an upstream analysis, and assessed spatial patterns of emissions damages coupled with a consumer utility model and an ideal tax or subsidy to internalize either the total or regional externalities of an EV.

With some exceptions (Anair and Mahmassani 2012; Choi et al. 2013; Emery et al. 2017; Freire and Marques 2012; Holland et al. 2015; Michalek et al. 2011b), most of the reviewed literature focuses on either the environmental effects or private costs, rather than combining both. While some studies examine fleets (Emery et al. 2017; Jenn et al. 2016a; Sengupta and Cohan 2017; Traut et al. 2012; Weis et al. 2015; Yoon and Cherry 2015) the reviewed literature also generally focuses on private actors rather than the motivations of municipal fleet operators and how they may attempt to comingle fleet electrification with other emissions reductions energy efforts. Holland et al. (Holland et al. 2015) attempts to address the operator motivation gap, by measuring the spatial differences in impacts from different pollution sources. Holland et al. (Holland et al. 2015) then uses this to create a framework to influence consumer behavior on the basis of perceived utility. This would be of use to actors more interested in local effects, such as municipal governments, however, municipalities generally account for pollution by emissions scope, not pollution fate and transport (ICLEI 2017). This is in accordance with the ICLEI international, and national variant, standards (ICLEI 2017). Additionally, fleet operators would more likely be interested in annual monetary flows and performance metrics. A more comprehensive literature review consisting of 36 studies beginning in 2007 is included in Table I-1 and Table I-2.

In this chapter, I conduct an environmental life cycle assessment and cost benefit analysis of the electrification of the City of Pittsburgh's municipal light-duty vehicle fleet and also the installation of PV systems on the City's parking facilities. I consider GHGs, criteria air pollutants such as NO_x and SO_2, private costs, and upstream environmental impacts. I also compare the scope and potential locational effects of emissions and how this might be relevant to the decision-making of different actors. Many cities account for their GHG emissions in their climate action plan by using emission scopes, which were defined by the World Resource Institute in the GHG protocol for Cities (Fong et al. 2014) and products (Bhatia et al. 2011). Scopes are classified in 3 groups: Scope 1 contains all emissions directly released by the actor or process of interest; Scope 2 contains all emissions released in the production of energy procured by the actor or process of interest;

and Scope 3 contains the embodied emissions in all the materials and processes used by the actor or process of interest that are not contained in the other scopes. In the case of a vehicle fleet, Scope 1 would reflect all tailpipe emissions, Scope 2 include the emissions for generating electricity for EVs and Scope 3 include the emissions associated with the production and transport of the vehicles themselves and the production of fuels for transportation and electricity. A local government body has various levels of control regarding the total emissions and emissions intensity across each emissions scope, and may use different weights for making decisions about reducing emissions in each scope. They may be concerned only with the effects of emissions primarily felt by their constituents, or only with those emissions that they are held responsible for from an accounting perspective (ICLEI 2017). In both of these cases emissions from these 3 scopes may be weighted differently from each other.

The importance of emission scopes and boundaries is illustrated by Mathews et al. (Matthews et al. 2008) and this method is common in the life cycle assessment literature. Matthews et al. showed that when using an Economic Input-Output LCA, the average economic sector reports only 14% of GHG as coming from direct production (Matthews et al. 2008). This figure rises to only 26% when accounting for direct energy production emissions (Matthews et al. 2008). Reporting only the emissions that an entity directly emits or contracts out will often leave out the majority of emissions. It is important to acknowledge the difference among these emissions as actors have more control over the emissions they directly emit or contract and these emissions often have a different spatial profile than emissions higher upstream. Regulations also may also prescribe different actions to mitigate pollution based upon which scope they origination from, necessitating this calculation.

Table I-1 summarizes several studies on the cost/benefits and environmental effects of vehicle electrification. The Grid Assumption column details whether the emissions from electricity generation used average grid emissions or estimated the marginal emissions needed to produce electricity in response to new demand.

Table I-1 Summary of Assorted Studies Investigating the Cost Benefits, Environmental Effects and/or Life Cycle of Vehicle Electrification

Study	**Vehicle Types**	**Regions**	**Scope**	**Grid Assumption**	**Costs and Pollutants Investigated**
Duvall et al, 2007 (Duvall et al. 2007)	PHEV	US: NERC Sub-regions	Use Phase	Marginal	GHGs
Lund and Kempton, 2008 (Lund and Kempton 2008)	BEV, CV	Denmark	Use Phase: Scopes 1 and 2	Marginal	CO_2
Samaras and Meisterling, 2009 (Samaras and Meisterling 2008a)	PHEV, HEV, CV	US	Full Life Cycle	Both	GHGs
Hadley and Tsvetkova, 2009 (Hadley and Tsvetkova 2009)	PHEV, CV	US: NERC Sub-regions	Use: Scopes 1 and 2	Marginal	CO_2, SO_2, NO_X
McCarthy and Yang, 2010 (McCarthy and Yang 2010)	BEV, PHEV, HFCV (Hydrogen Fuel Cell Vehicles), CV	US: California	Use Phase: Scopes 1, 2 and Partial 3	Marginal	CO_2
Michalek et al, 2011 (Michalek et al. 2011b)	BEV, PHEV, HEV, CV	US	Full Life Cycle	Average	CO, NO_x, PM, SO_2, VOCs, GHGs, Oil Dependence and Market Effects
Peterson et al: 2011 (Peterson et al. 2011)	PHEV	US: PJM and NYISO	Use Phase: Scopes 1 and 2	Marginal	CO_2
Anair and Mahmassani, 2012 (Anair and	BEV, PHEV, HV, CV	US: eGRID sub-regions	Use Phase	Average	Direct Private Cost, GHGs

Study	Vehicle Types	Regions	Scope	Grid Assumption	Costs and Pollutants Investigated
Mahmassani 2012)					
Freire and Marques, 2012 (Freire and Marques 2012)	BEV, CV	Portugal	Full Life Cycle	Average	Direct Private Cost, GHGs
MacPherson et al, 2012 (MacPherson et al. 2012)	PHEV	US: NERC Regions, sub-regions and States	Full Life Cycle	Average	GHGs
Thomas, 2012 ((Sandy) Thomas 2012)	BEV, PHEV, HV	US: NERC Sub-regions	Use Phase: Scopes 1 and 2	Marginal	GHGs
Choi et al, 2013 (Choi et al. 2013)	BEV, CV	US: Eastern Interconnect	Full Life Cycle for pollutants, Use for Costs	Marginal	Direct Private Capital and Use Costs, CO_2
Graff Zivin et al, 2014 (Zivin et al. 2014)	BEV, PHEV, HV, CV	US: eGRID sub-regions	Use Phase: Scopes 1 and 2	Marginal	CO_2
Archsmith et al, 2015 (Archsmith et al. 2015)	BEV, CV	US: NERC Regions	Full Life Cycle	Marginal	GHGs
Holland et al, 2015 (Holland et al. 2015)	BEV, CV	US: NERC, States and Political Counties	Use Phase: Spatial Damage Scoping	Marginal	Direct Private Costs, CO_2, SO_2, $PM_{2.5}$, NO_X
Nealer et al, 2015 (Nealer et al. 2015)	BEV	US: eGRID sub-regions	Full Life Cycle	Average	GHGs
Onat et al, 2015 (Onat et al. 2015)	BEV, PHEV, HV, CV	US; NERC Region	Full Life Cycle	Both	GHGs
Tamayao et al, 2015 (Tamayao et al. 2015)	BEV, PHEV, HV, CV	US NERC Region	Full Life Cycle	Both	CO_2

Study	Vehicle Types	Regions	Scope	Grid Assumption	Costs and Pollutants Investigated
Yuksel and Michalek. 2015 (Yuksel and Michalek 2015)	BEV	US: NERC Region	Use Phase: Scopes 1 and 2	Marginal	CO_2
Crossin and Doherty, 2016 (Crossin and Doherty 2016)	BEV, CV	Australia: NEM	Full Life Cycle, Including Disposal	Both	Comprehensive Externality Life Cycle Inventory and Assessment
Weis et al. 2016 (Weis et al. 2016)	BEV, PHEV, HV, CV	US: PJM	Full Life Cycle	Marginal	External Cost of Air Emissions, CO_2, SO_2, $PM_{2.5}$, NH_3, NO_X, VOCs
Yuksel et al, 2016 (Yuksel et al. 2016)	BEV, PHEC, HV, CV	US: NERC and Political Counties	Full Life Cycle	Marginal	GHGs
Emery et al. 2017 (Emery et al. 2017)	BEV, CV (B0, Diesel), CV (B20, Diesel), CV (E10 Gasoline), CV (E85 Gasoline)	US: Western Ohio Military Instillation	Private Purchase Costs, Use Phase, Private Costs, Scopes 1, 2 & 3	Average	Private Costs, GHGs, VOC, CO, NO_x, PM_{10}, $PM_{2.5}$, SO_x
Sengupta and Cohan 2017 (Sengupta and Cohan 2017)	BEV, PHEV, HEV, CNG (Natural Gas), CV	Houston, Texas	Full Life Cycle	Average	Private Costs, GHGs, NO_x
This Study	BEV, PHEV, HV, CV	US: PJM and RFC-W	Full Life Cycle	Both	Life Cycle Private and External Costs, GHGs, SO_2, NO_X

Table I-2 summarizes several recent studies on the cost/benefits, sizing and environmental effects of PV systems. The third column details the source of project's sizing, which could be from a theoretical or real system case study, extrapolated from aerial imagery or other map data, or in terms of units of power.

Table I-2 Summary of Assorted Studies Investigating the Cost Benefits, Sizing, Environmental Effects and/or Life Cycle of PV Systems

Study	**Regions**	**Source of Project Size**	**Scope**	**Grid Assumption**	**Variables Investigated**
Fthenakis et al, 2008 (Fthenakis et al. 2008)	Europe, US	Per Unit Power	Life Cycle	Average	GHGs, NO_x, SO_x, Heavy Metals
Izquierdo et al, 2008 (Izquierdo et al. 2008)	Spain	Aerial Photography, GIS Maps, Population Density	Use: Power Generation Potential	N/A	Available Area, Power Generation Potential
Denholm et al, 2009 (Denholm et al. 2009)	Western US	Per unit power, Current Grid Mix, Assumed Future Mix	Use phase Scopes 1 and 2	Marginal	CO_2, SO_2, NO_2, Natural Gas and Coal Replacement
Ayompe et al, 2010 (Ayompe et al. 2010)	Ireland	Per unit of power	Project Private NPV, Use phase Scopes 1 and 2	Average	Private NPV, Social NPV (GHGs)
Sherwani et al, 2010	World	Per unit of power	Life Cycle	Average	GHGs
Wiginton et al, 2010 (Wiginton et al. 2010)	Canada: South Eastern Ontario	Aerial Photography	Use: Power Generation Potential	N/A	Power Generation Potential
Vardimon, 2011 (Vardimon 2011)	Israel	Aerial Photography	Use: Power Generation Potential	N/A	Power Generation Potential
Kim et al, 2012 (Kim et al. 2012)	World	Per unit power	Life Cycle	Average	GHGs

Study	Regions	Source of Project Size	Scope	Grid Assumption	Variables Investigated
Hsu et al, 2012 (Hsu et al. 2012)	World	Per unit power	Life Cycle	Average	GHGs
Hunter et al, 2013 (Hunter et al. 2013)	US: Boston, MA	State Provided GIS Map and Aerial Photography	Project Private NPV and Use Phase: Scopes 1 and 2	Average	Private NPV, Social NPV, CO_2, SO_2, NO
Kim et al, 2014 (Kim et al. 2014)	Malaysia	Per unit power	Life Cycle, no disposal	Average	GHGs; Coal, Natural Gas and Petroleum Usage
Chung et al, 2015 (Donald Chung et al. 2015)	US	Per Unit of Power, Case Studies	System Cost	N/A	Private System Cost
Fu et al 2015 (Fu et al. 2015)	China	Per unit of Power	Life Cycle-Production to Use	Average	GHGs; Acidification, Eutrophication, and Ozone depletion and Human Toxicity Potential
This Study	US: PJM and RFC-W	Aerial Photography	Full Life Cycle	Both	Life Cycle Private and External Costs, GHGs, SO_2, NO_X

Additionally, I compare the results from a marginal and average grid perspective, while looking at the possible effects of current renewable energy credit (REC) purchases, or potential integrated solar PV projects. Assessing the marginal grid and average component directly can help to show if this simplification is significant enough to alter recommendations. By providing a comprehensive life cycle assessment and analysis this study provides a method for municipalities, counties, states, and other stakeholders to evaluate the potential benefits and costs of fleet vehicle electrification.

2.2. Methods

2.2.1. Municipal Light Duty Fleet Overview

This analysis focuses on Pittsburgh's municipal permitting, licensing, and inspection vehicle fleet. Currently the city has a civilian passenger vehicle fleet of 118 vehicles travelling 1,160,000 km a year (Lowell 2015). This leads to an average (5-day workweek) travel of 37.7 km per workday per vehicle for the fleet.

The life cycle cost components of operating a vehicle fleet are the purchase price, the cost of fuel needed for daily operations, and the cost of regular maintenance. Therefore, the prices of gasoline, electricity and maintenance are relevant to understand the costs of managing a municipal vehicle fleet containing electric vehicles. Table I-3 shows the Manufacturers Suggested Retail Price (MSRP) and fuel economy characteristics of typical conventional (ICV), hybrid (HEV), plug-in hybrid electric (PHEV), and battery electric (BEV) vehicles. I use these vehicles in our analysis, as they currently under consideration for use by the city of Pittsburgh, except for the conventional Ford Fusion. This was done for model consistency with the HEV and PHEV. The 2016 Ford Fusion did not include a BEV so the Focus was used instead. This is a cheaper model line, leading to a slight underestimate in cost for BEVs to compare equivalent vehicles. Maintenance prices come from an the Electric Power Research Institute (Alexander and Davis 2013). Battery capacities are from Ford's website for each specific model and year (Ford Motors 2015a; b; c). Gasoline prices are from 2015 US wholesale prices, since municipal fuel is untaxed (EIA 2015). Electric price assumptions of $0.06/kWh came from discussions with City officials, and are consistent with regional institutional electricity prices. On-site levelized costs of electricity were estimated for solar PV costs and were derived from the integrated renewable garage analysis in Section 2.2.4 and 2.2.5. The calculations are presented in Section 2.2.3.

Table I-3 Vehicle Characteristics

Vehicle Model	MSRP ($) (EPA n.d.)	All Gasoline City Fuel Economy	All Electric City Fuel Economy*	All Electric Range	Maintenance Cost ($/km) (Alexander and Davis 2013)	Battery Capacity (kWh) (Ford Motors 2015a; b; c)
2016 Ford Focus Electric	$29,170	n/a	19.04 kWh/100 km (EPA n.d.)	122 km (EPA n.d.)	$0.0054	23
2016 Ford Fusion Energi Plug-in Hybrid	$33,900	6.12 l/100 km (EPA n.d.) (combined)**	22.99 kWh/100 km (EPA n.d.) (combined)**	32 km (EPA n.d.)	$0.0127	7.6
2016 Ford Fusion Hybrid FWD	$25,675	5.47 l/100 km (EPA n.d.)	n/a	n/a	$0.0115	1.4
2016 Ford Fusion FWD	$22,750	9.05 l/100 km (EPA n.d.)	n/a	n/a	$0.0243	n/a

*Effective electric fuel consumption is about 11% greater due to ≈ 90% charging efficiency (Cooney et al. 2013)

**Source does not separate PHEV's electric fuel economy into City and Freeway measures

The City of Pittsburgh currently has a contract to buy wind power Renewable Energy Certificates (RECs) for 30% of its municipal electricity needs and is planning to increase its renewable purchases to 100% by 2030. I discuss the challenges of actual emissions changes from using RECs below, and assess electricity emissions here both with and without RECs. To bound the REC case, I assume the purchased wind power is from local sources and therefore displacing other fuels in PJM (the regional transmission organization), and ignore additional emissions resulting from intermittency when calculating time-dependent marginal costs. The effects of RECs are very likely to be less than a 100% reduction per kWh, and research suggests it could approach 0 (Gillenwater 2013; Gillenwater et al. 2014). However Pittsburgh currently follows an accounting protocol allowing for full replacement in accounting (City of Pittsburgh 2017; ICLEI 2017). In the Pittsburgh residential market wind power has about a $0.015 premium per kWh over conventional electricity (PA PUC 2015). I assumed this premium to be the same that the city pays for all RECs.

In addition to capital cost of the vehicle and its fuel, electric vehicles require charging infrastructure. This analysis assumed that each vehicle would require one Level 2 charger. After a review of current literature and EV manufacturer guidance, I used a range of costs for equipment and installation of Level 2 charging units in commercial garages, listed in Table I-5 ("Electric Vehicle Charging Infrastructure Deployment Guidelines for the Greater San Diego Area." 2010; Taxi & Limousine Commission 2013; Tesla 2015).

PHEVs are able to travel on electricity, gasoline, or a combined gasoline and electric mode, depending on specific model. PHEVs for the Pittsburgh municipal fleet were assumed to travel on a mix of 81.2% electricity and 18.9% gasoline, accounting for the 30.6 km EV range and 37.7 km average daily travel (Lowell 2015) (D.O.E. n.d.). While there is some research suggesting that using this method overestimates the electric share (Neubauer et al. 2013), the fleet usage scenario used here suggests much less variability with daily driving range and charging patterns than general use, justifying this assumption here. I test this assumption in the sensitivity analysis.

For the net present cost (NPC) analysis, Pittsburgh Municipal bond and U.S. Treasury rates were used to estimate a discount rate. Current 20 and 30-year US treasuries carry coupon rates of 2.62% and 2.93% (US Treasury 2015), while I used the 30-year Pittsburgh Municipal bond rate of 5% (MunicipalBonds.com 2013). Social discount rates are considered separately and are based on those used on the impact assessment of EPA's clean power plant regulation (EPA 2014b, 2015b). The NPC analysis considered 8 scenarios over a 15-year vehicle life time. In all scenarios, each vehicle was assumed to travel the fleet average yearly amount of travel. The scenario names, assumptions and energy sources are summarized in Table I-4. RFC-Tran stars, on year 1, with 30% RECs and increases by 5% each year till year 15, the final year of analysis, when it reaches 100%. The PV scenario looks to investigate what the final effects are if vehicle charging were to be entirely covered by on site solar powered electricity. The potential marginal component of solar power and EV demand is ignored in this scenario. The separate effects of PV power generation are explored in the Integrated Renewable Garages section. Note that if EVs or PHEVs increase pollution under other scenarios charging the EVs by PVs would still increase pollution compared to building the PV systems and sending it to grid while using conventional vehicles. Each scenario had a base case value and a different possible range of variable values, summarized in Table I-5. The emissions rates from the different fuel sources are summarized in Table I-6.

Table I-4: Scenario Nomenclature

Scenario	RECs %	Grid Energy Source
Average	0%	PJM Average
Marginal 08-17	0%	PJM Marginal 8AM-5PM
Marginal 18-07	0%	PJM Marginal 6PM-7AM
REC Average	30%	PJM Average
REC Marginal 08-17	30%	PJM Marginal 8AM-5PM
REC Marginal 18-07	30%	PJM Marginal 6PM-7AM
PV	N/A	On Site Solar PV
Transitional Average	30-100%, increases linearly 5% each year, over 15 years	PJM Average
Transitional Marginal	30-100%, increases linearly 5% each year, over 15 years	PJM Marginal 6PM-7AM

Table I-5: Parameter Value ranges

Variable	Maximum Value	Base Case Value	Minimum Value
Private Discount Rate	7%	5%	3%
Non GHG Social Discount Rate	7%	3%	3%
Electric Price $/kWh			
On-Site Solar PV Price	$1.08	$0.88	$0.75
Premium for REC $/kWh	$.015	$.015	$.015
Gasoline Price $/liter (EIA 2015)	$1.06	$0.53	$0.39
EV Charger Price $	$8,000	$4,000	$0
Social Cost of CO_2 $/kg (EPA 2015a)	$0.105	$0.073	$0.042
Social Cost of NOx $/g (EPA 2014b, 2015b)	$0.039	$0.026	$0.012
Social Cost of SOx $/g (EPA 2014b, 2015b)	$0.115	$0.047	$0.042

Table I-6: Emissions Rates

Source or Scenario	g SO_2 / kWh (g/l) (g/kg)	g NO_x / kWh (g/l) (g/kg)	kg CO_2 / kWh (kg/l) (kg/kg)
Gasoline Direct (EPA 2008)	0.00	4.41	2.35
PJM Average Direct (EIS n.d.)	0.73	0.35	0.46
PJM Marginal 08-17 direct (Monitoring Analytics 2016) (A. Elgowainy et al. 2016)	1.03	0.656	0.703
PJM Marginal 18-07 Direct (Monitoring Analytics 2016) (A. Elgowainy et al. 2016)	0.944	0.586	0.671
PJM Marginal 07-19 Direct (Monitoring Analytics 2016) (A. Elgowainy et al. 2016)	1.03	0.655	0.702
Gasoline Upstream (A. Elgowainy et al. 2016)	1.110	1.294	0.573
PJM Average Upstream (EIS n.d.) (A. Elgowainy et al. 2016)	0.0453	0.055	0.115
PJM Marginal 08-17 Upstream (Monitoring Analytics 2016)	0.0341	0.0814	0.173
PJM Marginal 18-07 Upstream (Monitoring Analytics 2016)	0.0329	0.078	0.170
PJM Marginal 07-19 Upstream (Monitoring Analytics 2016)	0.0341	0.0814	0.173
Solar PV Upstream (Hsu et al. 2012)			0.070
Wind Upstream (Dolan and Heath 2012)			0.011

Source or Scenario	g SO_2 / kWh (g/l) (g/kg)	g NO_x / kWh (g/l) (g/kg)	kg CO_2 / kWh (kg/l) (kg/kg)
Battery Assembly Emissions (A. Elgowainy et al. 2016) (g or kg)	96.0	62.7	54.9
HEV Battery Pre-Assembly Emissions (A. Elgowainy et al. 2016) (g or kg / kg)	48.6	10.0	6.98
PHEV Battery Pre-Assembly Emissions (A. Elgowainy et al. 2016) (g or kg / kg)	51.4	7.75	4.94
HEV Battery Pre-Assembly Emissions (A. Elgowainy et al. 2016) (g or kg / kg)	43.8	7.98	4.75

In addition to private costs, the monetized values of emissions from electricity and gasoline combustion on air pollutant and greenhouse gas (GHG) emissions are important to municipal decision makers. Sulfur dioxide (SO_2) emissions are not measurably emitted from conventional gasoline vehicles, but will be indirectly emitted by electric vehicles, due to the current regional grid containing some coal-fired generation. Most of the electric vehicle analysis literature reviewed reports either the average or the marginal emissions characteristics of the grid, and this study uses both the average and the marginal emissions values. In the near-term, additional electric demand is supplied by power plants in an economic dispatch curve, and will be fulfilled by the units available with the lowest marginal costs for a given level of demand during the hour demanded, subject to a variety of constraints. These marginal units change based upon load, time of day, season, relative fuel prices, and the evolving units available in the regional grid. This study used average and time of day-based marginal emission factors from the PJM Regional Transmission Organization (Monitoring Analytics 2016), which covers Pittsburgh (PJM 2017). Marginal factors are the PJM reported 2015 marginal emission factors, and listed in Table I-6. Significant additional demand could increase or decrease the marginal emissions as different fuels and units are brought online. Nighttime and daytime marginal emission factors were taken as the average of each hourly marginal emission factor from the time period covered. Daytime charging consisted of the hours 8AM through 5 PM while nighttime charging consisted of the hours 6PM through 7AM.

In addition to the direct emissions from combustion from gasoline and electricity generation, there are also upstream emissions from the production and transport of fuels, listed in Table I-6. Upstream gasoline emissions come from the 2015 GREET model (A. Elgowainy et al. 2016). Upstream electricity emissions are based upon the 2015 GREET model (A. Elgowainy et al. 2016) for fossil fuels and nuclear power, while PV and wind emissions come from Hsu et al (Hsu et al. 2012) and Dolan and Heath, respectively (Dolan and Heath 2012). PV emissions were adjusted for Pittsburgh's solar irradiance (National Renewable Energy Laboratory 2015). The composition of grid electricity represented the conditions in PJM for 2015, for both average (EIS n.d.) and marginal (Monitoring Analytics 2016). Solar PV and wind upstream emissions are all reported in terms of kg CO_2-equivalent for a 100-year Global Warming Potential (GWP) using IPCC AR5 values (Pachauri et al. 2015). Vehicle manufacturing emissions were taken from the GREET model. The differences between vehicle manufacturing emissions were assumed to be entirely due to the extra batteries required, as listed in Table I-3. This assumption ignores the extra components necessary in HEVs and PHEVs, which need to run on both gasoline and electricity, when compared to ICVs and BEVs. BEVs and ICVs also have components not in common with each other. These emissions are expected to be much smaller than battery manufacturing, which themselves were found to be much less significant than use phase emissions. Calculations for vehicle manufacturing emissions are based upon the GREET model (A. Elgowainy et al. 2016) and described in section 2.2.3.

All emissions were divided into the 3 scopes common for life cycle assessment (Bhatia et al. 2011; Fong et al. 2014; Matthews et al. 2008). Scopes 1 and 2 comprise direct emissions; with Scope 1 covering direct vehicle gasoline combustion and Scope 2 covering combustion from power generation. Scope 3 covers all upstream emissions for fuel, power and vehicle production and transport. This is summarized, for each vehicle type, in Table I-7.

Table I-7: Costs/Emissions Scopes for Each Vehicle Type

Vehicle	Private Costs	Scope 1	Scope 2	Scope 3
BEV	Vehicle Purchase, Vehicle Maintenance, Charger Purchase and Installation, Electricity Costs	n/a	Electricity Generation Combustion	Battery Manufacturing, Electricity Upstream
PHEV	Vehicle Purchase, Vehicle Maintenance, Charger Purchase and Installation, Electricity Costs, Gasoline Costs	Gasoline Combustion	Electricity Generation Combustion	Battery Manufacturing, Electricity Upstream, Gasoline Upstream
HEV	Vehicle Purchase, Vehicle Maintenance, Gasoline Costs	Gasoline Combustion	n/a	Battery Manufacturing, Gasoline Upstream
ICV	Vehicle Purchase, Vehicle Maintenance, Gasoline Costs	Gasoline Combustion	n/a	Gasoline Upstream

Potential differences in emissions for these scopes is of particular importance when considering the decision-making rationale of municipalities when compared to a national or regional analysis. Since the impacts of GHGs are global, municipalities would view GHG reduction efforts from an accounting perspective, depending on which life cycle scopes they are including. When considering non-GHG air pollutants, however, this might not be the case. Nations joining the Paris agreement are not obligated to consider the externalities of non-GHG pollutants. This shows that many policy makers have decided to separate responsibilities for GHG and non-GHG air pollution externalities and, in this case, only accept addition responsibility for GHG effects. Therefore, cities that have pledged to reduce GHG emissions can be expected to weigh the effects of non-GHG emissions on their constituents more highly than those that can be exported. Scope 1 emissions are the only emissions guaranteed to occur entirely where the vehicles are driven, likely inside of the borders of the municipality themselves. Electricity consumed in the municipality may be produced at a great distance from the people living there, and air pollutant transport and damages to residents of the municipalities depend on factors such as distance, power plant pollution control equipment, and wind patterns. Holland et al. (Holland et al. 2015) suggests that, on average 43% of gasoline emissions effects stay within the census county that they occur in. For electricity they suggest that on average, only 1% of the effects of emissions from electricity demand are borne by the county in which they were demanded (Holland et al. 2015). Scope 3 emissions from fuels and battery manufacturing are primarily a function of geography and trade and are not guaranteed to entirely occur even in the same country where they were demanded.

High and low estimates for the social costs of SO_2 and NO_x, are from an EPA regulatory impact analysis on pollution standards for existing power plants (EPA 2014b, 2015b), while base case assumed the average of the two values. Social costs for SO_2 and NO_x were based on premature mortality alone, in the eastern region of exposure for 2020. High and low SO_2 values were taken from 3% and 7% discount rates, respectively. NO_x values were taken from the sum of effects of NO_x as $PM_{2.5}$ and Ozone; with high and low ozone values being from the 4% and 7% ranges, respectively. CO_2 costs are from the interagency report on the social costs of carbon (EPA 2015a): 2020 values were used with the 3% discount rate estimate used for the base case and the 5th and 95th percentile values being used for high and low costs, respectively. Costs due to emissions were not discounted for the NPC analysis. All values were converted to $2015 using the Bureau of Labor Statistics CPI calculator (BLS n.d.). All emission rates are listed in Table I-5.

2.2.2. Grid Emissions Assumptions

The following assumptions were used when calculating the emissions for grid electricity,

- Marginal grid emissions (Monitoring Analytics 2016) for any given fuel were assumed to be the same as those of averaged fuel emissions (EIS n.d.) for PJM where the sources gave the same fuels
    - This leads to a likely underestimated as less efficient plants are likely to be used on the margin than as average
    - Marginal coal emissions were weighted by the PJM average mix of "Bituminous and Anthracite" and "Sub-Bituminous" coal
    - Marginal “Diesel” and “Light Oil” were both assumed to have the same emissions as average “Oil - Distillate Fuel Oil”

    - Marginal "Heavy Oil" was assumed to have the same emissions as average "Oil - Distillate Fuel Oil"
    - Marginal "Miscellaneous" was assumed to have the same emissions as average "Other"
    - Marginal "Missing Data" was assumed to have no emissions
        - This counted for <1% of the marginal mix for every averaged hour
- All Upstream emissions, except solar and wind, were taken from GREET (A. Elgowainy et al. 2016)
    - Solar and wind are only calculated in terms of $CO_{2\text{-eq.}}$
- Estimated transmission efficiency was assumed to be the estimated losses / the total supply of electricity for PA in 2015, according to the EIA (EIA 2017)
- Upstream GREET Assumptions
    - Coal was assumed to come from a US Non-Distributed: Coal Fired Steam Plant
    - Diesel was assumed to come from US Low Sulfur Diesel from crude, with the equivalent efficiency of a US Non-Distributed: Residual oil Steam Fired plant
    - Heavy oil was assumed to come from a US Non-Distributed: Residual oil Steam Fired plant
    - Kerosene was assumed to have an equivalent upstream as diesel
    - Landfill gas and municipal solid waste, being trash, were assumed to have 0 upstream
        - This ignores the infrastructural investment, which GREET also ignores
    - Light oil was assumed to have an equivalent upstream as diesel

- Miscellaneous and Missing data were both assumed to have 0 emissions
  - Both were less than 1% of the mix, each, for every averaged hour
- Natural gas was assumed to come from a Us Non-Distributed: natural gas combined cycle plant
- Waste Coal was assumed to have an equivalent upstream as coal

2.2.3. Municipal Light-Duty Fleet Calculations

This section describes the equations used to estimate emissions factors for gasoline and electricity and the NPC of the different vehicles. Variable definitions and units are shown in Table I-8.

Table I-8: Municipal light duty fleet variables

Variable Name	Definition	Units
α_{gas}	Annual gasoline consumption per vehicle	l
α_{elc}	Annual electricity consumption per vehicle	kWh
F_{eGas}	Vehicle Gasoline Fuel Economy	l / 100 km
F_{eElc}	Vehicle electric Fuel Economy	kWh / 100 km
V_{KmT}	Vehicle km Traveled per year	km
$\%_{gas}$	% of travel in gasoline mode	% / 100
$\%_{Elc}$	% of travel in electric mode	% / 100
D_R	Daily vehicle range	km
E_R	PHEV EPA rated all electric range	km
$\gamma_{vehicleGas}$	Vehicle annual Gasoline emissions	g or kg of pollutant (for CO_2)
γ_{gas}	Gasoline emissions	g or kg of pollutant (for CO_2) / l
$\gamma_{elc_{up}}$	Electric upstream emissions	g or kg of pollutant (for CO_2) / kWh
$\gamma_{fuel_{up}}$	Electric upstream emissions for a specific fuel	g or kg of pollutant (for CO_2) / kWh
$\%_{grid_{fuel}}$	The % of the electric grid supplied by specified fuel	% / 100
E_{trans}	Grid transmission efficiency ≈ 96.6% for PA in 2015	% / 100
$\gamma_{fuel_{prof}}$	Emissions to get 1 kWh of heating potential of fuel to power plant	g or kg of pollutant (for CO_2) / kWh
E_{tech}	Efficiency of plant type used to produce electricity	% / 100
$\%_{tech}$	The % of the grid supplied by the specified plant type for its fuel	% / 100
$\gamma_{vehicleElc}$	Vehicle annual electric emissions	g or kg of pollutant (for CO_2)
$\gamma_{\mathrm{grid}_{\mathrm{ij}}}$	Electric emissions for grid i in year j	g or kg of pollutant (for CO_2) / kWh
$\%_{grid_{i_{fuel}}}$	The % of the electric grid supplied by specified fuel for hour i of an average day	% / 100
$\%grid_{i_{day_{fuel}}}$	The % of the electric grid supplied by specified fuel for hour I of day k	% / 100
$days_{year}$	Days in the year of data, 2015, = 365	days
$\gamma_{marg_{ij}}$	Marginal emission factor from time period i till j, using 24:00 time	g or kg of pollutant (for CO_2) / kWh
γ_{mar_i}	marginal emission factor for hour i, using 24:00 time	g or kg of pollutant (for CO_2) / kWh
$C_{RECx\%}$	Total cost of electricity with x% REC purchase	$ / kWh
C_{elc}	Cost of grid electricity	$ / kWh
C_{REC}	Cost premium for REC	$ / kWh
$\%_{REC}$	% of electricity covered by REC	% / 100

Variable Name	Definition	Units
$\gamma_{RECx\%}$	Electric emissions with x% RECs	g or kg of pollutant (for CO_2) / kWh
γ_{wind}	Emissions from wind	g or kg of pollutant (for CO_2) / kWh
C_{m^2L}	Low PV Canopy Cost	$ / m^2
$P_{C_{m^2}}$	Frick project PV Panel costs = $178.93 (Sharrard 2016)	$ / m^2
δ_{PC}	Estimated decrease in PV prices between 2015 and 2020 = 7.44% (Donald Chung et al. 2015)	% / 100
$S_{C_{m^2}}$	Frick project structural costs = $379.34 (Sharrard 2016)	$ / m^2
C_{kWh}	PV LCE vost	$ / kWh
C_{m^2}	PV system Cost	$ / m^2
S_{irr}	Solar irradiance = 1392 (National Renewable Energy Laboratory 2015)	kWh / m^2
N_{PV}	System life = 25	years
i	Discount rate = 3%, 5%, 7%	% / 100
M	Annual maintenance rate, as % of total system costs = 0.35% (Donald Chung et al. 2015)	% / 100
P_t	Power generation in year t	kWh
$\gamma_{veh_{elcup_{pollutant}}}$	Vehicle upstream emissions	g, or kg (for CO_2)
$\gamma_{Battery_{Assemblyup_{polutant}}}$	Emissions from the battery assembly process	g, or kg (for CO_2)
$W_{battery}$	Battery weight	kg
$\gamma_{battery_{parts_{pollutant}}}$	Pre-assembly battery emissions	g or kg of pollutant (for CO_2) / kg of battery
$C_{battery}$	Battery Capacity	kWh
$D_{battery}$	Battery density = 80 (Samaras and Meisterling 2008a)	Wh / kg
NPC_P	Vehicle private NPC	$
C_{veh}	Vehicle capital costs	$
$C_{charger}$	Capital costs of charger,0 for CVs and HEVs	$
C_{main}	Vehicle maintenance costs	$ / km
C_{gas}	Gasoline costs	$ / l
$(P\|A, i, N_V)$	Present value factor of an annuity of N_V years at a discount rate of i	unitless
N_V	Vehicle lifetime = 15	years
NPC_1	Vehicle scope 1 NPC	$
$\gamma_{veh_{gas_{D_{pollutant}}}}$	Annual direct vehicle pollutant emissions from gasoline	g or kg of pollutant (for CO_2)
$C_{pollutant}$	Social cost of pollutant	$ / g
NPC_2	Vehicle scope 2 NPC	$
$\gamma_{veh_{Elc_{D_{pollutant}}}}$	Annual direct vehicle pollutant emissions from electricity	g or kg of pollutant (for CO_2)

Variable Name	Definition	Units
NPC_3	Vehicle scope 3 NPC	$
$\gamma_{Veh_{man_{Pollutant}}}$	Vehicle manufacture emissions,pollutant	g or kg of pollutant (for CO_2)
$\gamma_{veh_{fuelup_{pollutant}}}$	Annual vehicle upstream emissions from fuel for pollutant	g or kg of pollutant (for CO_2)
$NPC_{y_{elc}}$	NPC of scope y from electricity	$
$\gamma_{pollutant_{jy}}$	Emissions of pollutant in year j for scope y	g or kg of pollutant (for CO_2)
$(P\|F,i,j)$	Present value factor for a future value in j years at an i discount rate	unitless

Annual Gasoline and Electricity Consumption

Equation I-1 and Equation I-2 were used to calculate gasoline and electricity consumption. This assumes constant fuel economy, F_e, for each vehicle; constant fuel percentage usage, $\%_{fuel}$, for PHEVs; and constant travel, V_{kmt}, for all vehicles. Gasoline or electric consumptions is then just the product of these three values.

Equation I-1

$$\alpha_{gas} = \frac{F_{eGas}}{100} * V_{KmT} * \%_{gas}$$

Equation I-2

$$\alpha_{elc} = \frac{F_{eElc}}{100} * V_{KmT} * \%_{Elc}$$

PHEV Gasoline and Electricity Use

Equation I-3 and Equation I-4 were used to calculate the percentage of energy that a PHEV derives from electricity and gasoline. This is done by estimating the electric percentage, $\%_{elc}$, as the fraction of the daily driving amount that the rated electric range covers. This assumes that travel amount is constant every day and that the electric range rating is accurate for the type of travel that the vehicle is performing.

Equation I-3

$$\%_{elc} = \frac{D_R - E_R}{D_R}$$

Equation I-4

$$\%_{gas} = 1 - \%_{elc}$$

Annual gasoline emissions

Equation I-5 was used to calculate annual gasoline emissions of a single vehicle. This was simply the product of the vehicle's gasoline consumption and gasoline's emission rate.

Equation I-5

$$\gamma_{vehicleGas} = \alpha_{gas} * \gamma_{\text{gas}}$$

Upstream Electricity Emission Factors

Equation I-5 and Equation I-6 were used to calculate the upstream electricity emission factors, per kWh. Equation I-6 sums the product of the emissions of each fuel, their share of the electricity grid and the transmission efficiency. Equation I-7 calculates the emissions of each fuel, with the sum product of the emissions of each potential technology that uses that fuel, their efficiencies and shares of power production, for that fuel.

Equation I-6

$$\gamma_{elc_{up}} = \sum \gamma_{fuel_{up}} * \%_{grid_{fuel}} * E_{trans}$$

Equation I-7

$$\gamma_{fuel_{up}} = \sum \gamma_{fuel_{prod}} * E_{tech} * \%_{tech}$$

Annual electricity emissions

Equation I-8 calculates the annual electric emissions. This is the sum of electric consumption and emissions, for the year in question.

Equation I-8

$$\gamma_{vehicleElc} = \alpha_{elc} * \gamma_{\mathrm{grid}_{\mathrm{ij}}}$$

Marginal fuel mix

Our source (Monitoring Analytics 2016) gave marginal fuel usage factors in terms of percent of marginal fuel mix for each hour of the year. The percentage of each fuel for each average hour was taken as its average usage for that hour over the entire years, as shown below, in Equation I-9.

Equation I-9

$$\%_{grid_{i_{fuel}}} = \frac{\sum \%grid_{i_{k_{fuel}}}}{days_{year}}$$

Marginal emission factors

Marginal emission factors were used by averaging the hourly marginal emission factors for each hour of the daily time-period of interest, as shown below, in Equation I-10

Equation I-10

$$\gamma_{marg_{ij}} = \frac{\sum(\gamma_{marg_i})}{j - i}$$

Electricity REC Price

Equation I-11 was used to calculate the price of electricity, when RECs were purchased for a specified percentage of electricity consumed. This is done by applying the REC premium, C_{REC}; on the electric price, C_{elc}; weighted by the percentage of RECs purchased, $\%_{REC}$.

Equation I-11

$$C_{RECx\%} = C_{elc} * (1 - \%_{REC}) + (C_{REC} + C_{elc}) * \%_{REC}$$

REC Emission Factors

Equation I-12 was used to adjust electric emission factors to account for REC purchases. REC purchases from the city were for wind power so wind emission factors were used in place of grid ones for the portion of RECs purchased. Wind only had upstream, scope 3 emissions, scope 1 and 2 emissions are simply reduced by the REC percentage amount. Scope 3 emissions then have the wind upstream emissions added to the reduced emissions, weighted by the REC amount.

Equation I-12

$$\gamma_{RECx\%} = (1 - \%_{REC}) * \gamma_{grid_{ij}} + \%_{REC} * \gamma_{wind}$$

PV Price

Equation I-13 was used to calculate the price of electricity for the PV scenario. First costs per square meter were calculated. These were then used to calculate a simplified LCOE over the system's lifetime production. High cost per square meter taken from a recent solar carport facility at the Frick Park in Pittsburgh (Sharrard 2016). Low cost per square meter were derived by holding the structural costs constant, while decreasing PV cell prices by an estimated price decrease over the 5 years 7.44% (Donald Chung et al. 2015). Base case cost per square meter was the average of the high and low costs.

Equation I-13

$$C_{m^2 L} = P_{C_{m^2}} * (1 - \delta_{PC}) + S_{C_{m^2}}$$

PV Cost per kWh

LCOE were derived from the estimated lifetime production of a square meter, and a square meter's share of total costs over the project lifetime. This was annualized as shown in Equation I-14.

Equation I-14

$$C_{kWh} = \left(C_{m^2} + C_{m^2} * M\left[\frac{i}{1-(1+i)^{-N_{PV}}}\right]\right) * \frac{1}{\sum P_t * (1+i)^{-t}}$$

Vehicle Manufacturing Emissions

Vehicle manufacturing emissions were taken as relative among the vehicles, not absolute. The differences were assumed to be entirely due to the extra batteries required in EVs. This assumption ignores the extra equipment necessary in HEVs and PHEVs, which need to run on both gasoline and electricity, when compared to ICVs and BEVs. ICV and BEV relative upstream emissions are therefore shown to be slightly higher than reality. These emissions are expected to be much smaller than battery manufacturing, which themselves are found to be much less significant than use phase emissions. Calculations to find the emissions rate are shown in Equation I-15 and Equation I-16.

Equation I-15

$$\gamma_{veh_{elc_{up_{polutant}}}} = \gamma_{Battery_{Assembly_{up_{polutant}}}} + W_{battery} * \gamma_{battery_{parts_{pollutant}}}$$

Equation I-16

$$W_{battery} = \frac{C_{battery}}{D_{battery}}$$

Battery assembly and pre-assembly emissions were taken from the GREET model (A. Elgowainy et al. 2016). Battery capacities and technology where taken from Ford's website for each specific model and year. Specific Lithium Ion technology was assumed to be LFP and in series. Battery density was taken from a range of values given by Samaras and Meisterling (Samaras and Meisterling 2008a). The chosen value was used as it put the Ford Focus's battery weight within its known range of 600-700 lbs. (Ramsey 2012). The impacts from the manufacturing of the standard SLI battery were omitted across all vehicles, as it is common to include it in EVs for cross model component voltage compatibility (ALABC 2013).

Private Costs

Private costs included the purchase price of the vehicle, the purchase price of any necessary vehicle charger, the cost of vehicle maintenance and the cost of fuel for the vehicle. Equation I-17 was used to calculate private NPC.

Equation I-17

$$NPC_P = C_{veh} + C_{charger} + \left(\alpha_{gas} * C_{gas} + \alpha_{elc} * C_{kWh} + C_{main} * V_{KmT}\right) * (P|A, i, N_V)$$

Scope 1 Costs

Scope 1 costs, in this analysis, include the external effects of pollution from tailpipe emissions. Equation I-18 was used to calculate Scope 1 NPC. The cost of emissions were not independently discounted, Emission costs are already discounted and given in specific years, stated in Section 2.1 of the main text (EPA 2015a; b). The social discount bounding values are those used in the EPA's clean Power plan assessment (EPA 2014b, 2015b) and are reported in Table I-6: Emissions Rates.

Equation I-18

$$NPC_1 = \left(\gamma_{veh_{Gas_{D_{CO_2}}}} * C_{CO2} * N_V\right) + \left[\left(\gamma_{veh_{Gas_{D_{SO_2}}}} * C_{SO2}\right) + \left(\gamma_{veh_{Gas_{D_{NO_x}}}} * C_{NO_x}\right)\right]$$

Scope 2 Costs

Scope 2 costs include the external effects of energy purchased for use, but not directly generated. In his project that is electricity purchased for EVs. Scope 2 costs were calculated using Equation I-19.

Equation I-19

$$NPC_2 = \left(\gamma_{veh_{Elc_{D_{CO_2}}}} * C_{CO2} * N_V\right) + \left[\left(\gamma_{veh_{Elc_{D_{SO_2}}}} * C_{SO2}\right) + \left(\gamma_{veh_{Elc)D}{}_{NO_x}} * C_{NO_x}\right)\right]$$

Scope 3 Costs

Scope 3 costs include all the upstream effects that the project decisions made require, but don't produce in Scope 1 or 2. For this project I included vehicle manufacturing emissions; gasoline extraction, production and transport emissions; and electricity fuel extraction, production and transport emissions. Manufacturing emissions were all assumed to occur on the start of the first year. Scope 3 NPC was calculated using Equation I-20.

Equation I-20

$$\begin{aligned} NPC_3 = &\left[\left(V_{KmT} * \gamma_{VehMan_{CO_2}} + \gamma_{veh_{gasup_{CO_2}}}\right) * C_{CO_2}\right] \\ &+ \left[\left(\gamma_{veh_{gasup_{SO_2}}} + \gamma_{veh_{elcup_{SO_2}}}\right) * C_{SO_2} + \left(\gamma_{veh_{gasup_{NO_x}}} + \gamma_{veh_{elcup_{NO_x}}}\right) * C_{NO_x}\right] \\ &+ \sum_{Polutant}^{CO_2,SO_2,NO_x} \left(\gamma_{veh_{elcup_{polutant}}} * C_{Polutant}\right) \end{aligned}$$

Social NPC

Social NPC is the sum of private and all external scope NPCs, calculated above, and calculated using Equation I-21.

Equation I-21

$$NPC_S = NPC_P + NPC_1 + NPC_2 + NPC_3$$

Modifications to NPC Calculations for Transitional Scenario

As emissions for electricity in transitional scenarios vary year to year neither simple annuities nor constant annual emissions can be used. As this only affects electricity emissions, this only applies to scopes 2 and 3. For scopes 2 and 3 all $\gamma_{elc}'s$ and anything directly multiplied them should be removed from the NPC equation. Equation I-22 was added to the NPC_2 and NPC_3 equations above instead, to account for the yearly changes in electricity emissions. Doing this in a non-transitional grid will not change any results, as the annual emissions would be constant.

Equation I-22

$$NPC_{y_{elc}} = \sum \left(\gamma_{CO_{2\,jy}} * C_{CO_2}\right) + \sum \left[\left(\gamma_{SO_{2\,jy}} * C_{SO_2} + \gamma_{NO_{x_{jy}}} * C_{NO_x}\right)\right]$$

2.2.4. On-Site PV Generation Overview

While electrification may decrease GHG and NOx, emissions, it will increase SO_2 emissions as long as regional SO_2 caps are not yet exceed. This is because gasoline vehicles produce negligible direct SO_2 emissions, while coal-fired power plants without pollution control technologies have considerable SO_2 emissions. While many plants are installing advanced SO_2 control devices, another way to reduce air pollutant emissions is to increase the portion of electricity that is generated from renewable and low-emissions sources. The actual amount of emissions reduction achieved depends on the region, the relative amounts of generation, prices, policies, and other factors that would affect an economic dispatch curve. Photovoltaic generation is one possible renewable source to consider for distributed generation in an urban region. Unless the PV panels are directly connected to EV chargers, there is no guarantee that electricity generated from the PV system will be specifically used to charge EVs. However, generation from PV systems at the margin would shift the fossil units in an economic dispatch, which may result in more or less emissions depending on the fuels and units in the system. In addition, cities are interested in PV systems because they can include total generation from these systems in municipal GHG accounting. One potential location for PV arrays under the control of municipalities would be on city-owned parking facilities. Structural canopies can be constructed over city-owned surface lots or garages.

Currently the Pittsburgh Parking Authority owns and operates ten parking garages with parking on the roofs in the downtown business district, and one large unshaded surface lot (PPA n.d.). These properties are shown on a map in Figure I-1, except for the Shadyside facility, outside of the downtown area. The total surface area of these garage roofs and the lot was estimated to be 52,000 square meters, using Google Earth satellite images. If 80% of this area were to be used for photovoltaic cells and using 0.145 kW_p/m^2 power intensity for commercial rooftops (Alan Goodrich et al. 2012), this would result in a peak power capacity of 6,000 kW_p. According to NREL's System Advisor Tool solar irradiance in Pittsburgh is approximately 3.81 $\frac{kW\,hr}{m^2\,day}$ (National Renewable Energy Laboratory 2015). This estimate is averaged from 1991 to 2010 and from the TMY3 data set for Pittsburgh International Airport (National Renewable Energy Laboratory 2015). Using the 14.5% PV efficiency provided in NREL's PV cost summary (Alan Goodrich et al. 2012) I estimate electricity production of about 8.4 million $\frac{kWh_{DC}}{year}$, ignoring shade and system degradation. Systems of this type can be expected to degrade in efficiency by about 0.5% per year (Jordan and Kurtz 2013), leading to an end of life generation rate of 7.4 million $\frac{kWh_{DC}}{year}$, a decrease of about 12%.

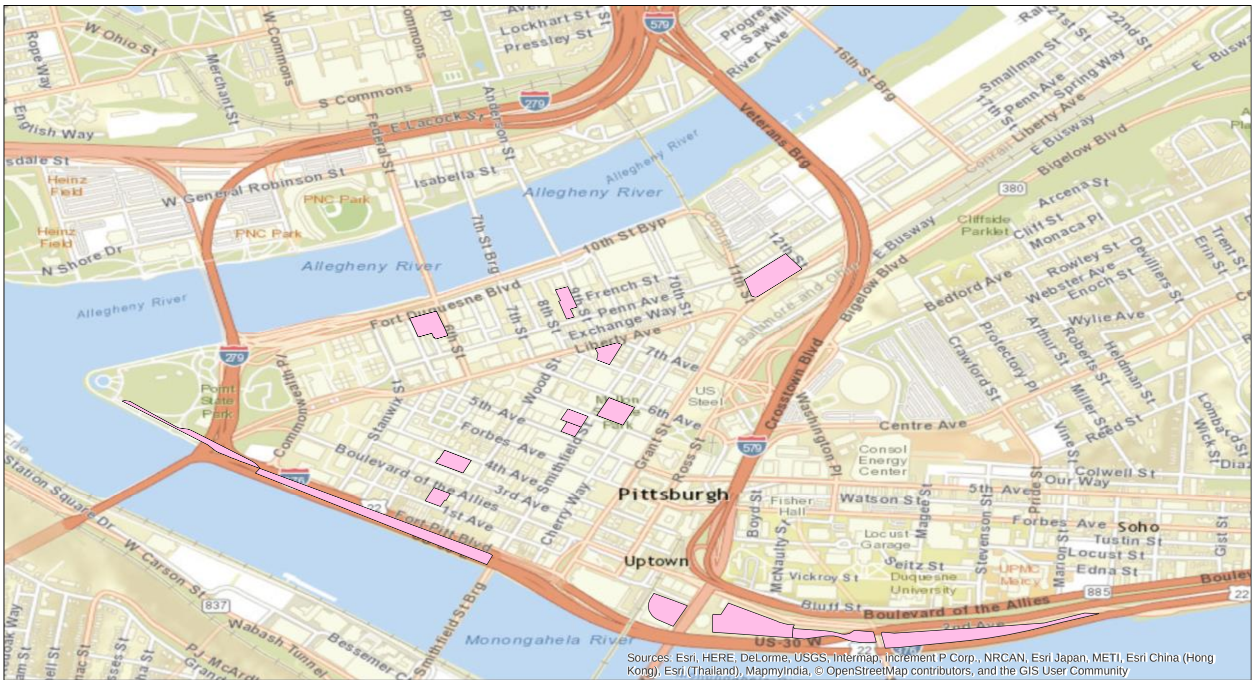

Figure I-1: Pittsburgh Parking Authority Locations in Downtown Pittsburgh, PA

The sunniest day in Pittsburgh, from 1991 to 2010, had a solar irradiance of about 342 W/m^2. The least sunny day had 29 W/m^2 (National Renewable Energy Laboratory 2015), a difference of more than 1000%. This leads a large amount of variability in the EV range one can generate from PV for each parking spot covered with a solar PV canopy. City of Pittsburgh ordinances set a standard sized parking space at 90° to be 9 by 18.5 feet, or 15 m^2 (City of Pittsburgh 2016). By aerial observation PPA garages were found to average about 33.1 m^2 of roof space for each parking space provided, while the surface lot averaged about 23.7 m². Using the efficiency of the BEV in this analysis and the variability in local irradiance, a histogram of the EV range provided for each space over an average year is shown in Figure I-2.

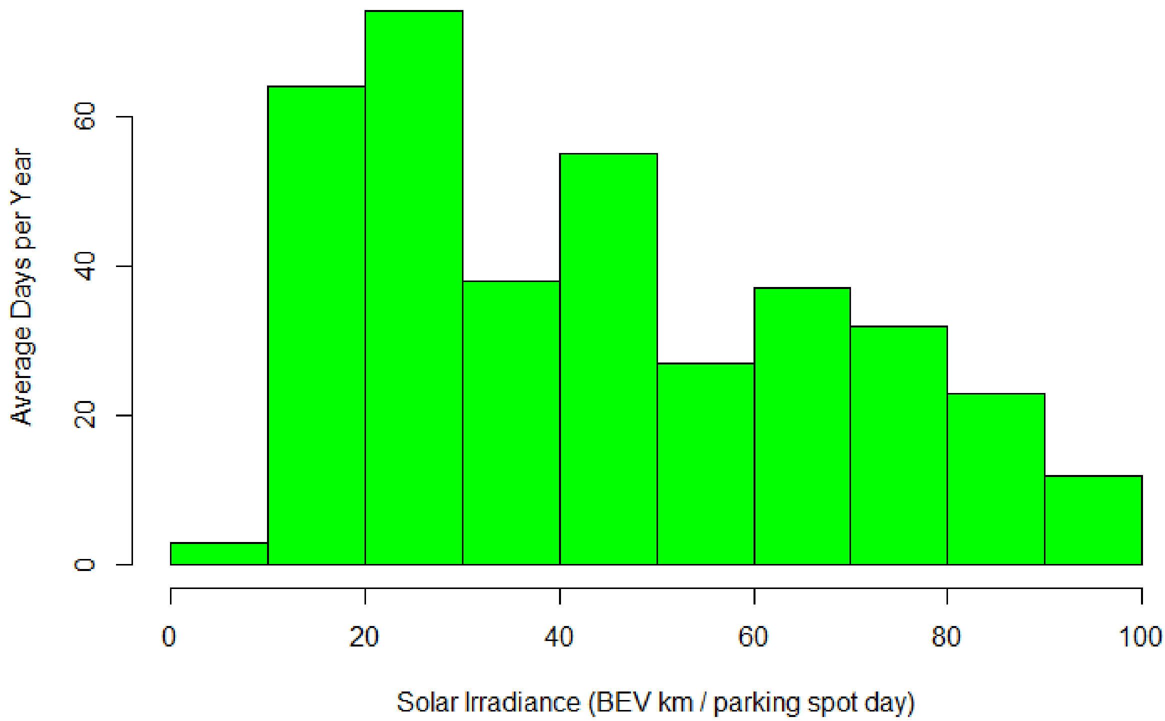

Figure I-2: Histogram of Solar Irradiance in Pittsburgh, BEV km / parking spot day

The economics of such a system is dependent upon the price of PV modules and systems, which have rapidly declined in recent years. In 2015 commercial rooftop prices per W_p averaged \$2.15 and NREL estimates that they will drop to \$1.99 by 2020 (Alan Goodrich et al. 2012; Donald Chung et al. 2015). These assumptions result in a system price between \$12,000,000 and \$13,000,000. This excludes the cost of the structures required for a canopy, which are required in order to continue to allow for parking access. A recent local solar canopy project of 162 kW_p cost \$624,000, of which \$200,000 was for the PV modules (Sharrard 2016). This is a cost of roughly \$560 per square meter. This suggests a project price of providing PV on city-owned parking facilities between \$28 and \$29 million, if I assume that panel costs could be the same 7% lower assumed above, while structural costs remain constant. Additionally the average maintenance cost of commercial rooftop PV projects in the US is about 0.35% of the PV system cost each year, specifically for the tilt-axis sun tracing models (Department of Energy 2011). I assumed that the saving in maintenance for a stationary system are equivalent to the increase in structural maintenance for canopies. Discount rates varied between 3% and 7% while electricity prices varied between \$0.04 and \$0.10 per kWh. Externalities were calculated for both grid average and grid marginal assumptions, with the marginal hours assumed to be 7AM to 7PM (Monitoring Analytics 2016).

2.2.5. On-Site PV Generation Overview Calculations

This section describes the equations used to estimate the PV system NPV. Variable definitions and units are shown in Table I-9.

Table I-9: On-Site PV generation variables

Variable Name	Definition	Units
P_t	System power produced in year t, first year = 0	kWh
$P_{\frac{kWh}{m^2 day}}$	PV power production	$\frac{kWh}{m^2 day}$
A	Total available system area ≈ 52,000	m^2
U	Space utilization rate = 80%	% / 100
S_{irr}	Pittsburgh Solar irradiance = 3.81 (National Renewable Energy Laboratory 2015)	$\frac{\text{kWh}}{\text{m}^2\text{day}}$
E	System efficiency = 14.5% (Donald Chung et al. 2015)	% / 100
D	"System degradation rate = 0.05% (Jordan and Kurtz 2013)	% / 100
C_{PV}	PV system cost	\$

Variable Name	Definition	Units
$C_{\frac{PV}{m^2}}$	PV system cost per area	\$ / m^2
$R_{\frac{PV}{yr}}$	Revenue from PV system	\$ / year
C_{elc}	Electricity price	\$ / kWh
$\gamma_{S_{PV_{off_{pollutant}}}}$	Scope S emissions offset	g, or kg (for CO_2), of pollutant / year
$\gamma_{S_{grid}}$	Scope S emissions from specified grid	g, or kg (for CO_2), of pollutant / kWh
$\gamma_{PV_{up}}$	Yearly scope 3 emissions	kg CO_2 / year
$\gamma_{\frac{PV_{up}}{kWh}}$	Scope 3 emissions	kg CO_2 / kWh
$\gamma_{\frac{AVG_{PV_{up}}}{kWh}}$	Average PV scope 3 emissions = 57 (Hsu et al. 2012)	kg CO_2 / kWh
$S_{irr_{avg}}$	Average solar irradiance = 1700 (Hsu et al. 2012)	$\frac{kWh}{m^2 year}$
$S_{Irr_{Pitt}}$	Pittsburgh Solar irradiance =1392 (National Renewable Energy Laboratory 2015)	$\frac{kWh}{m^2 year}$
NPV_P	Private NPV	\$
NPV_2	Scope 2 NPV	\$
NPV_3	Scope 3 NPV	\$
NPV_S	Social NPV	\$

Annual Power Production

Equation I-23 and Equation I-24 describe how the annual power production of the PV system was estimated. This is based on this size of the system, A and U; the areas irradiance S_{irr}; the systems efficiency, E; and a yearly linear degradation rate, D.

Equation I-23

$$P_{\frac{kWh}{m^2}} = (S_{irr} * E)$$

Equation I-24

$$P_t = P_{\frac{kWh}{m^2 day}} * A * U * \frac{365.25\ days}{yr} * t * (1 - D)^t$$

PV System Price

Equation I-25 describes how the total system capital costs were estimated. This includes the simple rooftop PV and canopy carport PV systems. It is assumed the costs scale linearly with system size and that there are no economies of scale to be had. This assumption may be appropriate for projects using a significant percentage of the available space, as they are already utility scale, but not be appropriate for smaller projects.

Equation I-25

$$C_{PV} = A * C_{\frac{PV}{m^2}} * U$$

PV System Revenue

Equation I-26 describes how potential revenue from the PV system was estimated. This assumes no time variability in electric pricing.

Equation I-26

$$R_{\frac{PV}{yr}} = P_{\frac{kWh}{yr}} * C_{elc}$$

Offset Emissions

Equation I-27 describes how the emissions from power generation that could be avoided by building the PV system were estimated. This is simply the product of the grid emission rate and PV power generated.

Equation I-27

$$\gamma_{S_{PV_{off_{pollutant}}}} = P_{\frac{kWh}{yr}} * \gamma_{S_{grid}}$$

PV Scope 3 Emissions

Equation I-28 describes how the upstream emissions from the PV system were estimated. These emissions only include CO_2. The source (Hsu et al. 2012) was a meta study that provided an average emission rate and solar irradiance. This was adjusted for Pittsburgh's solar irradiance, in Equation I-29.

Equation I-28

$$\gamma_{PV_{up}} = \gamma_{\frac{PV_{up}}{kWh}} * P_{\frac{kWh}{yr}}$$

Equation I-29

$$\gamma_{\frac{PV_{up}}{kWh}} = \gamma_{\frac{AVG_{PV_{up}}}{kWh}} * \frac{S_{irr_{avg}}}{S_{Irr_{Pitt}}}$$

Private Solar NPV

Equation I-30 describes how private NPV was estimated for the PV system. This is sum of the present value of the annual cash flow and the capital cost. The annual cash flow is the difference between the revenue and maintenance costs.

Equation I-30

$$NPV_P = \left[R_{\frac{PV}{yr}} - (C_{PV} * M)\right] * (P|A, i, N_{PV}) - C_{PV}$$

Scope 1 NPV

As the city in this analysis is not involved in direct fossil fuel power production, there are no scope 1 emissions or costs.

Scope 2 NPV

Equation I-31 describes how scope 2 NPV was estimated. As a social value, this was not discounted and therefore is just the sum product of the emissions and pollutant costs.

Equation I-31

$$NPV_2 = \gamma_{2_{PV_{off_{CO_2}}}} * C_{CO_2} + \gamma_{2_{PV_{off_{SO_2}}}} * C_{SO_2} + \gamma_{2_{PV_{off_{NO_x}}}} * C_{NO_x}$$

Scope 3 NPV

Equation I-32 describes how scope 3 NPV was estimated. As a social value, this was not discounted and therefore is just the sum product of the emissions and pollutant costs. This first term is to decrease the GHG reduction benefits by the upstream emissions associated with PV.

Equation I-32

$$NPV_3 = \left(\gamma_{3_{PV_{off_{CO_2}}}} - \gamma_{PV_{up}}\right) * C_{CO_2} + \left(\gamma_{3_{PV_{off_{SO_2}}}} * C_{SO_2} + \gamma_{3_{PV_{off_{NO_x}}}} * C_{NO_x}\right)$$

Social NPV

Social NPV is the sum of private and all external scopes NPVs, as shown in Equation I-33.

Equation I-33

$$NPV_S = NPV_P + NPV_2 + NPV_3$$

2.3. Results and Discussion

2.3.1 Fleet Electrification Analysis

Under a private cash flow analysis, costs for the EVs considered would have to fall or gasoline costs would have to rise in order for the private net present value of the EV option to be higher than the considered conventional efficient gasoline vehicle. This is in part due to the capital costs of the vehicles and EV chargers and the fact that Pittsburgh light-duty civilian municipal vehicles travel on average about 9,800 km per year. This is fewer km than most light-duty vehicles used by the general population, which travel between 16,000-24,000 km per year (US DOT 2017b).

Marginal emissions per 100 km for SO_2, NO_x and CO_2 equivalent are shown in Figure I-3 through Figure I-5. Average grid emissions are show in Figure I-6 through Figure I-8. Since Pittsburgh plans to increase REC purchases up to 100% over 15 years, a transitional scenario emissions reports in the average yearly emissions over the 15-year assumed vehicle lifetime. These values are also listed in Table I-10. These scenarios are defined in Table I-4 through Table I-6. Under all scenarios the BEVs, in the model line that the city was considering, have lower GHG emissions than the CVs. BEVs have lower GHG emissions than HEVs in all scenarios, except for the marginal daytime without RECs scenario. In the marginal daytime without RECs scenario BEVs have negligibly higher GHG emissions than HEVs. PHEV GHG emissions are higher than HEV emissions under current grid marginal conditions, when I ignore the possible effects of RECs. PHEV GHG emissions remain lower than HEVs under grid average assumptions. This reversal shows that grid average assumptions are a simplification that can change recommended actions. This agrees with prior work, such as Tamayao et al (Tamayao et al. 2015). SO_2 emissions are higher for EVs than HEVs for all current grid scenarios, but lower for the average year in a rapidly transitioning scenario and also for the immediate solar scenario. This is due primarily to the absence of significant SO_2 emissions from gasoline combustion compared to the prevalence of high sulfur yielding coal generation in the power grid. The potential for improvement, in all pollutants, is made clear when observing cleaner grid assumptions as the GHG emissions from traditional cars remain constant as the grid transfers to cleaner fuels. BEV and PHEVs maintain a clear and constant advantage for NO_x emissions in all assumed scenarios. The yearly rate of grid emissions decreases over 15 years necessary for the average rate of emissions of BEVs to equal HEVs is approximately 10% for SO_2, under grid marginal nighttime conditions when ignoring RECs. Between 2010 and 2015 average

PJM SO_2, Scope 2, emissions dropped by 69% (EIS n.d.). Between 2010 and 2015 Nighttime Marginal SO_2 Scope 2 emissions dropped 72% (EIS n.d.; Monitoring Analytics 2016).

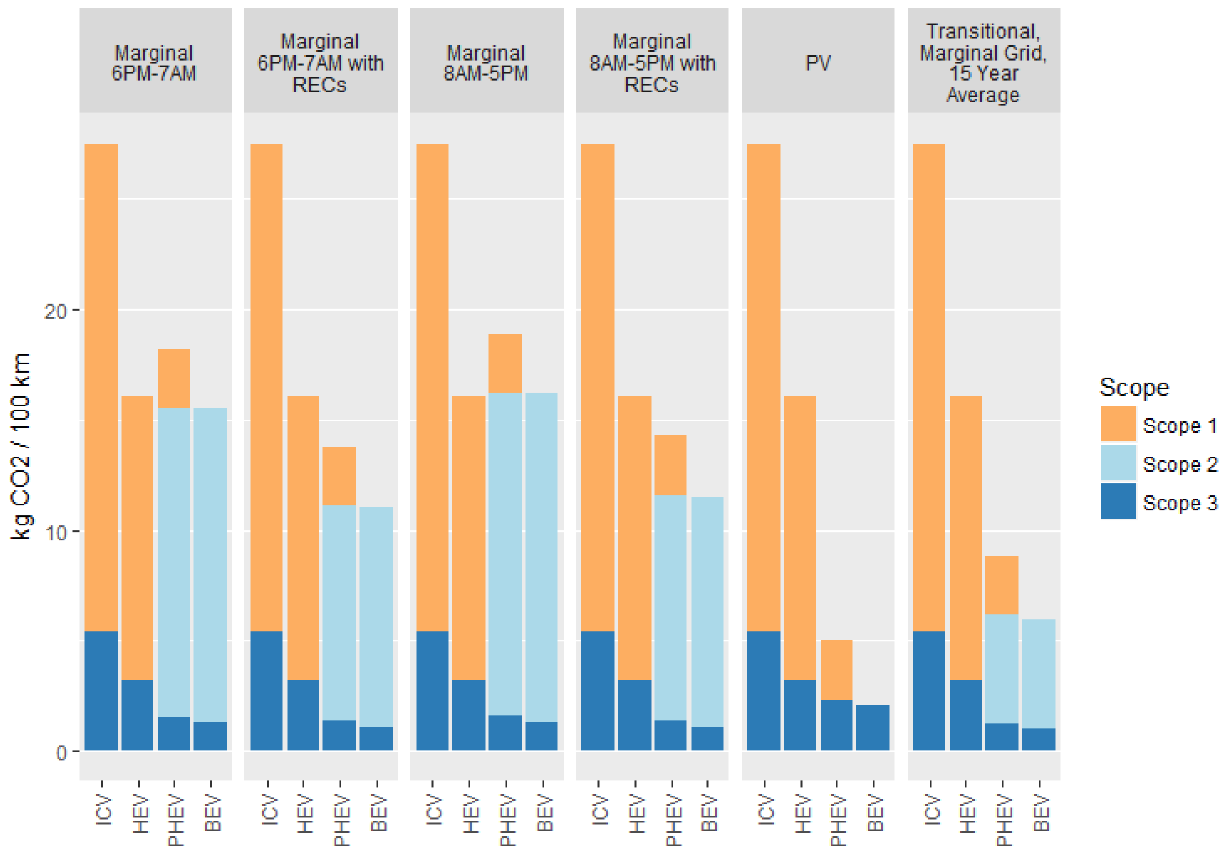

Figure I-3: Light-Duty Vehicle GHG Emissions (kg per 100 km) Across Various Marginal Emissions Scenarios

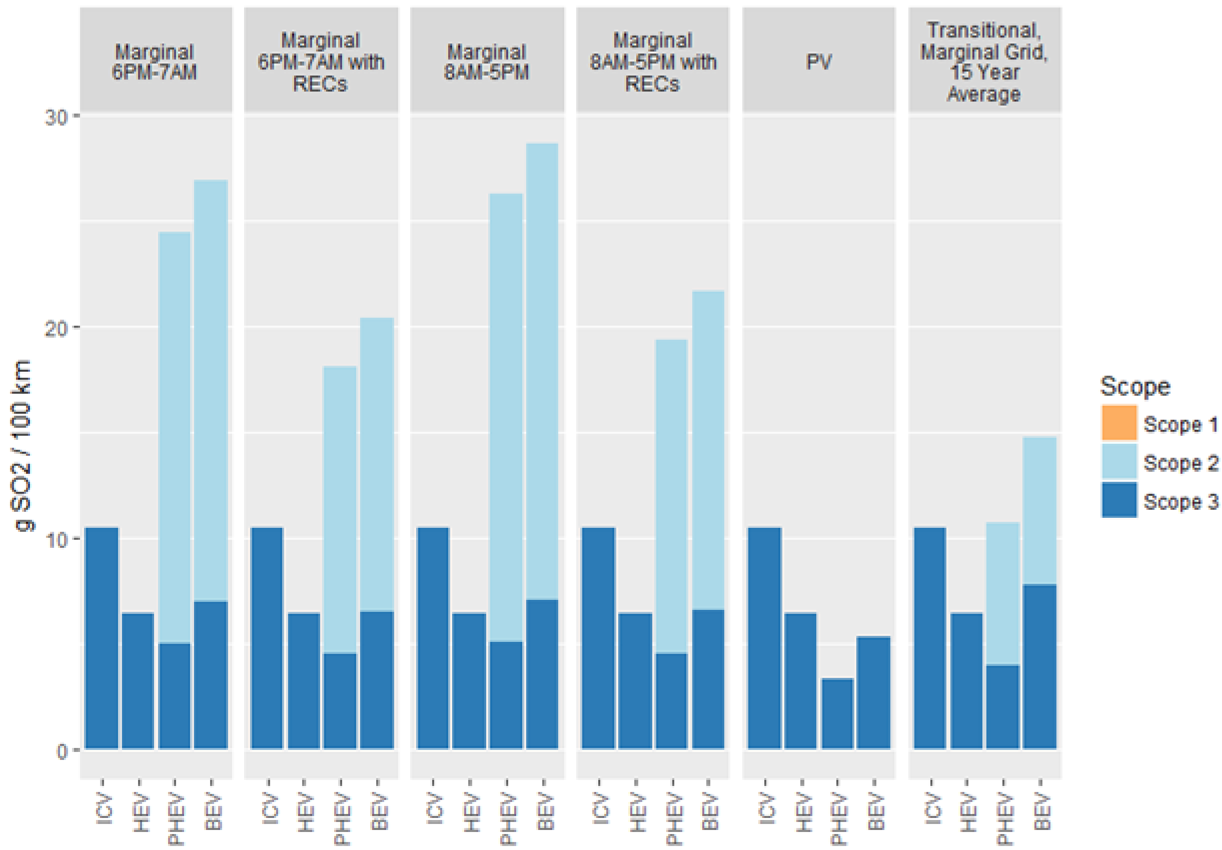

Figure I-4: Light-Duty Vehicle SO_2 Emissions (g per 100 km) Across Various Marginal Emissions Scenarios

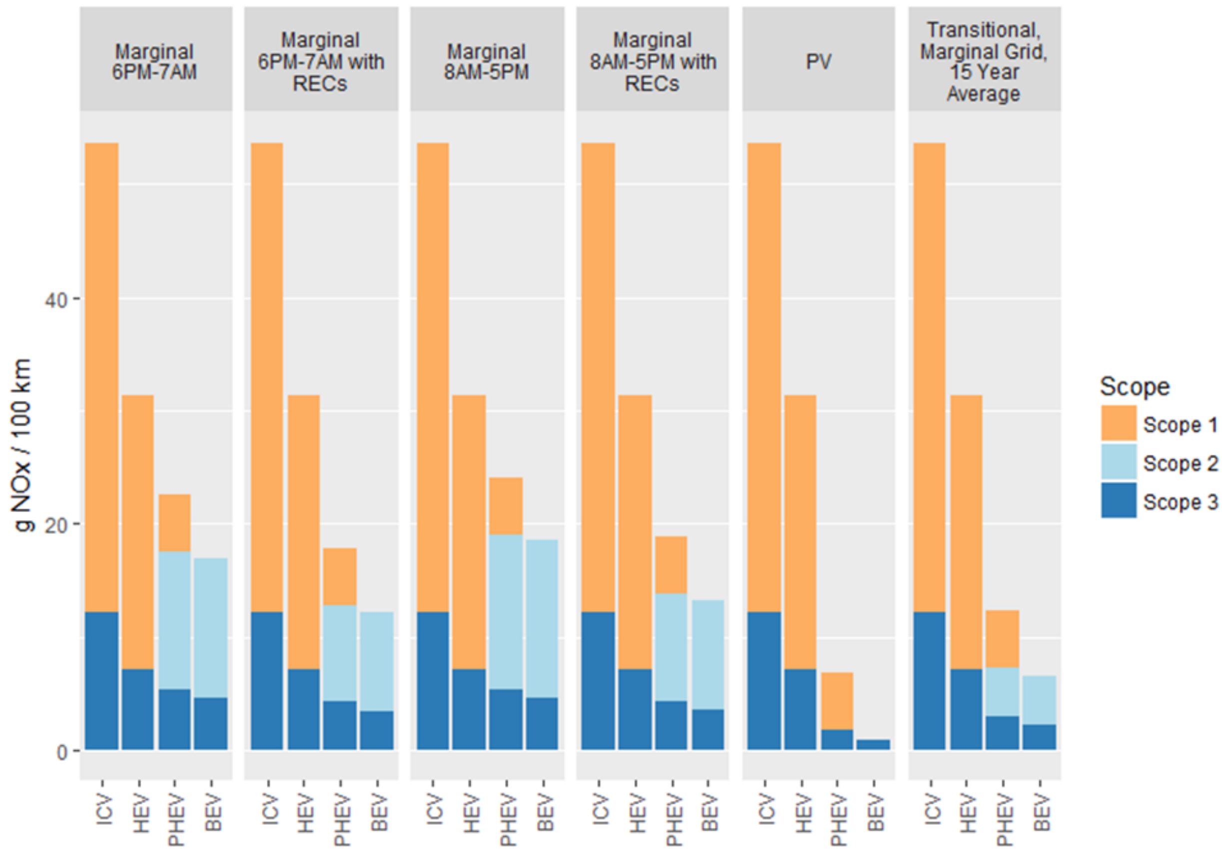

Figure I-5: Light-Duty Vehicle NO_x Emissions (g per 100 km) Across Various Marginal Emissions Scenarios

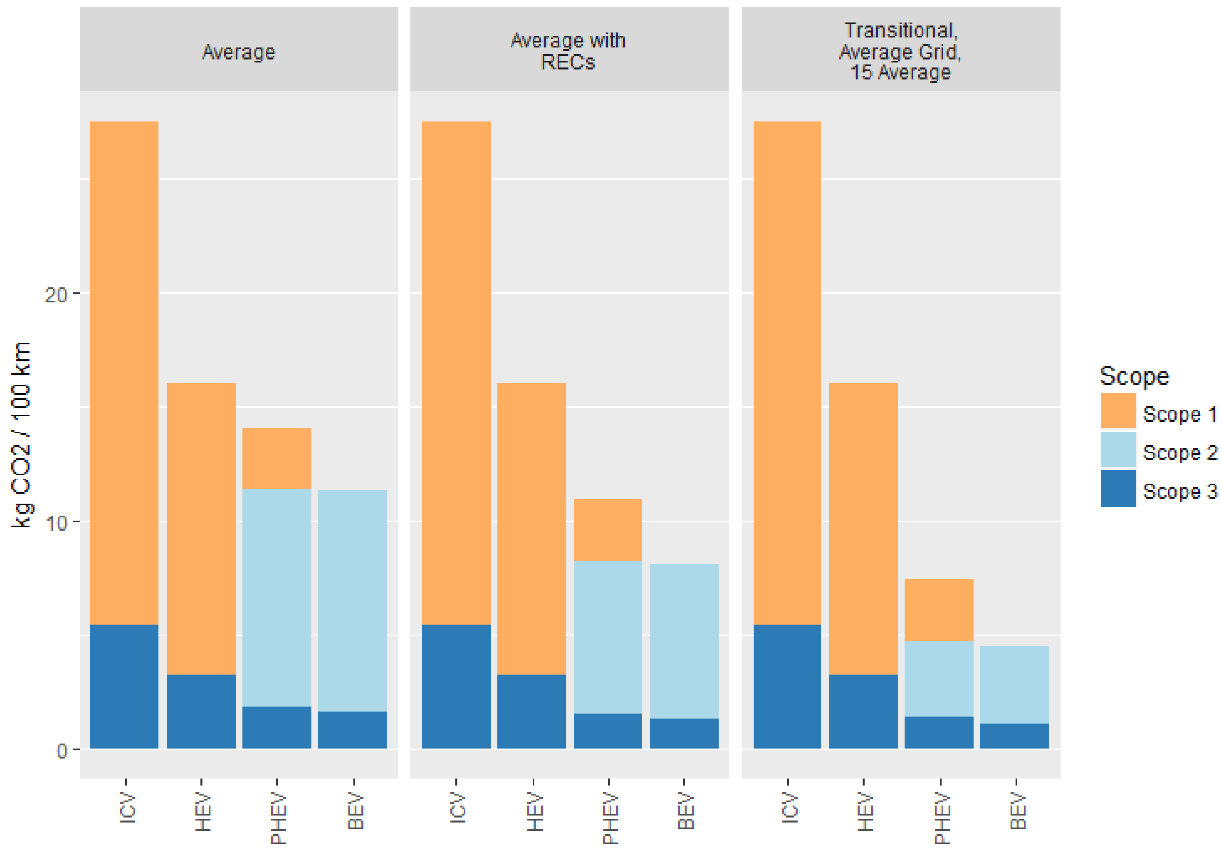
Average
Average with RECs
Transitional, Average Grid, 15 Average
kg CO2 / 100 km
20
10
0
ICV
HEV
PHEV
BEV
Scope
Scope 1
Scope 2
Scope 3

Figure I-6: Light-Duty Vehicle GHG Emissions (kg per 100 km) Across Various Average Emissions Scenarios

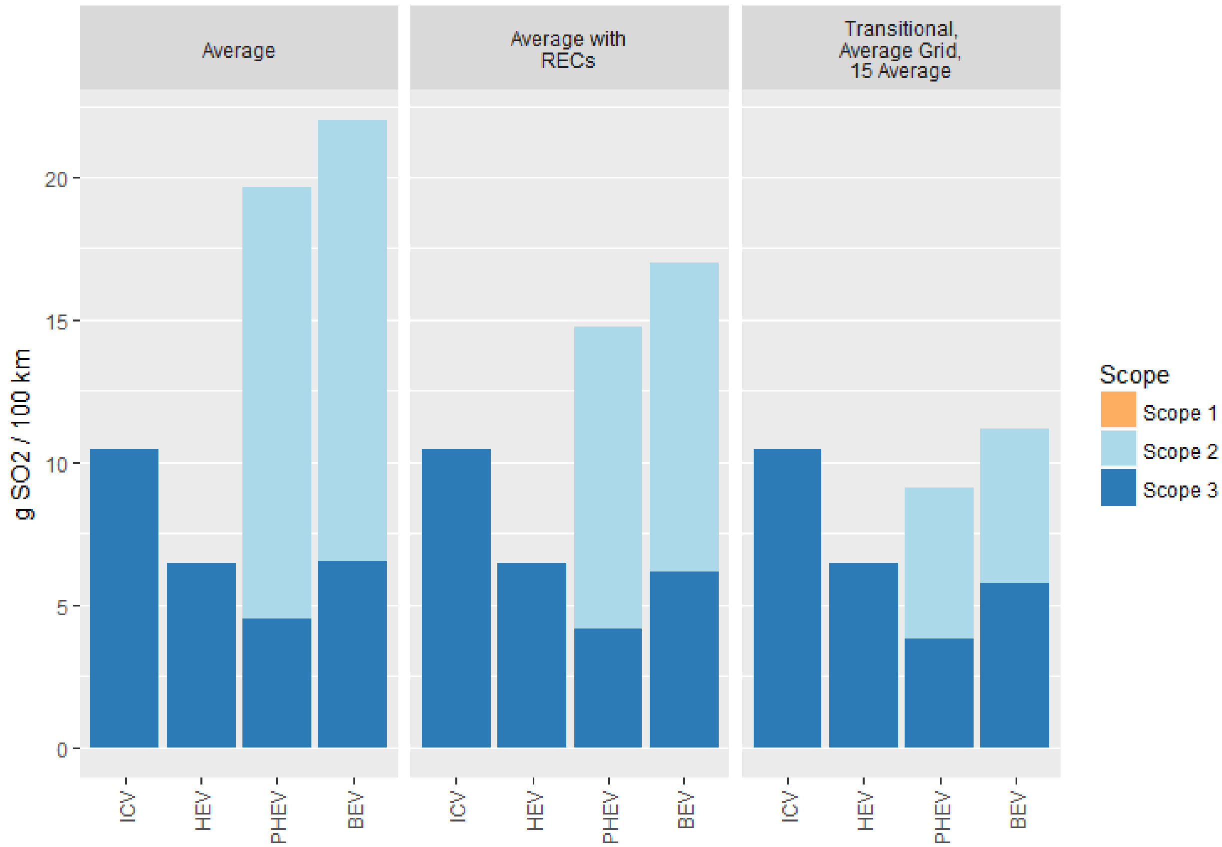

Figure I-7: Light-Duty Vehicle SO_2 Emissions (g per 100 km) Across Various Average Emissions Scenarios

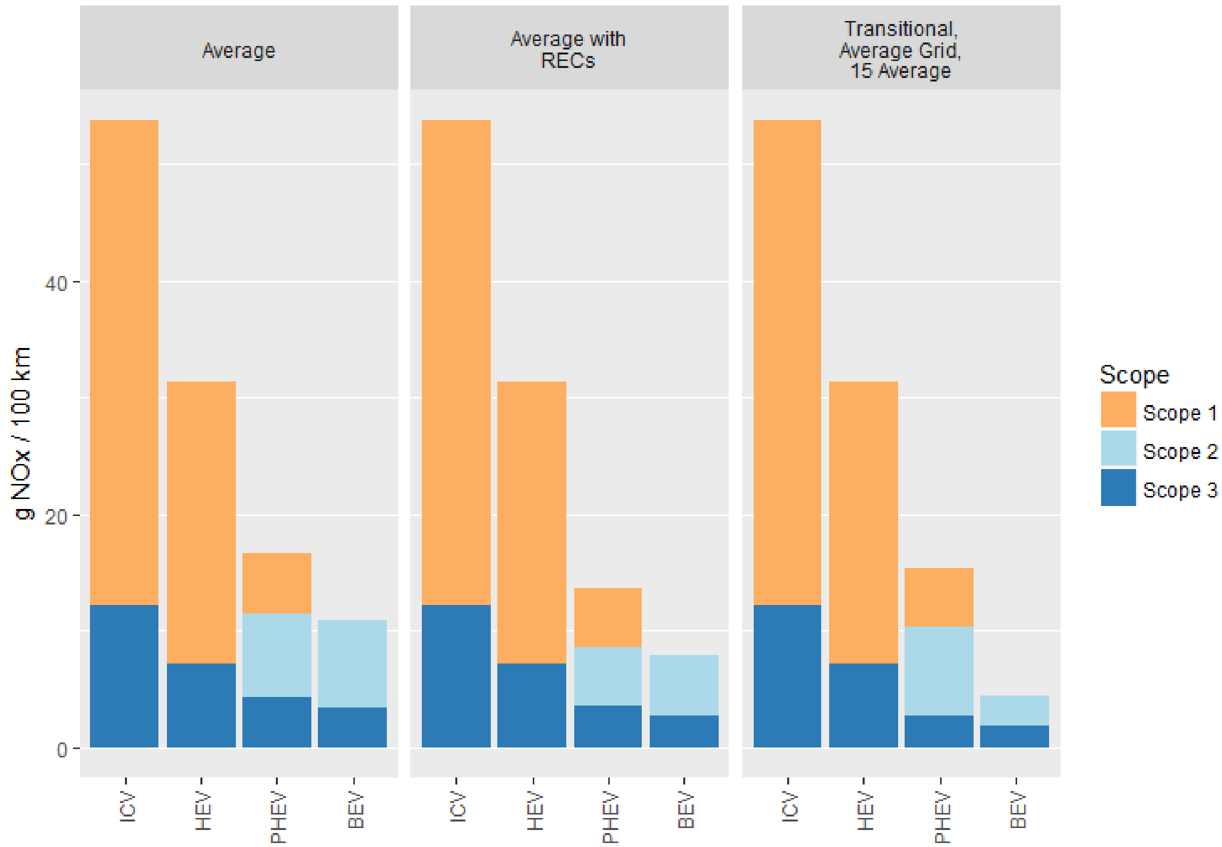

Figure I-8: Light-Duty Vehicle NO_x Emissions per (g 100 km) Across Various Average Emissions Scenarios

Table I-10: Results of Life Cycle Emissions Values Across Vehicles

Vehicle	Conventional	Hybrid	PHEV	BEV
Scope 1 (Same for all grids)				
kg CO_2 / 100 km	22.1	12.8	2.7	0
g SO_2 / 100 km	0	0	0	0
g NO_x / 100 km	41.5	24.1	5.08	0
Grid Average				
Scope 2				
kg CO_2 / 100 km	0	0	9.54	9.73
g SO_2 / 100 km	0	0	15.2	15.5
g NO_x / 100 km	0	0	7.3	7.44
Scope 3				
kg CO_2 / 100 km	5.39	3.21	1.82	1.56
g SO_2 / 100 km	10.4	6.47	4.52	6.52
g NO_x / 100 km	12.2	7.18	4.21	3.42
Marginal Daytime				
Scope 2				
kg CO_2 / 100 km	0	0	14.6	14.9
g SO_2 / 100 km	0	0	21.2	21.6
g NO_x / 100 km	0	0	13.6	13.9
Scope 3				
kg CO_2 / 100 km	5.39	3.21	1.59	1.32
g SO_2 / 100 km	10.4	6.47	5.07	7.08
g NO_x / 100 km	12.2	7.18	5.42	4.66
Marginal Night				
Scope 2				
kg CO_2 / 100 km	0	0	13.9	14.2
g SO_2 / 100 km	0	0	19.4	19.8
g NO_x / 100 km	0	0	12.2	12.4
Scope 3				
kg CO_2 / 100 km	5.39	3.21	1.56	1.30
g SO_2 / 100 km	10.4	6.47	5.00	7.01
g NO_x / 100 km	12.2	7.18	5.35	4.59
PV				
Scope 2				
kg CO_2 / 100 km	0	0	0	0
g SO_2 / 100 km	0	0	0	0
g NO_x / 100 km	0	0	0	0
Scope 3				
kg CO_2 / 100 km	5.39	3.21	2.33	2.07
g SO_2 / 100 km	10.4	6.47	3.38	5.36
g NO_x / 100 km	12.2	7.18	1.83	1.00
Transitional Marginal Night				
Scope 2				
kg CO_2 / 100 km	0	0	4.87	4.97

Vehicle	Conventional	Hybrid	PHEV	BEV
g SO_2 / 100 km	0	0	6.8	6.94
g NO_x / 100 km	0	0	4.25	4.34
Scope 3				
kg CO_2 / 100 km	5.39	3.21	1.27	1.00
g SO_2 / 100 km	10.4	6.47	3.95	7.81
g NO_x / 100 km	12.2	7.18	3.06	2.25

SO_2 emissions are generally the dominating factor in valuing the social costs of vehicle electrification, due to the potential high human health damages associated with SO_2. This finding is in line with prior research, such as Weis et al. (Weis et al. 2016) and Michalek et al. (Michalek et al. 2011b). The external cost difference between BEVs and HEVs is negative under PV, grid average, grid marginal nighttime with RECs, and transitional grid scenarios. Under current grid marginal assumptions BEVs have higher externalities than HEVs. For grid average and transitional assumptions BEVs were found to have lower externalities than the hybrids, further reinforcing the importance of grid marginal versus average assumptions. Due to the sensitivity of the model to RECs it is important to note that their effects on reducing marginal emissions is likely to be a fraction of their purchased amount, as described in the Section 2.3.6. Private costs dominate the total social costs scenarios, with HEVs being the least socially cost intensive option in all scenarios, being about $300 less costly than conventional. The total social NPCs of electrification for 15-year lifetimes, base case scenarios, are shown by scope in Figure I-9 and Figure I-10, for marginal and average grid assumptions, respectively. Possible variation in values due to defined parameter ranges are shown with error bars. Base case scenarios results are listed in Table I-11. As private costs dominate all scenarios all actors should make the same decisions. If Scope 1 costs were to instead dominate, municipal actors may prefer EVs, even if total social costs remained the same. This is due to the fact that much more of the effect of Scope 2 emissions will be exported out of the municipality than scope 1 emissions (Holland et al. 2015). National actors should make the same decisions, regardless of which scope dominates, as long as total social costs remain the same and occur within national boundaries.

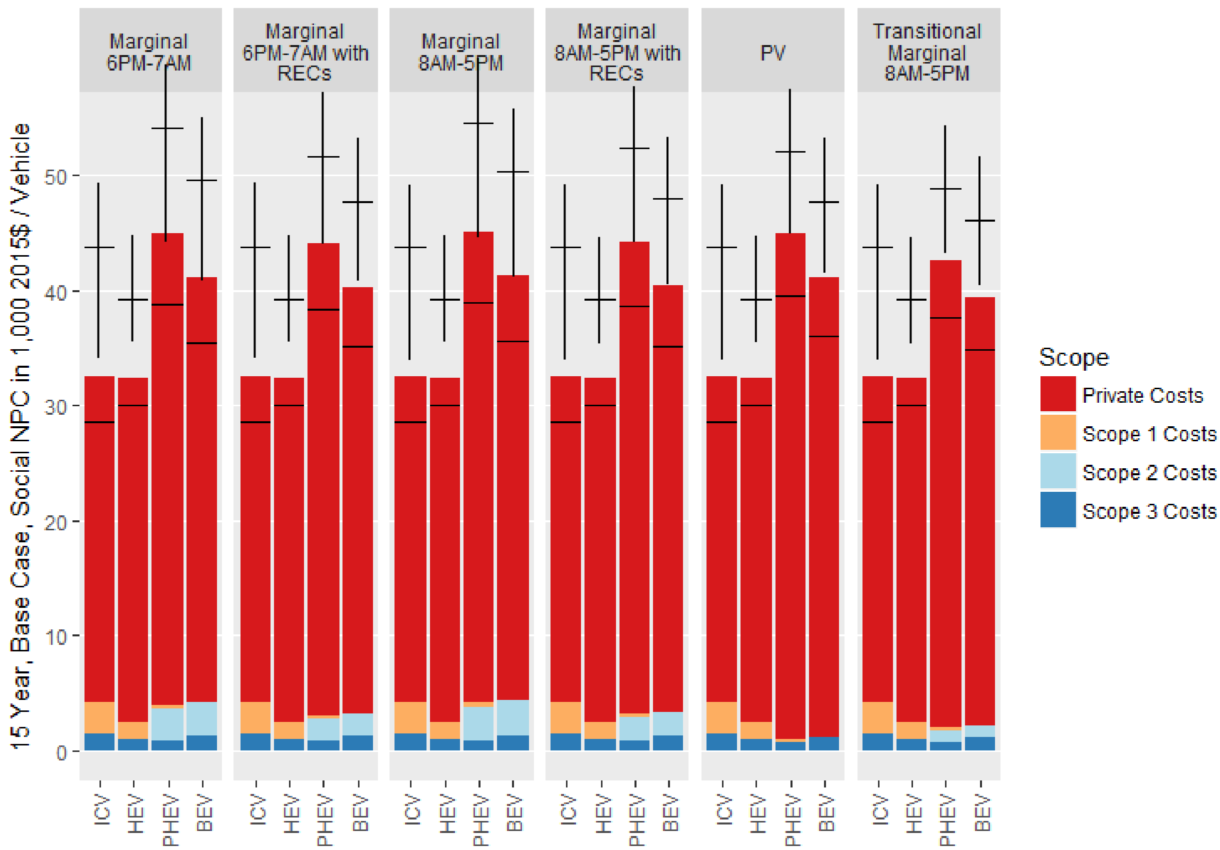

Figure I-9: 15-Year, Social NPC of Vehicle Options for the Municipal Light-Duty Fleet in Pittsburgh, PA, Across Various Marginal Emissions Scenarios

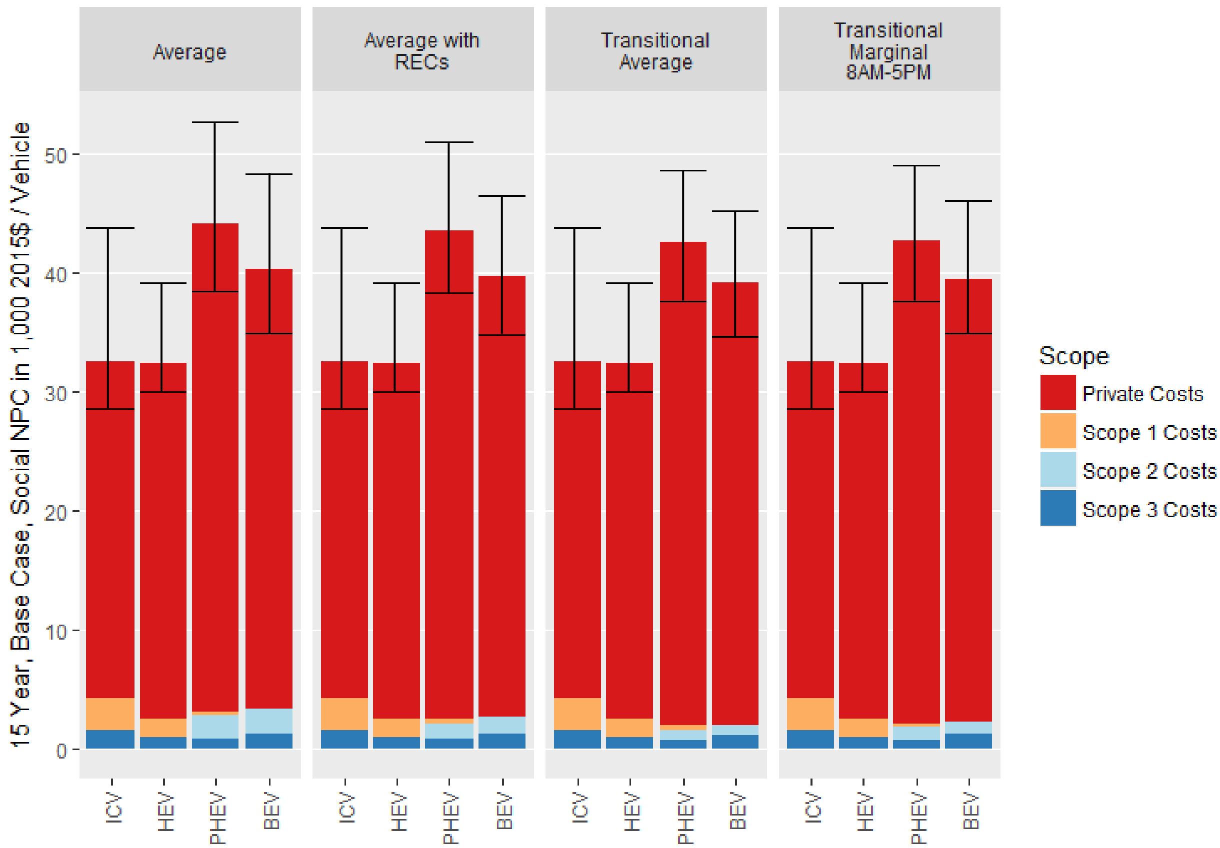

Figure I-10: 15-Year, Social NPC of Vehicle Options for the Municipal Light-Duty Fleet in Pittsburgh, PA, Across Various Average Emissions Scenarios

Table I-11: Base Case Social NPC, per vehicle, by Scope

Scenario	Conventional	Hybrid	PHEV	BEV
Private Cost				
PJM Average	$28,000	$30,000	$41,000	$37,000
PJM Marginal 08-17	$28,000	$30,000	$41,000	$37,000
PJM Marginal 18-07	$28,000	$30,000	$41,000	$37,000
REC PJM Average	$28,000	$30,000	$41,000	$37,000
REC PJM Marginal 08-17	$28,000	$30,000	$41,000	$37,000
REC PJM Marginal 18-07 Emissions	$28,000	$30,000	$41,000	$37,000
PV	$28,000	$30,000	$44,000	$40,000
Transitional PJM Average	$28,000	$30,000	$41,000	$37,000
Transitional PJM Marginal 18-07	$28,000	$30,000	$41,000	$37,000
Scope 1	Conventional	Hybrid	PHEV	BEV
PJM Average	$2,800	$1,600	$340	$0.00
PJM Marginal 08-17	$2,800	$1,600	$340	$0.00
PJM Marginal 18-07 Emissions	$2,800	$1,600	$340	$0.00
REC PJM Average	$2,800	$1,600	$340	$0.00
REC PJM Marginal 08-17	$2,800	$1,600	$340	$0.00

Scenario	Conventional	Hybrid	PHEV	BEV
REC PJM Marginal 18-07	$2,800	$1,600	$340	$0.00
PV	$2,800	$1,600	$340	$0.00
Transitional PJM Average	$2,800	$1,600	$340	$0.00
Transitional PJM Marginal 18-07	$2,800	$1,600	$340	$0.00
Scope 2	Conventional	Hybrid	PHEV	BEV
PJM Average	$0.00	$0.00	$2,000	$2,000
PJM Marginal 08-17	$0.00	$0.00	$3,000	$3,000
PJM Marginal 18-07	$0.00	$0.00	$2,700	$2,800
REC PJM Average	$0.00	$0.00	$1,400	$1,400
REC PJM Marginal 08-17	$0.00	$0.00	$2,100	$2,100
REC PJM Marginal 18-07	$0.00	$0.00	$1,900	$2,000
PV	$0.00	$0.00	$0.00	$0.00
Transitional PJM Average	$0.00	$0.00	$890	$770
Transitional PJM Marginal 18-07	$0.00	$0.00	$1,000	$1,100
Scope 3	Conventional	Hybrid	PHEV	BEV
PJM Average	$1,600	$1,100	$1,100	$1,800
PJM Marginal 08-17	$1,600	$1,100	$1,100	$1,900

Scenario	Conventional	Hybrid	PHEV	BEV
PJM Marginal 18-07	$1,600	$1,100	$1,100	$1,900
REC PJM Average	$1,600	$1,100	$1,000	$1,800
REC PJM Marginal 08-17	$1,600	$1,100	$1,000	$1,800
REC PJM Marginal 18-07	$1,600	$1,100	$1,000	$1,800
PV	$1,600	$1,100	$920	$1,700
Transitional PJM Average	$1,600	$1,100	$830	$1,600
Transitional PJM Marginal 18-07	$1,600	$1,100	$860	$1,800
Social NPC	Conventional	Hybrid	PHEV	BEV
PJM Average	$33,000	$33,000	$44,000	$41,000
PJM Marginal 08-17	$33,000	$33,000	$45,000	$42,000
PJM Marginal 18-07	$33,000	$33,000	$45,000	$42,000
REC PJM Average	$33,000	$33,000	$44,000	$40,000
REC PJM Marginal 08-17	$33,000	$33,000	$44,000	$41,000
REC PJM Marginal 18-07	$33,000	$33,000	$44,000	$41,000
PV	$33,000	$33,000	$45,000	$42,000
Transitional PJM Average	$33,000	$33,000	$43,000	$40,000
Transitional PJM Marginal 18-07	$33,000	$33,000	$43,000	$40,000

As the city increases its REC purchases over the next 15 years, BEVs would likely have clear GHG accounting advantages over conventional gasoline vehicles in Pittsburgh, depending on the marginal units dispatched. The City of Pittsburgh has indicated that it will transition to purchasing RECs for 100% of municipal electricity use by 2030. As discussed, there are challenges with attributing local air pollutant reductions directly to RECs on a one-to-one basis and these uncertainties are greater for marginal emissions than averaged, however the combination of existing and proposed EPA power plant regulations and REC purchases highly increase the likelihood of a cleaner grid profile going forward. Yet SO_2 emissions from the power sector remain significant in a social net present cost analysis. SO_2 is the highest cost pollutant for vehicle externalities and is not emitted in large amounts from gasoline combustion (EPA 2008).

2.3.2. Sensitivity to the Percentage of Electric Travel by PHEVs

The percentage of vehicle km traveled by electricity or gas, for PHEVs, is not certain to be the same as the ratio of electric range to daily mileage. This can be due to the specific driving patterns, distribution of daily travel ranges and distribution of annual travel among the vehicles (Lin et al. 2012; Lin and Greene 2011). The possible ranges of actual % EV travel, however, cannot every make a PHEV the most cost effective option. This is because PHEVs are costlier than either a BEV or HEV and less efficient than either in EV and gasoline driven mode. A PHEV is only ever the best option when it is more cost effective than either both a ICV and HEV and performance requirements disallow a pure BEV. This is most likely to happen for high range applications, which were not observed in this case study. The total $ amount of sensitivity, in social NPC, due to %EV is listed for all scenarios below, in Table I-12. Sensitivity is in general about 5% of social NPV, except for the solar scenario, where it's about 25%, due to much higher electricity prices.

Table I-12: Social NPC, PHEV % EV Sensitivity for 0-100% EV Drive Mode

Scenario	**Total possible effect of % of travel EV ($)**
Average	$1,700
Marginal 8AM-5PM	$400
Marginal 6PM-7AM	$700

Average with RECs	$2,400
Marginal 8AM-5PM with RECs	$1,500
Marginal 6PM-7AM with RECs	$1,700
PV	$600
Transitional Average	$400
Transitional Marginal 8AM-5PM	$700

2.2.3. CAFE Effects of EV Sales

CAFE has special allowances for alternative fuel vehicles, including EVs. Prior work by Jenn et al. (Jenn et al. 2016b) has shown that these allowances will increase US fleet-wide emissions if used. They found this effect to be up to 60 tons of CO_2 or 7,000 gal (26,000 l) of gasoline. This is effect comes from CAFE treating EVs as zero emitting vehicles, which they are not, and counting each EV sale as 2 vehicles. In other words, the accounting fleet fuel economy drops as if two zero emitting vehicles were sold, allowing more high emitting vehicles to be sold to reach the limit, even though only one, still emitting vehicle, was sold. This report is focused on the Municipal scale of concern, as opposed to Federal scale, and therefore ignores this effect.

2.2.4. Location Effects of Pollution

Electrifying vehicles will not only change the amount and composition of airborne emissions, but also their location and the pattern of human exposure. Vehicle electrification will move emission concentrations away from the roadside and into a more diluted ambient air pollution, or, depending on the location of the power plants, less populated areas. Exposure to traffic has been linked to greater human health impacts than compound ambient air pollution's effects (Hoffmann et al. 2007; Peters et al. 2004). Additionally, Holland et al have found that, in general, 91% of electricity emissions' damages occur in a state other than the one where the electricity was consumed and 99% in another Metropolitan Statistical Area (Holland et al. 2015). The corresponding rate for gasoline emissions was found to be 18% for states and 57% for Metropolitan Statistical Areas (Holland et al. 2015). This report does not attempt to capture any locational specific effects on the value of emissions. Accounting for this might increase conventional vehicle emissions costs for the usage phase.

In this fleet situation, all Scope 1 emissions are from direct gasoline combustion and all Scope 2 emissions are from direct electricity purchases for fleet charging. Figure I-11 through Figure I-14 show the share of emissions' damages in each area of concern, assuming these averaged rates of migration hold. CO_2 emissions were excluded, as that damage is global in nature.

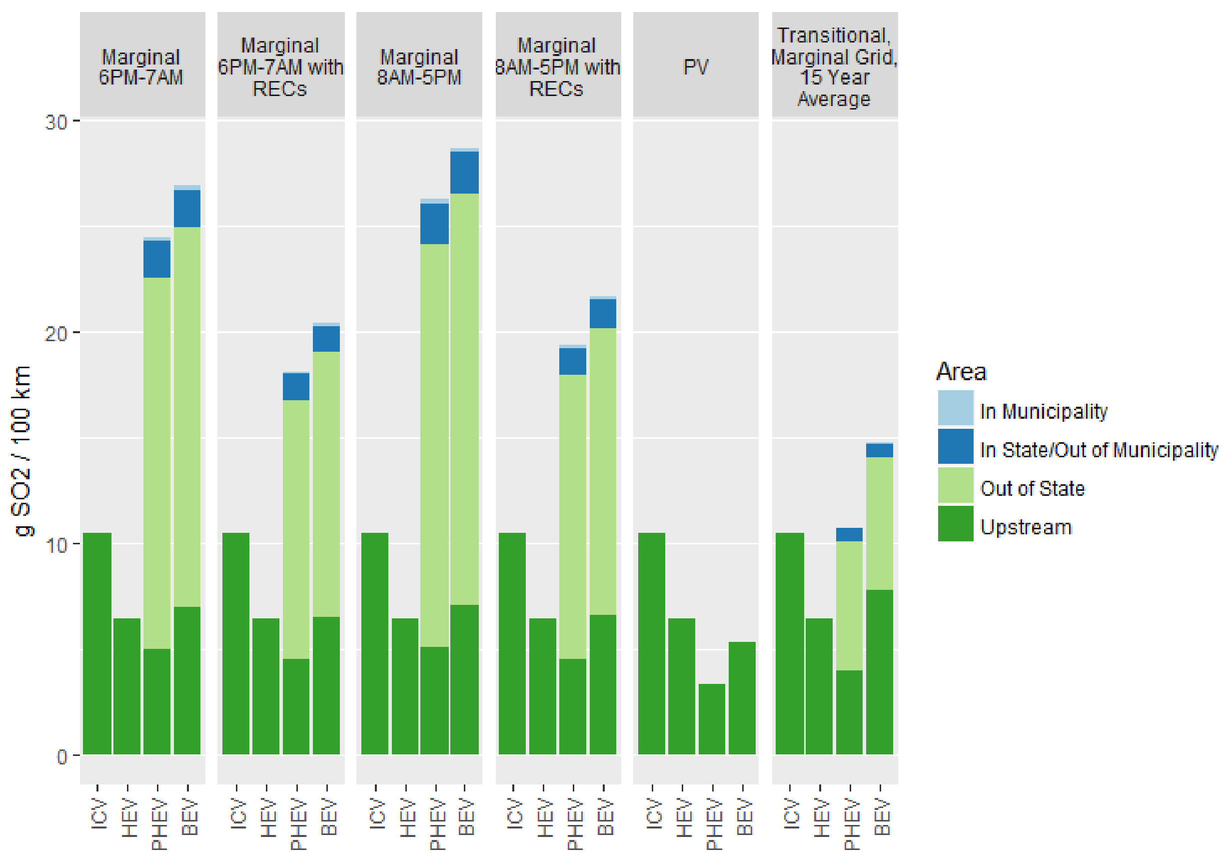

Figure I-11: Light-Duty Vehicle SO_2 Emissions per 100 km, by Area of Damage, Across Various Marginal Emissions Scenarios

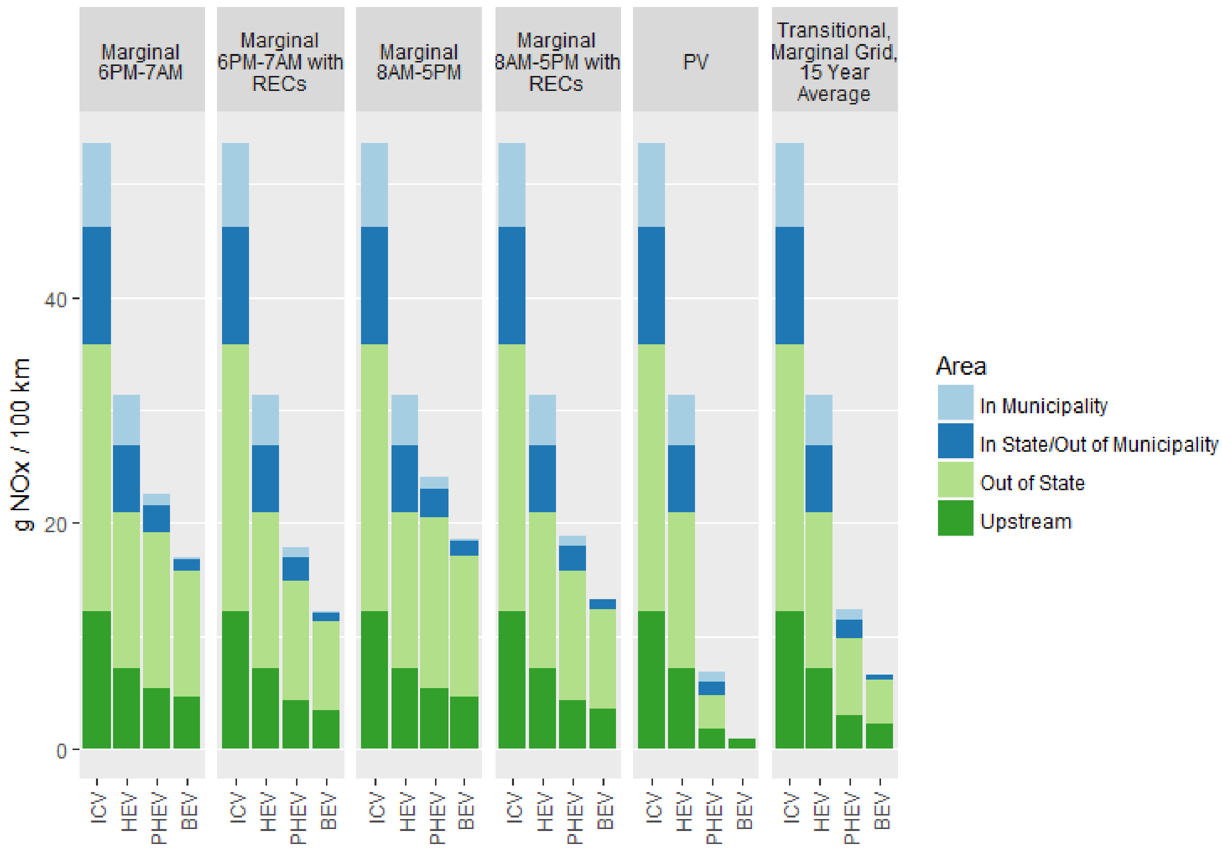

Figure I-12: Light-Duty Vehicle NO_x Emissions per 100 km, by Area of Damage, Across Various Marginal Emissions Scenarios

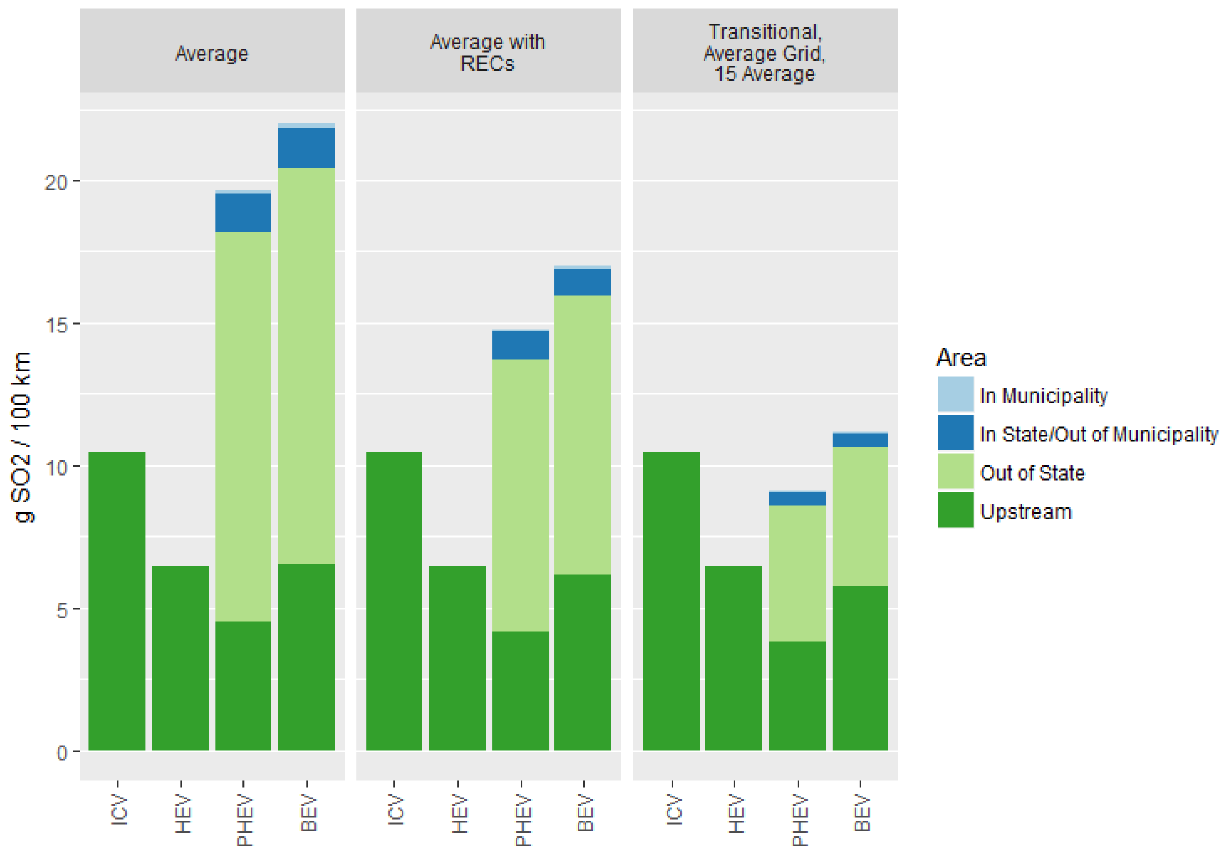

Figure I-13: Light-Duty Vehicle SO_2 Emissions per 100 km, by Area of Damage, Across Various Average Emissions Scenarios

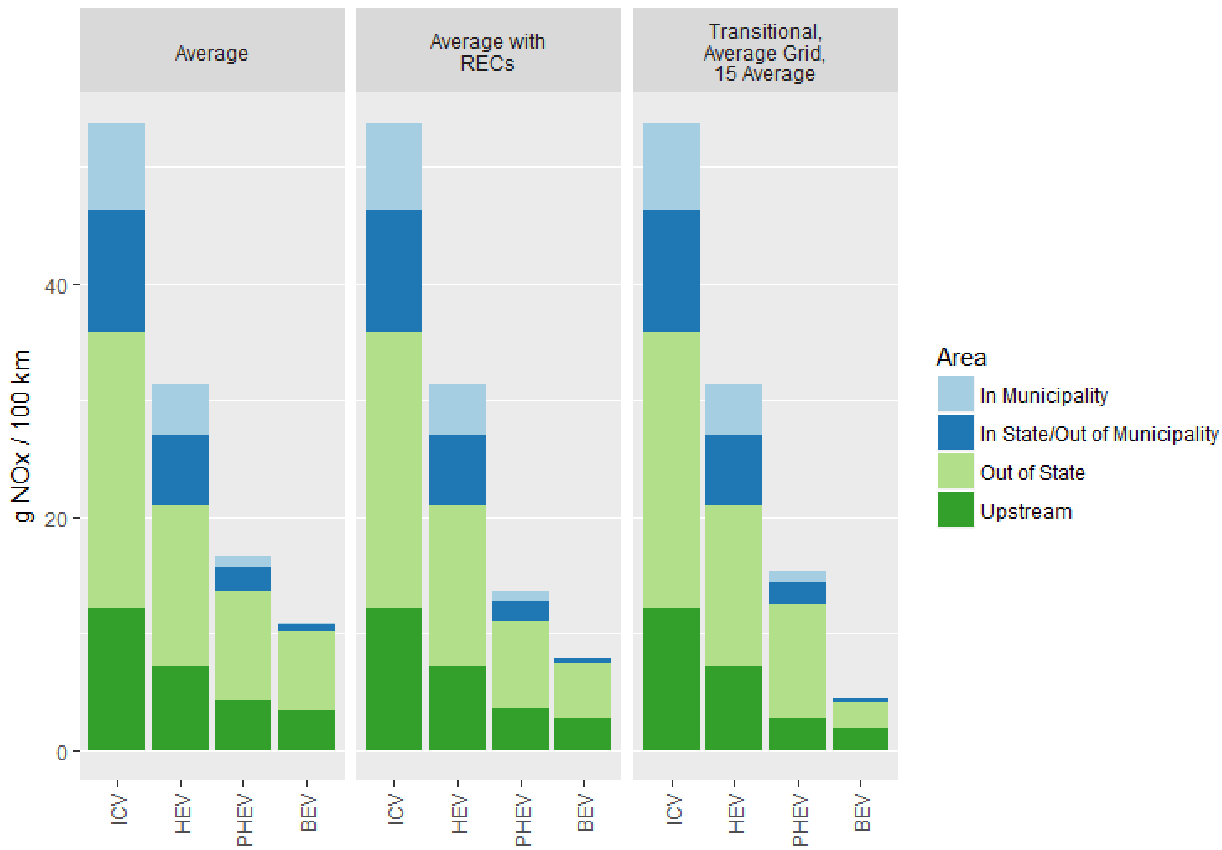

Figure I-14: Light-Duty Vehicle NO_x Emissions per 100 km, by Area of Damage, Across Various Average Emissions Scenarios

2.3.5. Integrating Distributed Generation Garages

Installing PV on the city-owned parking facilities in downtown Pittsburgh could potentially power the equivalent of 40 million km of electric vehicle travel per year; more 30 times the yearly travel of the city's civilian passenger vehicle fleet (Lowell 2015).

The private NPV of the PV system is calculated in as described in section 2.2.4 and summarized in Table I-13. In a private cost analysis, such a system only has a positive private NPV under the best-case conditions, without the cost of the necessary canopy supports. This highlights the financial benefits of constructing PV systems on other areas inside of municipalities besides parking canopies.

Table I-13: Private NPV of the PV System, $ Millions

Private NPV	**PV System Only** (Millions 2015$)	**With Canopy (Millions 2015$)**
Worst Case	-$8	-$24
Base Case	-$6	-$22
Best Case	$2	-$15

Accounting for the social cost of direct and upstream pollution greatly improves the value of the simple rooftop PV system, as calculated in section 2.2.4 and summarized in Table 4. A traditional PV system is likely to have a positive net present value when social costs are included. When accounting for the costs of the canopy structural supports the system holds a negative NPV, except in the best-case scenarios and the base case marginal scenario. Marginal grid assumptions lead to much higher system NPVs than average grid assumptions. While the exact timing of solar cannot be perfectly predicted, their generation shifts the marginal economic dispatch curve and would reduce emissions as long as fuel switching to coal did not occur.

Table I-14 Social NPV of the PV System, $ Millions

Social NPV	PV System Only (Millions 2015$)	With Canopy (Millions 2015$)
Worst Case, PJM Average	$1.2	-$15
Base Case, PJM Average	$13	-$4
Best Case, PJM Average	$32	$16
Worst Case, RFC- W Daytime	$5	-$11
Base Case, RFC- W Daytime	$21	$5
Best Case, RFC- W Daytime	$51	$35

The structural costs of PV canopy supports are likely to remain a challenge for justifying similar PV projects in the future. These structural costs are likely to remain relatively constant in real terms, and currently represent about two-thirds of the system cost. That the region's electric grid is expected to get cleaner in the near future, as coal plants are phased out (EPA 2014b, 2015b), compounds this challenge. Monetized environmental benefits of PV will likely decrease over time, while the costs of this specific PV application will remain bounded by the structural component.

2.3.6. Attributing Emissions Reductions to RECs

Attributing pollution from electric demand is a complex task (Weber et al. 2010), therefore, it is important to note the significance of the local sourcing of renewable power assumption and of ignoring the intermittency effects from renewables. Our price assumptions were based on the general market, which includes wind power sourced in Texas. Texas has its own grid, with very limited trading with the eastern interconnect, and does not have the ability to export the amount of excess wind it currently generates in west Texas (Krauss and Cardwell 2015). Instead excess wind capacity has reduced power prices in Texas to close to or below zero at night, when demand is low (Krauss and Cardwell 2015). This means that additional purchases of Texas wind RECs will not have a one-to-one reduction effect on electricity emissions in the Pittsburgh region. An additional consideration is that even renewables on the eastern interconnect, which includes Pittsburgh, may not have a one-to-one effect on reducing emissions in Pittsburgh, depending on locations, prices, and timing.

While climate change is affected no matter where the location where GHG emissions are emitted, the location and utilization of coal and natural gas plants directly affects air pollutants and air quality in the region downwind of these plants. This means that fossil fuel plants near Pittsburgh could be partially or completely operationally unaffected by REC purchases in the near-term. Additionally, the intermittency of these sources may also result in additional emissions from natural gas/coal-fired generation for balancing. However, due to low natural gas prices, EPA pollution control and GHG regulations and retiring of existing coal plants, the local electricity grid will likely get cleaner over the study period. Besides increased amounts of natural gas and renewables, the eastern interconnect is likely to continue to reduce the amount of coal generation, as well as install modern pollution controls on any existing coal plants without these technologies.

Without clean electric sources BEVs can increase air pollution, compared to conventional vehicles. It is possible that the city's renewable energy purchases will allow electric vehicles to decrease air pollution in the city. However, if these purchases are not structured to ensure reduction in Pittsburgh then BEVs could increase local air pollution.

Under generalized assumptions and strict economic accounting, paying a premium for renewables to fuel BEVs that have an existing (but declining) cost premium, is less effective at reducing emissions than just paying for renewables in general. This renewables contract is, not for the entire grid, but instead for one consumer in it. The BEVs pollute and cost more when using normal grid power. One could reduce pollution even more by not electrifying the fleet and spending the saved costs and the cost budgeted for the BEVs electricity on renewable power for another use. This would lead to a higher social benefit that buying the renewables for the BEVs and the BEVs. However, I recognize that policies have multiple objectives and that municipalities require mobility services in addition to a goal of pollution reduction, and hence a reallocation to the most efficient pollution reduction strategies should be examined wholly within a service category (mobility, electricity, heating, etc.).

2.3. Conclusions

Not only are there challenges in properly attributing any specific source of supply from additional electric demand, but the effects of this generation on any specific area is difficult to aggregate. Removing a multitude of point source pollutions in the city itself may have a positive effect for the municipality even when the new source of energy has higher associated emissions. This is because their costs may be more diffuse or borne by stakeholders outside of the municipality. Electrification in the area can be expected to increase total air emissions at present and in the immediate future, and the costs of directly offsetting this appear to outweigh the benefits. Despite this, a municipality may still see benefit in electrifying their fleet, either due to the current spatial effects, the GHG benefits alone, and/or expected future changes in grid composition.

This chapter has contributed to the literature by providing a life cycle LCA of vehicle electrification and solar PV canopies from a municipal perspective. This was done for the Pittsburgh area, separated by the standard accounting emission scopes used by the city and included separate and joint analyses for vehicle electrification and the PV system. This report looked at the specific vehicle model line that they City of Pittsburgh was considering for procurement. Different classes of EVs can be expected to have different fiscal and social performance when compared to different classes and makes of CVs and HEVs. This chapter also investigated the difference results that grid average and marginal assumptions provided. Combining these aspects are important as they reflect a municipal decision-making process. The spatial characteristics of emissions do not perfectly line up with the GHG protocol scopes, but policy is a political process where using standard accounting methods is important. These two projects might be entirely disconnected and best considered separately, but the same politics that pushes one forward may join the other. It is the responsibility of analysts to provide objective assessments of these decisions, and make recommendations that can reduce emissions and improve social outcomes. GHGs alone cause only a minority of the external costs, which themselves are a small part of the total costs. The choice of marginal or average electricity emissions assumptions is also capable of changing whether a technology is seen as useful, while marginal assumptions themselves are dependent upon the times and assumptions chosen. Reporting on the sum of these allows for a more comprehensive analysis to help inform local policy makers.

Chapter II Effectiveness of Incentives on Electric Vehicle Adoption in Norway

The results from this chapter were published as (Mersky et al. 2016).

The previous chapter discussed how to evaluate the net social benefit of adopting a new technology, from a municipality's perspective. It used the example of electrifying the city's permitting and vehicle fleet. This chapter discusses aspects of predicting the adoption rate of a new technology.

Battery Electric vehicles (BEVs) shift pollution off the road and to potentially less damaging and more varied sources than petroleum. Depending on the source of electricity, a transition to electrified personal transportation can dramatically reduce greenhouse gas (GHG) emissions and air pollutants. However, current EVs tend to be more expensive and have shorter range, which can hinder public adoption. Government incentives can be used to alleviate these factors and encourage adoption. Norway has a long history incentivizing BEV adoption including measures such as exemption from roadway tolls, access to charging infrastructure, point of sale tax incentives, and usage of public bus use limited lanes. This chapter analyzes the sales of electric vehicles on a regional and municipal basis in Norway and then analyzes these against the corresponding local demographic data and incentive measures to attempt to ascertain which factors had the highest and most significant predictive power for BEV adoption. While causation was not tested for, it was concluded that access to BEV charging infrastructure, being adjacent to major cities, and regional incomes were the most significant predictors for the growth of BEV sales. Each of these factors is either a physical requirement, chargers, or decreases the effective cost of EV driving. This provides a theoretical basis of linkage and, along with the correlation, suggests the usefulness of using these variables as predictors for planning purposes. It was also concluded that short-range vehicles showed somewhat more income and unemployment sensitivity than long-range vehicles. Toll exemptions and the right to use bus designated lanes do not seem to have statistically significant predictive power for BEV sales in our linear municipal-level models, but this could be due to neighboring major cities containing those incentive features, acting as a correlating variable.

3.1: Introduction

EVs, specifically BEVs, which do not require petroleum fuel, can provide many benefits over internal combustion engine-based vehicles. They produce no on-road GHG emissions or criteria air pollutants and the upstream pollution they do produce can be considerably less severe, depending on the electricity source used for battery charging and the energy intensity of manufacturing (Holdway et al. 2010; Michalek et al. 2011a; Samaras and Meisterling 2008b). In addition, since electricity can be produced from a variety of conventional and renewable technologies, BEVs allow for diversification of transportation energy sources. BEVs however, have limitations compared to their internal combustion competitors. They are currently more expensive, have more limited ranges, longer refueling times and fewer public infrastructure refueling opportunities than petroleum-fueled vehicles ("Alternative Fueling Station Counts by State" 2014; Traut et al. 2013). Additionally, charging technology is significantly slower than refueling with liquid hydrocarbons. As with other technologies that provide environmental benefits, governments have used various policy mechanisms to encourage BEV adoption (Michalek et al. 2012; Skerlos and Winebrake 2010). Using an analysis of Norway's experience in encouraging

BEVs, this chapter contributes to the literature by examining the sales of electric vehicles in Norway on a regional and municipal basis and cross analyzing those with corresponding local demographic data and incentive measures to examine which factors most significantly associated with higher BEV adoption at a local level. The maturity of the Norwegian BEV market enables this study to inform BEV policy more broadly, as other countries prepare their own incentives and support regimes for BEVs.

Norway has a long history of research and government incentives for battery powered electric vehicles (BEVs, EV used equivalently). Its EV market has been described as going through "five distinct phases" (Erik Figenbaum and Marika Kolbenstvedt 2013). The concept development phase took place from 1970-1990; consisting of the government funding private companies, to produce Norway's first modern EV prototypes. This was followed by the first test phase, from 1990-1999, in which the first government incentives were offered, to encourage commercialization. These included vehicle-related tax exemptions, toll exemptions and free parking in spaces owned by certain municipalities. This phase ended with the bankruptcy of Think Motors and Kewet, the two providers of EVs in the market. Next was the third phase, from 1999-2009, characterized by sporadic EV supply. Ford bought Think and introduced a new model to market, but then divested and Think went through several owners and bankruptcies. During this phase, small imports of French EVs compensated for the stoppage of local production and the government allowed EVs free usage of bus only lanes and discounts on car ferries. 2009-2013 was characterized as the market introduction phase. In this period two new local companies, a reestablished Think and Pure mobility, entered the EV market and were joined by major manufactures such as Mitsubishi, Peugeot and Nissan. Price competition made EVs more affordable, but also led to the re-bankruptcy of the Norwegian EV manufacturers. In addition, the Norwegian government started building public charging stations in 2009 (with fast charging stations being built in early 2011) and Plug-in Hybrid Electric Vehicles (PHEVs) also entered the market, with reduced incentives. The current phase of the Norwegian EV market, starting in 2013, is characterized by a more rapid market expansion. EVs sales passed 10,000 units, and municipalities increased the EV share of their fleets (Erik Figenbaum and Marika Kolbenstvedt 2013).

Concurrent with the incentives offered in these phases has been a large growth in EV sales, with the EV share of new car sales growing to 5% by September 2012 (Håvard Vaggen Malvik et al. 2013). Absolute sales in Norway have reached numbers comparable to much larger countries such as France and Germany, thus making Norway an outstanding example of EV sales success (Håvard Vaggen Malvik et al. 2013). Figure 0-1 shows the growth of EV sales from 2000 to 2013. As can be seen, sales have increased rapidly since the latter half of 2010, when the government started its EV charging program. Therefore, the period of 2011-2013 was chosen as this chapter's study period, to reflect all incentives being available to Norway consumers.

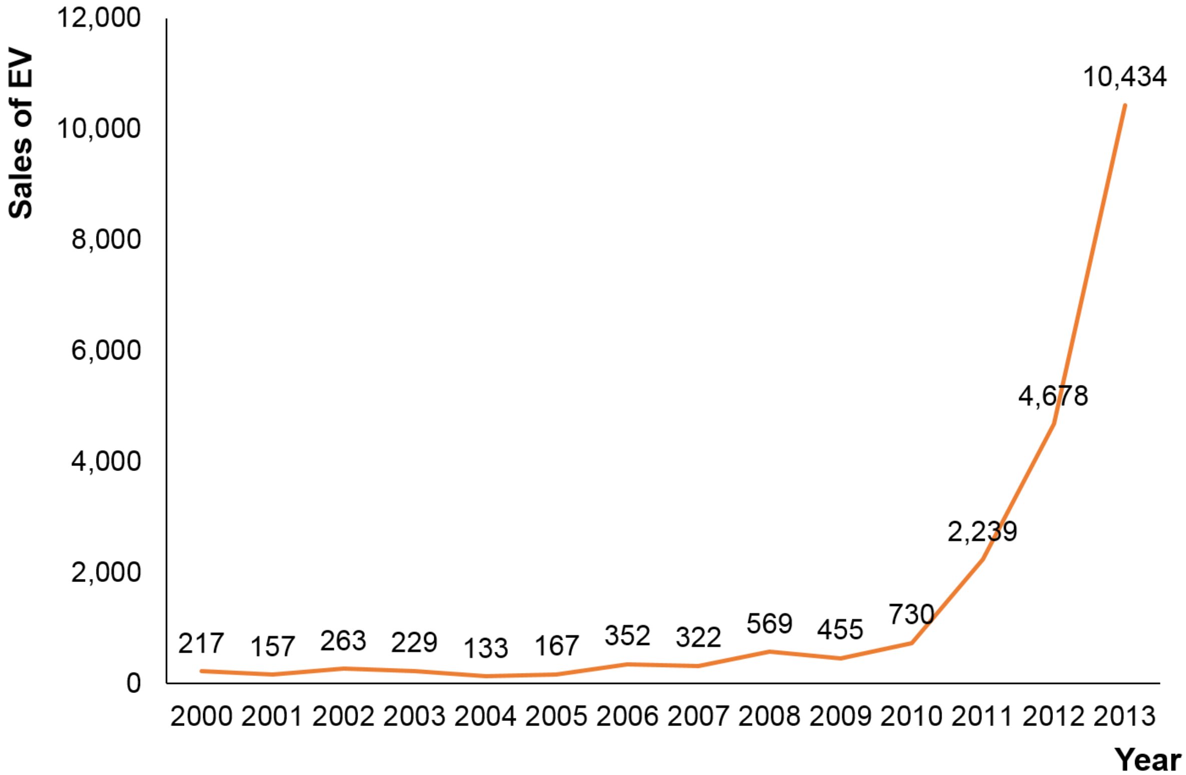

Figure II-1: EV sales in Norway 2000-2013 (Håvard Vaggen Malvik et al. 2013)

Table II-1 summarizes the incentives described above and their dates of introduction. In total, the incentives can be summed up to be somewhere in between 12 000 to 20 000 Euro depending on how they are calculated (Sprei and Bauner, 2011; Mock and

Yang, 2014)[1]. These can be compared to the US, where the federal and some state governments offer a tax credit to buyers and several states offer free access to High Occupancy Vehicle lanes ("Electric Vehicle Incentives around the world" 2014). In addition, some cities and municipalities offer other benefits, including reduced electric rates and parking benefits ("Electric Vehicle Incentives around the world" 2014). Other EU countries also have EV incentives. For example, the UK, France and Sweden offer purchase incentives, however none of these amount to the same reduction of costs as the tax exemptions in Norway. The only other country with similar high incentives is Denmark. For PHEVs, the Netherlands also has a high level of incentives. While many other countries offer benefits similar to Norway on a combined national-regional basis, Norway is unique in that it has a nationally uniform policy that includes every major incentive category: parking access, infrastructure usage pricing benefits, point of sale pricing benefits, infrastructure access benefits, and charging access benefits. The only benefit category not covered nationally in Norway that is covered elsewhere, is fuel pricing benefits. This is a benefit only offered regionally, in the form of reduced EV electricity rates, in some of the other named countries. Norway also has the longest continuous support for

[1] For example the exclusion of registration tax will depend on which vehicle is used as a comparison and the exemption from VAT will of course depend on the purchase price of the vehicle.

EVs, which has allowed the market time to mature and increased visibility of EVs an important factor in the diffusion of a new technology (Eppstein et al 2011).

Table II-1: Norwegian EV Policy Time Period of Introduction

EV Policy Incentive	Time Period of Introduction
Exemption from Registration Tax (Figenbaum and Kolbenstvedt, 2013)	1990s
Free public Parking (Erik Figenbaum and Marika Kolbenstvedt 2013)	1990s
Toll Exemptions (Erik Figenbaum and Marika Kolbenstvedt 2013)	1990s
Value Added Tax Exemption (Erik Figenbaum and Marika Kolbenstvedt 2013)	2001
Bus Lane Access (Erik Figenbaum and Marika Kolbenstvedt 2013)	2003 (Oslo) and 2005 (Nationwide)
Reduced Ferry Rates (Håvard Vaggen Malvik et al. 2013)	2009
Public EV Charging Station Construction (Erik Figenbaum and Marika Kolbenstvedt 2013)	2009

Most empirical studies that estimate sales of vehicles and the role of incentives are based on hybrid electric vehicles or PHEVs. Beresteanu & Li (Berensteanu, A. and Li, S 2011) develop a market equilibrium model with both demand and supply side based on hybrid sales statistics from multiple municipalities. They conclude that about 25% of hybrid sales result from incentives. Chandra et al (Chandra, A. et al. 2010) perform regression analysis on sale shares of hybrids in Canada and find that tax rebates generate about 25% of the hybrid sales. De Haan et al (De Haan, P. et al. 2007) instead rely on surveys of consumers who recently purchased a Toyota Prius and as control other equivalent non-hybrid Toyota models. Their main purpose is to assess if there is a rebound effect of purchasing a hybrid but they also conclude that tax rebates increase sales of hybrids. Jenn et al. (Jenn et al. 2013) found that U.S. sales of hybrid vehicles increased by 0.0046% per dollar of incentive, but only when the incentive provided was greater than $1000 (Jenn et al. 2013).

Gallagher and Muehlegger investigated the effect of state incentives on hybrid vehicle sales in the United States (Gallagher and Muehlegger 2011). They focused on tax benefits, single driver use of carpool lanes and gas prices. They concluded that state tax benefits had a significant effect on increasing hybrid vehicle sales. In addition, they found a modest increase in sales correlated with rising gasoline prices and little to no significant correlation of sales with access to carpool lanes. Diamond (Diamond 2009) similarly looked into US state level incentives on hybrid vehicle adoption, focusing on the growth of market share. Diamond concluded that rising gas prices were a much more significant incentive to increase hybrid market share than direct vehicle price tax incentives and that while tax incentives do have an effect, they are too costly to be viable. In addition, he concluded that commuter lane allowances were significant, but observed that much of that conclusion is based on one state, Virginia, which is consistent with Gallagher and Muehlegger's conclusions (Gallagher and Muehlegger 2011).

Since total EV sales are still a small percentage of overall vehicle sales, previous studies have primarily relied on stated preferences (Axsen, J. et al. 2009; Bolduc et al. 2008; Brownstone et al. 2000) or a model of the vehicle market demand (Eppstein et al. 2011; Mau et al. 2008; Mueller and de Haan 2009). One recent stated preference study was conducted by Axsen and Kurani in San Diego (Axsen and Kurani 2013). They compared stated preference for Hybrids, PHEVs and BEVs and found that a majority of respondents showed preference for PHEV, with the main reasons being the high costs and limited range and refueling opportunities of BEV while still wanting to support the environment and nation, by reducing gasoline consumption (Axsen and Kurani 2013). Based on the National Research Council study, Transitions to Alternative Vehicles and Fuels (National Research Council 2013), Greene, Par and Liu, develop scenarios predicting the growth of EV vehicles, and find a great deal of uncertainty around the areas of both technological change, and government policy, suggesting the importance of actions affecting those areas (Greene et al. 2014).

There are a few international comparisons that try to assess the role of incentives in the sales of EVs. Sprei and Bauner (Sprei and Bauner 2011) looked at the role of consumer incentives in 14 countries during the years 2009 to 2011. They found that incentives have a statistically significant effect but that effect is small and thus very high incentives are needed to significantly increase sales. Mock and Yang (Peter Mock and Zifei Yang 2014) compared fiscal incentives for BEVs and PHEVs in different countries. They concluded that fiscal incentives matter but that a direct relationship between incentives and EV sales is unclear, noting that the UK has seen a limited market growth despite financial incentives in place. The IEA summarized sales and market conditions for EVs at a global level (*Global EV Outlook* 2013). Sierzchula et al (Sierzchula et al. 2014) performed regression analysis on sales of EVs in 30 different countries and found financial incentives, charging stations and the presence of a local EV manufacturer as the most important factors contributing to sales. They found charging infrastructure availability to be the best predictor. Sánchez-Braza et al (Sánchez-Braza et al. 2014), rather than specifically looking at sales of EVs, compared municipalities in Spain and their choice of introducing EV-incentives and found that the size as well as distribution of population and environmental commitment were important factors.

EV incentives have advanced EV sales in Norway, which is reported in the literature. Malvik, Hannisdahl and Wensaas (Håvard Vaggen Malvik et al. 2013) investigated electric vehicle incentives and adoption across several European Union states, as well as their main focus state of Norway. They noted Norway's high EV sales per capita and tried to ascertain their causes. The report's methodology relied on noting which incentives in Norway were greater than, or exclusive from, the other studied countries, as well as a local analysis. The local analysis tended to focus on timings of EV sales spikes and the introduction of localized incentives. They concluded that, while the combination of incentives was important, import and sales/VAT tax exemptions were likely the greatest factors. Figenbaum and Kolbenstvedt (Erik Figenbaum and Marika Kolbenstvedt 2013) present a comprehensive report on the development of EVs sales in Norway providing both a historical perspective as well as looking at incentives, policies and charging infrastructure. Bjerkan et al (Bjerkan et al. 2016b) used surveys to look at stated importance of different incentives and found pricing, toll and bus lane access to be the most important.

This chapter contributes to the literature by analyzing individual EV sales in Norway and providing a more detailed assessment of the role of local incentives, as well as the distinction between private and business consumers within a country with a more mature EV market. This chapter performs a statistical analysis on the basis of AIC to find the models that best balance the total predictive power and model complexity and uses these models to inform on which factors are the most important predictors. Establishing causation would require additional analysis, to be performed in a future work.

The remainder of this chapter is organized as follows: Section 3.2 discusses the sources and content of the data used in the chapter, Section 3.3 describes the methodology used, Section 3.4 reports the results, Section 3.5 discusses the results and draws conclusions and Section 3.6 summarizes the chapter and notes its limitations and potential future work.

3.2: Data

The Norwegian government has made detailed BEV sales data available for this study, making a refined analysis from either the macro or single vehicle sale level possible. These data are described below.

3.2.1: Municipalities and Regions in Norway

Norway is divided into 430 municipalities. For official government statistical data, including the sales data used for this analysis, this is the lowest level of locality precision given. These municipalities are grouped into 20 different Counties, hereafter referred to as regions. Oslo is the sole municipality to constitute its own region, in entirety. Some municipalities have gone through consolidation and mergers. Between 2011 and 2013 two municipalities were merged out; Mosvik was incorporated into Inderoy and Bjarkoy was incorporated into Harstad ("Population" 2014). For the purposes of this study municipalities and their sales and demographic data reflect the municipal borders at the end of 2013. Data from the previous years were merged together, from the constituent municipalities, into the borders of the more recent one.

I found that 163 municipalities do not have EV sales from 2000 to 2013. This is because the division into municipalities and counties is an administrative division, thus a large share of these municipalities are not cities in the traditional meaning but rather rural areas, many with a very low number of inhabitants and thus no EV sales. In addition, many municipalities (especially those rural ones) do not have EV dealerships. For data consistency, the municipalities with no sales of EVs have been excluded from the analysis.

3.2.2: Incentive Data

The Norwegian government has provided several incentives for the private adoption of electric vehicles. These include free parking, access to public bus lanes, road toll waivers, a free network of EV charging stations and tax benefits (Erik Figenbaum and Marika Kolbenstvedt 2013)(Håvard Vaggen Malvik et al. 2013). Free parking and tax benefits were excluded from this analysis. Parking benefits were excluded as data at the municipal level were not available. Tax benefits, both point of sale and whole life, were excluded as they were constant across Norway. The incentives studied here have been considered in previous studies, such as both Malvik and Figenbaum's earlier research on EV developments in Norway (Erik Figenbaum and Marika Kolbenstvedt 2013; Håvard Vaggen Malvik et al. 2013) and Gallagher and Diamond's investigations into EV sales among the States in USA (Diamond 2009; Gallagher and Muehlegger 2011). The newer comprehensive Norwegian data should help to further the understanding of these incentives' effects.

Access to public bus lanes and road tolls were modeled as true/false binaries, measuring if they were present in the municipality. A municipality or region containing at least one restricted access bus lane and no toll roads would have values of 1 and 0 for the bus lane and toll road variables, respectively. Information about tolls was obtained from AutoPass the official website about road tolls in Norway ("Find a toll station" 2013). Data on bus lanes were collected from individual websites of the major cities in Norway. Vehicle charging points were taken as the absolute number of electric vehicle charging points open to the public, both privately owned and for fee and public and free, in the municipality in as reported in the charge point database of NOBIL. 2012 (http://www.elbil.no/nobil/index.php/english) was selected as the midpoint among the years studied, as this study looks only at location sensitivities, omitting time sensitivities.

Each of the previously listed measures was observed to be significantly correlated with high municipal populations. To model their effects on commuters, who may be traveling from nearby, less populated regions, another binary measure, testing if a city of population 150,000 or greater was adjacent, was used. Additionally, this measure was set to true for cities that fulfilled this condition themselves. Table II-2 shows the cities fulfilling the population requirement, their region, and the neighboring municipalities, by the distance definition given above.

Table II-2: Major Cities and Neighbors by Region

Major city	Region	Neighboring region	Neighboring municipalities
Oslo	Oslo	Akershus	Bærum
			Asker
			Nesodden
			Oppegård
			Ski
			Enebakk
			Lørenskog
			Skedsmo
			Nittedal
		Oppland	Jevnaker
			Lunner
		Buskerud	Ringerike
			Hole
			Lier
			Røyke
			Hurum
Bergen	Hordaland	Hordaland	Arna
			Haus
			Åsane
			Askøy
			Laksevåg
			Birkeland
Trondheim	Sør-Trøndelag	Sør-Trøndelag	Malvik
			Kæbu
			Melhus
Stavanger	Rogaland	Rogaland	Randaberg
			Sola
			Sandnes
			Rennesøy

3.2.3: Sales Data

Sales data were obtained from Norwegian Road ("Opplysningsrådet for Veitrafikken" n.d.), an organization of parties involved in road transport in Norway. Early data were supplied by Green Car, a project funded by a Norwegian organization aimed at diminishing the CO_2 emissions from the Norwegian transportation sector ("Grønn Bil" 2014).

These data include every electric vehicle sale in Norway, as well as the municipality of the sale, the manufacturer and model of the vehicle and the gender of the buyer, or if the buyer was a corporation. The data range from 2000 to 2013. This is the first such examination of this complete dataset.

3.2.4: Demographic Data

Demographic data, the municipalities' median household income, after taxes, in NOK, and unemployment rate, were obtained from Statistics Norway ("Registered unemployed" 2014) ("Households' income, geographic distribution" 2014). The unemployment rate came from 2012 data, while the income came from 2011. The average vehicle kilometers traveled, by personal vehicles, was obtained from Statistics Norway ("Vehicle Kilometers Travelled" 2014), for the 2012. Median household income, after taxes, was chosen to reflect the spending power of the decision making unit, which this chapter considers better represented by the household than individual. This is because it is not uncommon for earners to purchase vehicles for non-earners in the household. Data were left in the local currency to avoid any distortion from currency fluctuations. The unemployment rate used was the registered unemployment rate. This was chosen over other employment measures because it is the most general employment measurement provided by Statistics Norway on a municipal level. All information was collected at the municipal level. Population in 2012 for each of the municipalities was also collected, from Statistics Norway ("Population" 2014), but not directly used as an independent variable in the model. Table II-3 summarizes the characteristics of the collected data for all Municipalities used.

Table II-3: Data Characteristics of the 265 Municipalities Used

Data	Mean	Standard Deviation	Min	Max

Municipal Population (people)	17,000	42,000	210	580,000
Municipal Income (kroner)	450,000	45,000	370,000	580,000
Municipal Average Vehicle Kilometers Traveled	13,000	1,000	9,400	16,000
Charging Points in 2012	22	140	0	2,000
Total EV sales (2011-13) (vehicles)	67	200	0	1800
Male EV sales (2011-13) (vehicles)	31	83	0	810
Female EV sales (2011-13) (vehicles)	18	63	0	680
Corporate EV sales (2011-13) (vehicles)	18	70	0	680

3.3: Methods

3.3.1: Sale and vehicle classification and division

This study investigated only freeway legal passenger battery operated electric vehicles. Plug in hybrids were not included as their major introduction to the market started in late 2012, during the period of study. Additionally, PHEV sales are still quite small and they are given a different set of incentives than those studied here. Golf carts, trucks and motorcycles were excluded to focus on the passenger vehicles that have the most mileage. The vehicles investigated were further separated into two groups, short-range vehicles and long-range vehicles. Short-range vehicles are those with a range of 100 km or less, while long-range exceed 100 km. The 100 km threshold was used as both a price proxy and as a commuter-only and long-range division. As the average commute in Norway is 32 minutes (“Working time in the European Union: Norway” 2009) with freeway speed limits being 80 km/h the average daily commute is approximately 85 km. This makes a 100 km range sufficient for most commutes, but not for a longer vacation trip. Price itself was not used as a factor. Cars in each group were assumed identical; a separate chapter will investigate the differences between EV models, within the groups, and sales.

The groupings of the vehicles are as follows. As the dataset used here was only EVs, only the vehicle make and year are listed. Only Volkswagen had more than one EV model per year. Short-range vehicles included Buddy Electric, Piaggio, Renault, Citroen and Volkswagen Citystromers. Long-range vehicles included Toyota, Chevy, Fiat, Ford, Mia, Mitsubishi, Nissan, Peugeot, Smart, Think, Tesla, Volkswagen up!s, Tazzari, Baoya Variant 1A, BMW i3 and Mercedes-Benz SLS. This list is only for the years 2011 through 2013 (“Grønn Bil” 2014); EV manufacturers listed for only long range vehicles did sell short range vehicles in earlier years.

3.3.2: Regional Aggregation

All regional level sales and demographic data, with the exception of the unemployment rate, vehicle kilometers traveled and median household income, were summed directly from the municipalities with EV sales into their regional units. Only municipalities with non-zero EV sales were considered and the other municipalities in the regions were omitted. The other measures were taken as the average, weighted by municipal population, as shown in Equation II-1.

Equation II-1

$$Regional\ value = \frac{\sum Municipal\ value * Municipal\ Population}{\sum Municipal Populations}$$

The binary measures, showing the presence of tolls, bus lanes and major cities were kept as binary measures in the region. The binary measures in the region are taken as positive when at least one municipality in this region has toll, bus lanes or major cities present. Initial analyses were run with both pure binary and various scaled measures, for aggregations of the binary variables. These however, never offered significant improvements and were often worse and therefore dropped from the investigation.

3.3.3: Regression Methods

Sales for each municipality, region and vehicle category were divided by the area's population to find EV sales per capita. This was used as the dependent variable for all linear regressions. Sales per capita was chosen, as the dependent measure, over absolute sales, in order to estimate the independent variables' effect on the likelihood of one potential purchaser choosing to buy an EV. Using absolute sales would have hidden that with the effect of population. In addition, sales to people and sales to corporations were separated as their own groups, in order to test how the incentives worked differently on the two different buyers. The independent variables in the linear regressions were:

- The area's 2012 unemployment rate
- 2011 Median household income
- Average vehicle kilometers traveled (2011-2012)
- Number of EV charging stations (2012)
- The presence of tolls (as a binary) (by 2013)
- The presence of bus lanes (as a binary) (by 2013)
- If the area bordered a major city, as defined previously in Data, Demographic Data (as a Binary)

These variables were used in standard linear regression form, as shown in Equation II-2. EV sales were taken as the aggregate of 2011 through 2013 sales.

Equation II-2

$$EV\ Sales\ Per\ Capita = Constant + X_1 Unemplyment + \cdots X_7 MajorCity$$

Gasoline prices were not included since, over the year the variation among municipalities in Norway is low. One of the main reasons is that a large share of the price is determined both by taxes, roughly 60%, and by oil market prices, at least 30% (see e.g. www.statoil.no). The incentive variables for each region are listed in Table II-4. Number of charging station present has been rounded for presentation. Per capita sales were cross-analyzed against the independent variables for each municipality and region. Binary variables are represented with 1 = yes and 0 = no. The number of charging stations changes regularly and its value at the end of 2012 was used, while the major city binary is static. The toll and bus lane binaries have a distinct point in time in which they change and their value at the start of 2013 was used.

Table II-4: Regional Incentives

Region	Charging Stations in 2012	Toll Lanes Present by 2013 (Yes/No)	Bus Use Limited Lanes Present by 2013 (Yes/No)	Major City Present or Bordering (Yes/No)
Østfold	150	0	1	0
Akershus	700	0	1	0
Oslo	900	1	1	1
Hedmark	60	0	0	0
Oppland	50	0	0	1
Buskerud	240	0	1	1
Vestfold	60	1	0	0
Telemark	100	0	0	0
Aust-Agder	90	0	0	0
Vest-Agder	55	1	0	0
Rogaland	220	1	1	1
Hordaland	550	1	1	1
Sogn og Fjordane	70	0	0	0
Møre og Romsdal	70	0	0	0
Sør-Trøndelag	280	0	1	1
Nord-Trøndelag	50	1	0	0
Nordland	50	0	0	0
Troms Romsa	30	0	0	0
Finnmark Finnmárku	10	0	0	0

The independent variables are selected using a stepwise, forward selection procedure optimizing for Akaike information criterion (AIC). In addition the R-squared values for a linear regression model of sales per capita versus each of the independent variables were calculated and recorded, along with the direction of the correlation. The process was used first to find a standard linear model. Next, to see if the linear model was appropriate, common log regression analyses were also run, with the log of per capita sales and income being used instead of their absolutes. Log for sales per capita and for income is sometimes recommended in the econometric literature when the data are not normally distributed (Peter Kennedy 2008). However, log transformation may not be appropriate for this chapter since this study adopted median income, for each municipality, instead of categorical income levels. This study ran both the regular model and log-transformed model, to select the one with more statistical significance.

3.4: Results

3.4.1: Regressions

Table II-5 and Table II-6 present results of the final linear regression models that were produced. An "-" is used for variables that were not included in the final model. Scientific notation was used for the independent variable coefficients to allow for proper precision, while reflecting the difference in scales of the variables. The log-linear results appear less reliable than the linear ones, generally having low R-squared values, not being better than a constant in others and occasionally switching correlation directions. For these reasons, the linear results were taken as the superior and final results for deriving conclusions. Figure II-2 through Figure II-5 show actual and predicted EV sales per capita.

Table II-5: Linear Municipal Regression Results

coefficient (p-value)	**Short range, consumers**	**Long range, consumers**	**Short range, business**	**Long range, business**
Constant	0.00 (0.124)	-0.01 (0.047) **	0.00 (0.510) *	0.00 (0.000) ***
Unemployment rate (2012)	- -	- -	5.17E-06 (0.086) *	- -
Income after taxes, median (NOK)	1.68E-10 (0.043) **	2.33E-08 (0.000) ***	- -	- -
VKT 2012	- -	-3.07E-07 (0.029) **	- -	- -
2012 chargers	- -	- -	1.57E-07 (0.000) ***	1.75E-06 (0.035) **
Toll yes/no	- -	- -	- -	- -
Bus lane yes/no	2.73E-05 (0.129)	- -	- -	0.001 (0.027) **
Major City (yes/no)	2.42E-05 (0.127)	0.002 (0.001) ***	1.76E-05 (0.039) **	0.001 (0.002) ***
R-squared	0.063	0.218	0.105	0.158

Significance scale: *, **, *** shows P-Value < 0.1, 0.5, 0.01

Table II-6: Linear Regional Regression Results

coefficient/ p-value	**Short range, consumers**	**Long range, consumers**	**Short range, business**	**Long range, business**
Constant	6.47E-06 (0.094)*	0 (0)***	1.99E-4 (0.009) ***	0.00 (0.000) ***
Unemployment rate (2012)	- -	- -	- -	- -
income	- -	- -	-4.434E-10 (0.011) **	- -
VKT 2012	- -	- -	- -	- -
Sum Of 2012 chargers	9.64E-08 (0.000) ***	2.09E-06 (0.000) ***	1.08E-07 (0.000) ***	2.09E-06 (0.000) ***
Toll yes/no	- -	- -	- -	- -
Bus lane yes/No	- -	- -	- -	- -
Major city	- -	- -	- -	- -
R-squared	0.803	0.877	0.728	0.877

Significance scale: *, **, *** shows P-Value < 0.1, 0.5, 0.01

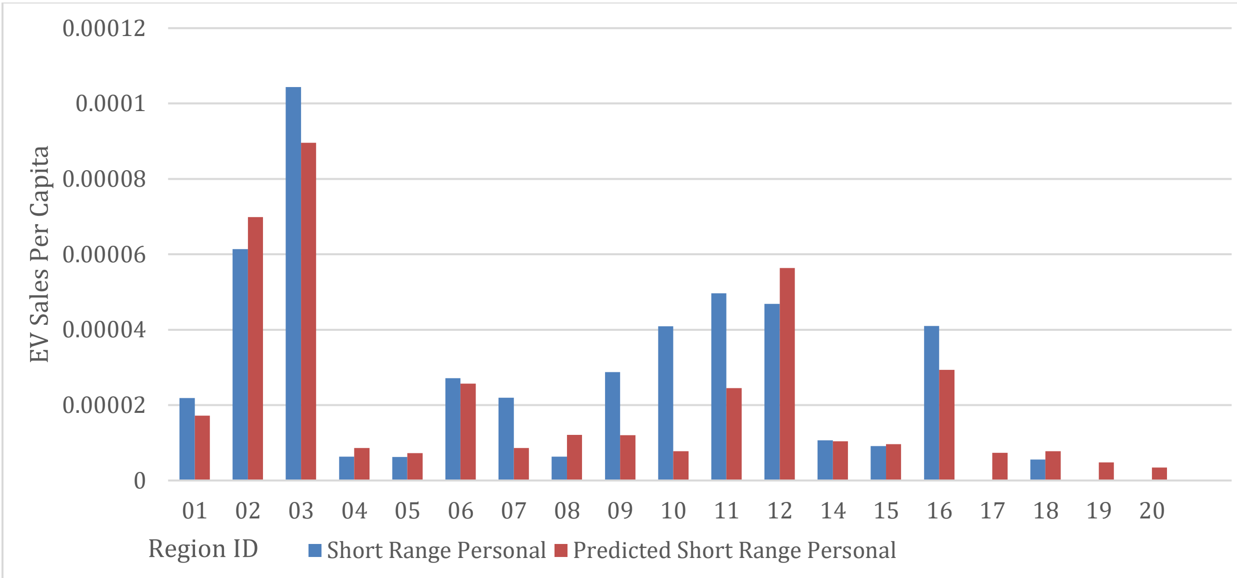

Figure II-2: Regional Short Range Personal Predicted Vs. Real Values

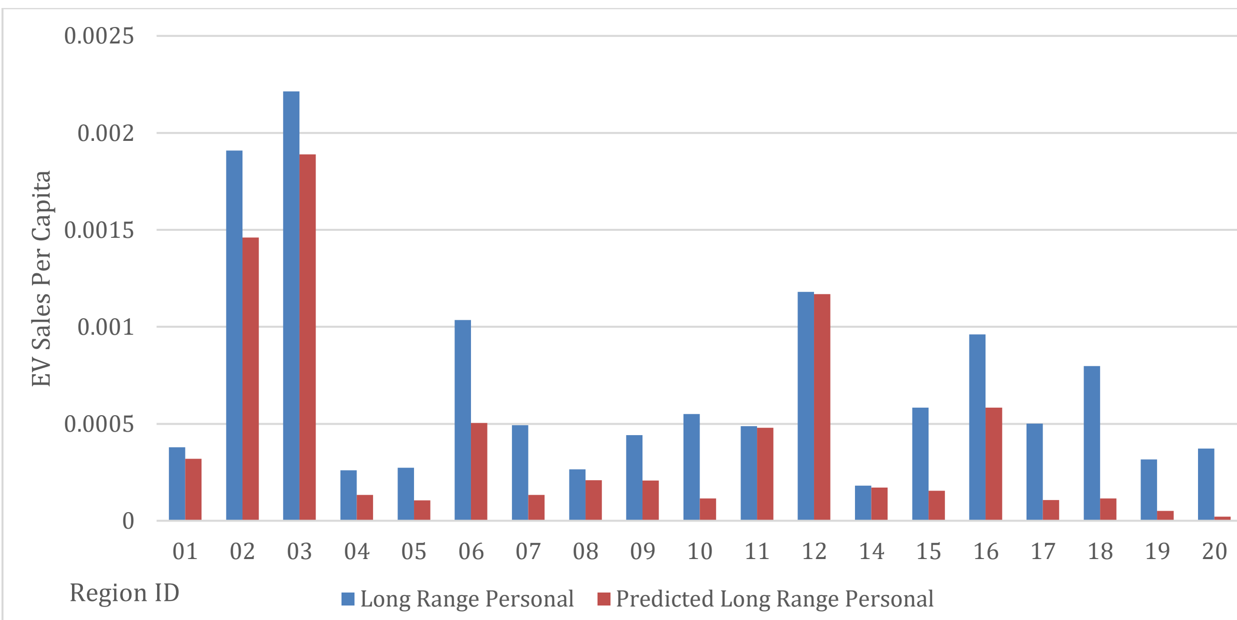

Figure II-3: Regional Long Range Personal Predicted Vs. Real Values

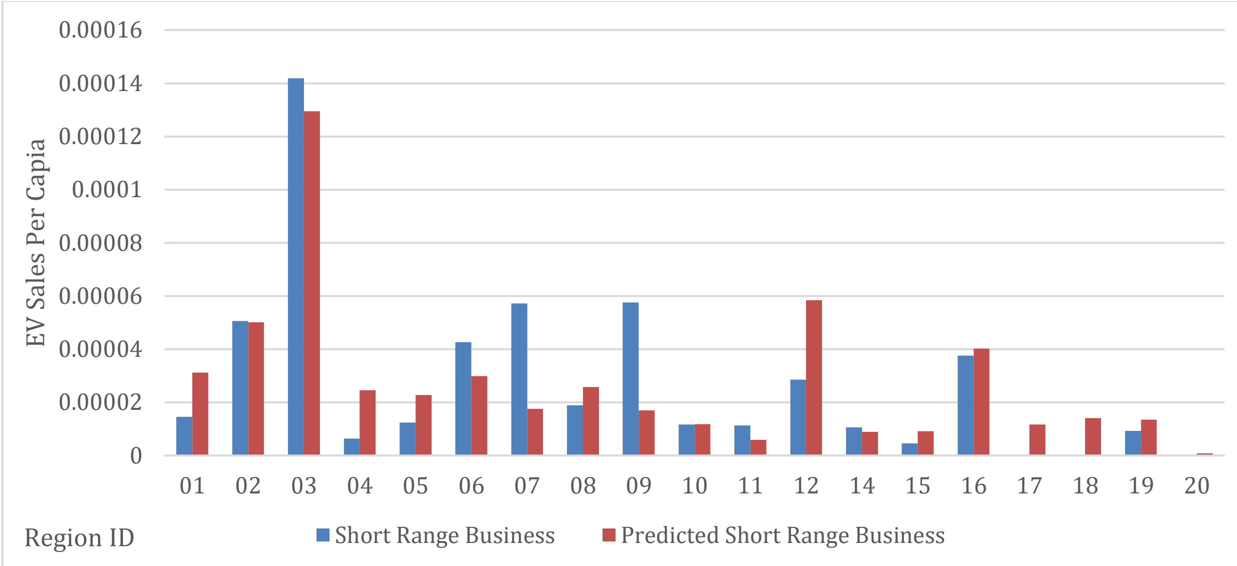

Figure II-4: Regional Short Range Business Predicted Vs. Real Values

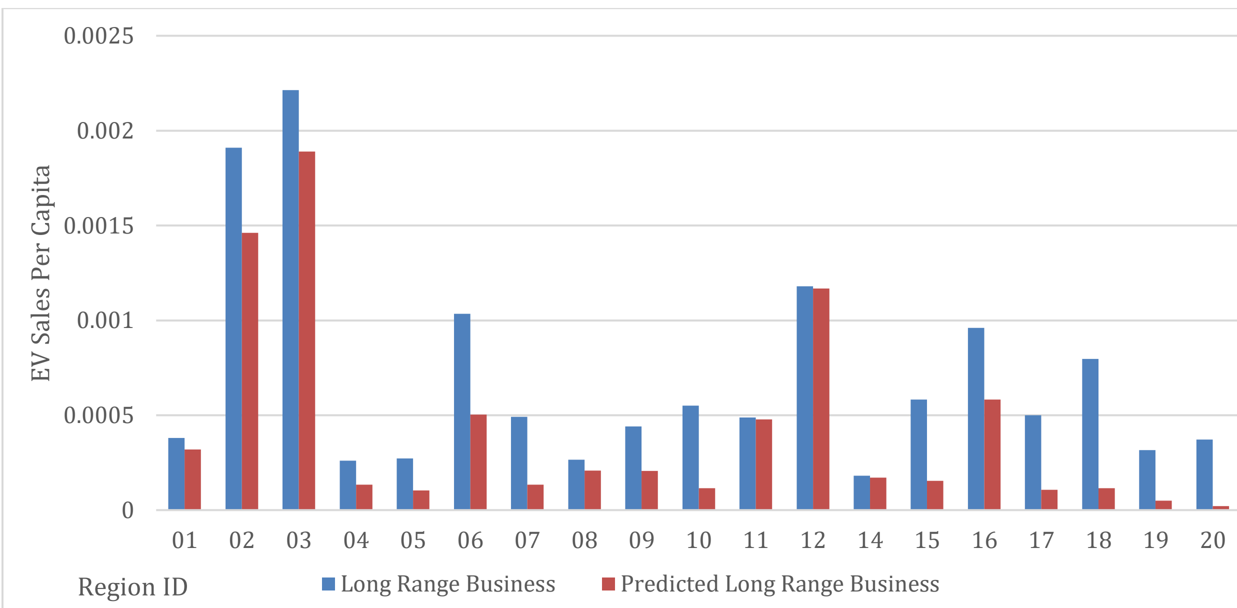

Figure II-5: Regional Long Range Business Predicted Vs. Real Values

3.5: Discussion and conclusions

3.5.1: Regional

Among all the predictors, the number of EV charging stations was found to have the highest predictive power and the most significance for regional per capita sales. On the linear regional models, no other measure was found to add significantly to its predictive abilities, with the exception of income for short-range corporate EVs. It should also be noted that for short-range corporate EVs the P-value for regional income was relatively low, at 0.011. This shows relatively high certainty about the accuracy of its effect in the model. Interestingly, while the coefficient on the number of charging stations is positive, the coefficient on income is negative. So while increases in the number of available charging stations increase the expected per capita sales of EVs, increase in median household income decrease expected sales per capita in one case. However, the model where that applies is for short-range corporate vehicles. While the result might not be expected, a possible cause is that people in higher income areas would demand better corporate vehicles and the companies respond by buying fewer short-range vehicles and more long-range ones. The presence of tolls and/or bus lanes was found to not be significant enough to be included, possibly due to the fact that on the regional level they are highly correlated with chagrining stations themselves.

As this chapter does not test for causation, it cannot be determined from this chapter if correlation of per capita sales with charging stations is purely due to the consumer incentive effect of the charging stations, or if the charging stations are being built in response to local EV demand. In addition, it could be expected for the government to focus its resources for EV chargers on the localities with the most need - those with or expected to have the most EVs. Charging infrastructure, however, is a physical requirement for BEV adoption and public access is necessary when residential access is unavailable. Accounting for this and the correlation suggest the importance of charging infrastructure in BEV adoption planning. The importance of charging stations for sales of EVs is also highlighted in literature, such as in Sierzchula et al (2014), which find it to be the best predictive factor. State preference and survey studies also find refueling possibilities an important factor for the adoption of a range of alternative fueled vehicles including EVs (Achtnicht et al, 2012, Egbue and Long, 2012, Tran et al, 2012).

3.5.2: Municipal

The municipal models are more complex than the regional models, as the variables differ with each municipal group studied. For both groups of private consumers, the income variable is positive and significant, which is expected since EVs have a relative high purchasing price and an increase in discretionary spending ability enables the purchase of additional household vehicles. Most households that have bought an EV have at least one other vehicle (Erik Figenbaum and Marika Kolbenstvedt 2013). Stated preference studies have found income to be an important factor (Hidrue, M. K. et al. 2011) while studies that have looked at cross country data on EV sales find it less conclusive (Sierzchula et al. 2014; Sprei and Bauner 2011), likely due to the low sales numbers rather than a real effect.

Another factor in common for both private consumer models is the closeness to a major city for which the long-range case is more significant. The lower effect on short-range vehicles might be due to the fact that these are less often used for commuting longer distances such as to a neighboring municipality. Another explanation is that bus lanes are correlated with this variable and since in the short-range model this variable appears as well, part of the effect might be included there. Earlier EV market research, in Norway, supports access to bus-lanes as an important reason for purchasing EVs (Bjerkan et al. 2016b; Prosam 2009). The major city variable might also explain why road tolls are not significant since it might capture their effect despite EVs often being used as commuter vehicles (Hjorthol, Randi 2013).

Vehicle Kilometers Traveled was negatively correlated with long-range personal sales. This could be representative of EV ranges not being viable for long distance commuters or just generally that people that travel long distances might have a driving pattern that is less suitable for EVs (Plötz, Patrick et al. 2014). Municipalities with greater percentages of commuters should have higher VKTs and most commutes should be within a 100km round trip range.

For the business purchasers, increases in unemployment were correlated with increased short-range corporate vehicle sales. This can be seen as the corollary of the income effect seen in the regional models; decreased employee bargaining power or wages appears to lead to an increase in short range vehicle sales. Its absence in long-range corporate sales seems to suggest that corporate demand for long-range vehicles is less elastic than for short range ones, an inference supported by the regional models. The reason for this is unclear, but it could be due to the nature of the corporate purchases. For instance, this would be expected if the short-range vehicles are used for shuttling employees or as perks, while long-range vehicles are being used in fleets, such as delivery vans and taxis. The short-range vehicles would then be elastic with respect to employee bargaining power while the long-range vehicles would instead be elastic with respect to direct usability considerations. Determining the reasons would require a survey into why corporations purchase their EVs. Also, since VAT is generally not paid for corporate vehicles the level of subsidies for corporate vehicles is much lower compared to private consumers and thus the sales numbers are also lower.

The number of charging stations was found to be significant for business sales on the municipal level. This might reflect the needs of fleet vehicles, rather than corporate cars for employee usage. A taxi is expected to mainly operate in one municipality, where it was given license, and only leave if a customer requests it. For this reason, those purchases would be particularly sensitive to the intra-municipality charging potential. Other users who regularly cross such boundaries might be more interested in the number of charging points in the vicinity. This may be seen in the major city binary, which is significant and positive for all groups. As city population is also correlated with higher numbers of charging points, as well as higher tolls and more exclusive bus lanes, this suggest that people who cross municipal boundaries are particularly interested in these features. That is people may be more likely to buy an EV if they are near a major city and are commuting into the city because they can take advantage of its EV infrastructure (Hjorthol, Randi 2013). Once again, however, whether the charging stations are causing higher EV sales, vice versa or if another factor is affecting both could not be determined from the study in this chapter.

In the long-range business model bus lanes also were significant, this may also be related to commuting. A portion of the business vehicles are vehicles provided by the employer as part of the wages. The employee can then use the vehicle to commute to work.

3.5.3: Municipal vs. Regional

The Municipal linear regressions had significantly decreased goodness of fit relative to the regional ones; with municipal R squared values varying between .06 and .22 while all regional values were above .73 and having decreased complexity. The municipal regression models were all more varied in terms of which predictors were represented in the final model. This is possibly due to the low absolute sales numbers for many of the municipalities, allowing for the random element of sales to overtake the effect of the incentives. In addition, all municipal models had the major city binary in their final model. Major cities were also all correlated with more bus exclusive lanes, tolls, limited/expensive parking, and charging stations. It can be assumed that this means that municipal buyers are sensitive to some combination of these measures in their greater vicinity and not only their municipality. It may also reflect that the buyers commute to a larger municipality but that they stay in the same region. For the regional models, the number of charging points was the most useful variable, being the sole important predictor for all but one model and used in every model. This also supports the previous inference as it shows buyers reacting to the number of charging stations that they would have access to, beyond their municipal borders.

3.5.4: Long Range vs. Short Range

Short range vehicles showed somewhat more income and unemployment sensitivity than long range vehicles, with one of the measures being included in three out of the four linear short range models and only one of the long range models. For corporate sales, this could be a reaction to employee bargaining power. Unemployment rate was significant in determining the per capita sales of short range business cars on the municipal level. Specifically, short-range corporate EV sales increased with unemployment, by itself counter intuitive. In the regional model, short-range corporate EV sales decreased with increases in household income, a similarly counter intuitive result. It is also worth noting here that the models were allowed to contain both unemployment and household income as they were found to be very weakly correlated, with an R squared of .09 on the municipal level.

3.5.5: Business vs. Consumers

On the municipal level, corporate vehicles were much more sensitive than personal vehicles to the number of charging stations. This could be due to the effect of taxi fleets and other operators, whose service is limited by those same political boundaries. It could also be fleet operators building chargers for their vehicles. While this chapter did not test for causation, the correlation and physical dependency of BEVs on charging infrastructure suggests the importance of planning for both jointly. It is worth mentioning that all municipal models had the major city binary in their final model. As major cities are also correlated with larger numbers of charging points and personal vehicles do not have the same municipal boundary restrictions as some fleets, this would seem to support the above conclusion. Private consumers may also be less dependent on public charging since they can fill up their battery at home and cover most of the days driving on that charge. Also as stated above, short range corporate sales seem to be correlated with factors relating to employee bargaining power, increasing with unemployment, on the municipal level, where labor is in greater supply; and decreasing with higher incomes on the regional level, possible reflecting higher skills. Personal municipal sales on the other hand, were more sensitive to household incomes. This would seem to reflect household budget constraints. This may be supported with rising VKTs indicating decreases in long range personal vehicle sales. Commuters may believe that the short range EVs are sufficient for their needs. Additionally, corporate sales are much lower than personal sales on a per capita basis. Mainly due to the fact that the VAT exemption does not affect them since corporations can deduct VAT from purchases and thus the price difference between EV and conventional vehicles increases. It is also important to note that the data does not allow an analysis that distinguishes between corporate fleet vehicles and those made available to employees for personal and commuting usage. Both of these could be expected to be affected differently by the investigated factors.

3.5.6: Policy Implications

The results of this study lead to some policy recommendations for localities that wish to increase EV sales. These recommendations can be separated into two sets: one for small localities, similar in size and population to the municipalities studied, and another for large, region sized, localities/legal units, corresponding in size and/or population to the regions included in this study. For the smaller localities, two recommendations could be made. The first is to create or increase pricing incentives for EVs. While this study did not directly investigate pricing incentives, as they were uniform throughout Norway, the correlations with income for personal sales suggest an element of price sensitivity. Combined with the previously noted findings (Berensteanu, A. and Li, S 2011; Bjerkan et al. 2016b; Chandra, A. et al. 2010; Gallagher and Muehlegger 2011; Håvard Vaggen Malvik et al. 2013; Jenn et al. 2013; Martin et al. 2012; Sierzchula et al. 2014), this recommendation is supported internationally. For business BEV sales, increasing the availability of charging stations may incentivize purchases of EVs. However, this study cannot determine if EV sales were increased by the presence of charging stations or vice versa. A similar recommendation can be applied for regional sized localities, with increasing access to charging stations appearing to be the best policy option, again with the caveat that it cannot be determined from this study alone if EVs incentivize the construction of charging stations or the opposite. Toll exemptions and the right to use bus designated lanes do not seem to have statistically significant predictive power for BEV sales in our linear municipal-level models, but this could be due to neighboring major cities containing those incentive features.

3.6: Summary

While electric vehicles could provide significant benefits relating to energy diversity, environment and public health, they currently require a purchase premium and lack a robust refueling infrastructure. Norway has the longest and most extensive national campaign to encourage EV adoption. This study investigated the effects of many of the incentives on per capita EV sales among the municipalities and regions (counties) of Norway, on a cross sectional basis. Basic economic data and EV infrastructure data were collected for these municipalities along with EV sales data, grouped by vehicle range and owner. Optimal linear regressions were run to see which variables were most useful for predicting per capita EV sales. On the regional level it was concluded that the number of charging stations had the highest indicative effect, though not necessarily causal. On the municipal level personal vehicles were found to be sensitive to median household income while corporate vehicles were sensitive the number of charging stations; though once again this relationship may not be causal. Additionally, all municipal EV sales were found to be sensitive to the presence of major cities; possibly providing a proxy for tolls, exclusive access bus lanes, charging stations, or just customers leaving the neighboring major city, to purchase their EVs, in other areas. There were also differences observed between short and long-range vehicles, with short-range vehicles being much more sensitive to economic measures, specifically income and unemployment. Combined, these suggest that pricing incentives and increased access to charging stations may be the best policies to increase EV sales.

3.6.1: Limitations

Certain Norwegian government incentives could not be analyzed in this study. Access to free parking could not be analyzed due to lack of data on the number of spots open on a municipal basis. In addition, all incentives that the consumer would see in the point of sale price are also ignored. This is due to the fact that all the pricing incentives are given nationally, allowing for no difference to be seen on a single nation study. Finally, this chapter did not test for causality and was performed in Norway which limits the transferability to the U.S. context. However, the association found with charging infrastructure is an important finding to understand the current dynamics behind EV adoption in Norway.

3.6.2: Future work

Future work could focus on answering the questions made evident in the study. In particular this study, by focusing on broad EV groups and looking at municipal and regional demographic and incentive data, did not consider much of the effect of price-demand elasticity. The prices and vehicle characteristics of BEVs are important features for BEV sales, and should be investigated. In addition, a time-series study, investigating how consumers respond to short- and long-term trends in gas pricing and other incentives would have benefit and may allow for some more information on causality to be gleaned. Certain incentives, such as bus lane access and tolling have a discrete start date that may aid in this effort. Investigation of vehicle purchase pricing sensitivity, which previous studies have suggested to be one of the primary drivers (*Global EV Outlook* 2013; Peter Mock and Zifei Yang 2014; Sierzchula et al. 2014; Sprei and Bauner 2011), however, would require expanding the investigation to other countries. This is due to the fact that the purchase pricing incentives for EVs are nationally based in Norway. Another study, based on post vehicle purchase questionnaires and similar to or used Bjerkan et al.'s results (Bjerkan et al. 2016b), may help tease out the effects of some of the incentives more easily. Proximity to cities was seen as important, but its cross correlation with incentives, such as bus lane access and free parking, made it difficult to see their joint effect. In addition, this may allow us to see which vehicles EVs were being compared against and see how important features, like range, are as incomes and number of owned vehicles changes.

Chapter III Synergies of Autonomous and Electric Vehicles

The previous chapter investigated the effects of different incentives on EV adoption, given different regional demographics. This chapter investigates the synergies between autonomous and electric vehicle technologies when building electric vehicle support infrastructure. This chapter is in preparation for publication in Transportation Research: Part C.

Electric vehicles are increasing market growth, while automated technologies will become increasingly part of new car offerings. This chapter presents a method to optimize stationary electric vehicle charger placement and distribution when accounting for the possible effects of privately owned autonomous vehicles. This chapter presents an optimization based on minimizing operator and commuter costs of commuters using the 2014 Household Travel Survey data simulated as electric vehicles (EVs). In the simulation, moving from levels 0-3 to level 4 and level 5 automation reduces the peak electrical load for EV charging by approximately 31% and 68%, respectively. Moving from no automation to level 4 automation decreased the optimal number of chargers by 65%, lowered total costs, including operator and commuter costs, by 46% and lowered operator costs by 47%. Moving from levels 0-3 automation to level 5 automation decreased the optimal number of chargers by 84%, total costs by 69% and operator costs by 75%. Without any automation, the cost borne by commuters, walking from their parking spots, is insignificant. This cost increases in importance in the level 4 automation scenario, but it is still only 0.5% of the total operator cost. The cost borne by commuters, their vehicles' operating cost for drop off and pick up, is much more significant with level 5 automation, where the cost borne by commuters is 24% of the operator's cost.

4.1: Introduction

A major cost impediment to widespread deployment of electric vehicles is the public infrastructure necessary to recharge them. Public charging stations are expensive, and generally have low charging utilization rates when cars remain in the spaces long after charging is complete. Analyses on optimizing alternative fuel and electric vehicle infrastructure are common for many different sets of criteria. A review of many recent papers on this subject is presented in Section 1.1. What has not been done, however, is to assess how higher levels of automation can change these results. Automation enables the ability to increase utilization and reduce spatial limitations of where vehicles charge. Additionally, it may give more control over timing of charging demand than traditionally-driven vehicles would allow. This chapter investigates these potential effects by analyzing the following research question: What are potential electric vehicle charging infrastructure siting efficiencies and associated energy and environmental impacts from level 4 and level 5 automation?

Level 4 automation, where a vehicle can direct itself absent human oversight in limited, controlled circumstances, and level 5 automation, where vehicles can control themselves absent human oversight in all conceivable normal-operation circumstances (SAE International 2014), both have the potential to increase charger utilization and improve the siting of charging stations. Under level 4 automation, a parking facility could be designed to allow for complete autonomous control within the facility, allowing for autonomous electric vehicles to navigate themselves once in the facility. Electric vehicles charging unattended currently take up the use of a charger for the whole time that the vehicle is parked, regardless of whether electricity is being delivered. Level 4 automation may allow for facilities to be set up where vehicles navigate themselves to an open charger and then, when completely charged, leave the charging space and go to a conventional parking spot. This would increase charger utilization, which would allow for fewer individual charging stations to be needed and therefore decrease charging infrastructure costs. This would allow for higher numbers of chargers to be installed in more areas, creating a larger and more comprehensive network. This could also enable demand smoothing with vehicles not being charged when first plugged in, but instead charging near continuously or with consideration to the price and stability signals of the power grid.

A larger and more comprehensive charging infrastructure network is necessary to extend the range of vehicles that are charged solely at home, as well as because charging vehicles is generally time-consuming. This requires current charging infrastructure to be located in traditional parking areas--generally within comfortable walking distance to trip origins and destinations. Level 5 automation, where vehicles could drop off and pick up passengers and travel in driverless mode to charging facilities, could relax or remove this restriction. Doing so would allow for chargers to be concentrated at fewer locations, reducing supporting infrastructure costs, or located away from areas with high real estate prices. Chargers can also only be installed in integer units giving any specific facility's charging capacity a piecewise function. The ability to move vehicles greater distances can improve upon the gains from level 4 automation by ensuring that vehicles whose demand would require an additional charger can be pooled together, even if their destinations are distant from each other. This would reduce the total number of chargers needed, compared to when you would have had to build an additional charger for each of those vehicles.

Vehicle automation and autonomous refueling infrastructure can be used to help smooth electric demand patterns. Commuters tend to travel in similar patterns and at similar times. Electric vehicle charging will add to current electricity grid demand. If these vehicles all plug in at similar times due to similar travel schedules, day time demand patterns for grid electricity may change significantly. Using smart charging or pricing systems on infrastructure is one way to potentially address this challenge, but automation may enable even greater smoothing opportunities with lower total infrastructure costs. A vehicle charging and queuing system may allow for demand to be moved to off-peak times, as well as move to other locations if there are local grid infrastructure constraints. This chapter contributes to the literature by developing an optimization to understand how commuter EV charger placement is affected by different levels of automation. This model minimizes operator and commuter costs. This chapter uses the Puget Sound 2014 Household Travel Survey (Neil Kilgren et al. 2015) unweighted trips and assumes 100% EV adoption for those trips in the dataset, which enable a simulation with existing commuter parking demand and distanced traveled in the survey sample. Operator costs are defined as real estate costs for a parking space, charging equipment capital cost, and charging equipment maintenance costs. Commuter costs are defined as either the costs of walking when using Levels 0-4 automated vehicles, or the costs of additional driving when using fully autonomous Level 5 vehicles. The chapter is organized as follows: Section 1 continues with a literature review and then lists the data sources used. Section 2 details the methods used to process the data into usable input for the optimization models and then defines the optimization models. Section 3 presents and discusses the results obtained from the optimization models. Section 4 summarizes the previous sections. Section 5 ends the chapter by listing the primary limitations of the results and models presented in this chapter and how future work can build and improve on the contributions made by this chapter.

4.1.1: Literature Review

Table III-1 summarizes several recent studies on the optimization or grid effects of electric vehicle charging. It notes: the region of study, whether the authors modeled electric vehicle adoption separate from vehicle ownership/travel, the source of travel data, the methodology of optimization or electric demand modeling, whether the vehicle was assumed to charge along route or while parked, whether the paper was focused on stations, vehicles, or the grid, and whether the study considered time of demand separate from the total. Only Huang et al. considered non-electric alternative fuels. Among all the papers reviewed, none investigated the effects that higher levels of automation will have on their optimization. This chapter adds to the literature by investigating the potential effects and synergies between autonomous technology and electric vehicle charging infrastructure optimization. This chapter also investigates the different effect that electric vehicles will have on electric demand under different automation scenarios.

Table III-1: Summary of Assorted Studies Investigating the Optimization or Grid Effects of Electric Vehicle Charging

Study	**Region**	**Electric Vehicle Adoption Variable**	**Travel Data Source**	**Method**	**While Parked or Along Route**	**Operator, Driver or Grid Focused**	**Time Dependent**
(Sweda and Klabjan 2011)	Chicagoland (Chicago)	No	US Census	Agent Based	Both	Operator	No
(Worley et al. 2012)	Chicagoland (Chicago)	No	None	Mixed Integer Optimization	Both	Operator	No
(Bae and Kwasinski 2012)	None	No	None	Fluid Dynamic Traffic Model & M/M/s Queueing	Along Route	Grid	Yes
(Knapen et al. 2012)	Flanders, Belgium	No	Multiple	Activity Based Model	Along Route	Grid	Yes
(Chen et al. 2013)	Puget Sound (Seattle)	No	Regional Household Travel Survey	Mixed Integer Optimization	While Parked	Operator	No
(Hilshey et al. 2013)	New England	No	National Household Travel Survey	Monte Carlo	While Parked	Grid	Yes
2013 (Nie and Ghamami 2013)	Chicago, IL to Madison, WI	No	None	Karush – Kuhn – Tucker Approach (KKT)	Along Route	Operator and Driver	No
(He et al. 2013)	None	No	None	Active-Set Algorithm & KKT	While Parked	Operator and Grid	No
(Sathaye and Kelley 2013)	Texas Triangle	Yes	US Census, TEXDot	Root Finding Method	Along Route	Operator	No
(Xi et al. 2013)	Central-Ohio	Yes	Mid-Ohio Regional Planning Commission	Linear Integer Programming	While Parked	Operator	No
(Frade et al. 2011)	Lisbon, Portugal	Yes	Multiple	Mixed-Integer Optimization	While Parked	Operator and Grid	Yes

Study	Region	Electric Vehicle Adoption Variable	Travel Data Source	Method	While Parked or Along Route	Operator, Driver or Grid Focused	Time Dependent
(Huang et al. 2015)	Sioux Falls (South Dakota)	No	None	Multipath Refueling Location Model (Fuel Capturing Location Model)	Along Route	Operator	No
(Ghamami et al. 2016)	Chicago–Madison–Minneapolis Corridor	Yes	Hybridcars.com	Mixed-Integer Non-Linear, Simulated Annealing	Along Route	Driver and Operator	No
(Mehta et al. 2017)	Singapore	Yes	Land Transport Authority Singapore	Genetic Algorithm	While Parked	Grid	Yes
(Zhu et al. 2016)	Beijing	No	None	Genetic Algorithm Based Method	While Parked	Operator	No
This Chapter	Puget Sound (Seattle, WA)	No	Regional Household Travel Survey	Linear Mixed Integer Optimization	While Parked	All	No

4.1.2: Data Sources

The primary data source for this chapter is the Puget Sound 2014 Regional Travel Survey (Kilgren 2015). This survey includes a list of respondent trips with origin and parking location by Travel Analysis Zone (TAZ), census tracts, census block, and, for parking location, location name. The locations of census tracts and TAZs were taken from the Puget Sound Regional Councils GIS database (Norton n.d.). Travel zones, census blocks, and census tracts include water in files to show shores and islands. For locational purposes, all water area was clipped from zonal, tract, and block shapefiles. Real estate assessment data was taken from King County GIS ("KCGIS Data Download" 2014). These data were from 2006. According to Zillow, King County real estate prices recovered from the recession and reached 2007 levels between 2015 and 2016 (Zillow Inc 2017); therefore, these data were used as given. EV fuel economy was estimated using a range of EPA fuel economy ratings (EPA n.d. X) and taken as 35 kWh per 100 mi. King County per capita income of $42,000 in 2015 is from the Census Bureau (U.S. Census Bureau 2017). Electric prices were taken from a Bureau of Labor Statistics report on the metropolitan area and used 2015 retail prices of about $0.10 per kWh (US DOL 2017). All monetary values are in 2015$.

4.2: Methods

4.2.1: Data Sorting and Calculations

Trips were aggregated from the trip data set of the Puget Sound 2015 Regional Travel (Kilgren 2015). This data set included about 48,000 trips total. Trips were included for our model if:

- The trip's purpose was travel to the person's workplace
- They were by a car or carpool
- The person recording the trip was the driver
- The vehicle was parked in either a parking lot or on the street near the destination, not in a Park N Go lot, for intermodality
- The trip started between 6 a.m. and 6 p.m.

Various additional filters were used to remove error values or incomplete responses that affected the data of interest. After filtering the data approximately 3,500 trips were used for our model.

From each trip, the following information was extracted:

- Destination census block group
- Trip distance
- Hour of arrival, rounded down
- Hour of exit, defined as the sum of the duration of time spent at destination and the hour of arrival, rounded down
- The person's ID associated with the trip

The maximum potential utilization rate of autonomous enabled charging was estimated using a 10,000 iteration Monte Carlo simulation. A random trip was sampled from all positive trips of the travel survey. This trip's distance was used, along with a 20 miles of range per hour charge rate for a 6.6 kW charger (Smith and Castellano 2015), to determine how long it would take for a full charge. After a full charge was achieved, 1 additional minute was assumed to be spent switching to the next vehicle. This continued until at least 8 hours had passed, when the vehicle left the charger. The utilization rate was the time that a vehicle was charging divided by the total time elapsed. Maximum utilization was found to have a mean of 31% and a standard deviation of 6.8%. The histogram of the maximum utilization iterations is shown in Figure III-1.

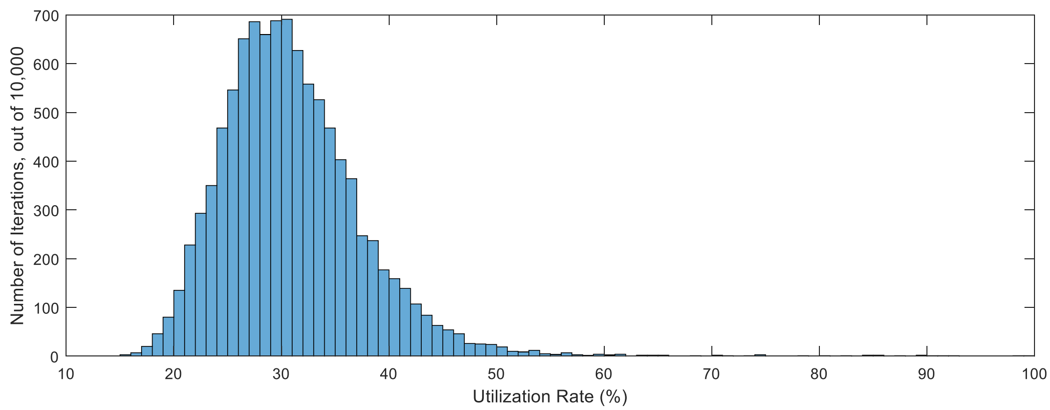

Figure III-1: Maximum Utilization Rate Histogram

Parking demand was aggregated based on destination census block. For each block, I calculated the peak number of spots demanded, the total number of trips ending in the block, the total number of miles traveled to the block, the average number of miles per trip for the zone, and the average number of trips demanded per peak spot demanded. The temporal number of spots demanded is calculated in Equation III-4. These were calculated from the Puget Sound 2015 Regional Travel Survey (Neil Kilgren et al. 2015), starting at values of 0 at 6 a.m. and ending at 6 p.m. First, for each hour and block group, jointly, the number of trips arriving, miles arriving, and trips leaving was calculated.

For each hour and zone jointly, the parking spot demand was calculated as shown in Equation III-1, starting at 6 a.m., with demand and departures of 5 a.m. defined as 0. Peak demand, for a zone, was defined as the maximum demand of all hours between 6 a.m. and 7 p.m. This calculates the maximum number of spots of parking in any zone that would be demanded for one specific hour, as cars both leave and arrive throughout the day.

Equation III-1: Hourly Parking Spot Demand

$$Demand_t = Demand_{t-1} + Arrivials_t - Depatures_{t-1}$$

The arrival rate, shown in Figure III-2, is highest in the early morning, peaking at 8 a.m. It then drops rapidly. Departures, shown in Figure III-3, are more evenly distributed and more focused in the early afternoon, peaking at 5 p.m. When taken together, these result in the peak commuter parking demand occurring at 9 a.m. Commute distances in Seattle, shown in Figure III-4, are highly concentrated around short distances. The peak is up to 2 miles and generally follows a normal distribution. Figure III-4 shows the histogram of the parking duration for the trips. Parking duration appears to follow a bimodal distribution with a small peak at 4 hours and a steep peak, nearly twice as high, at 9 hours long.

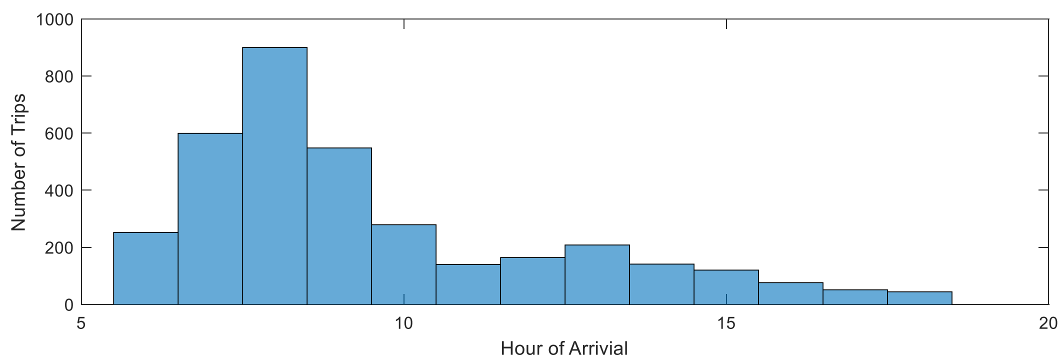

Figure III-2: Histogram of Commuter Arrival Times

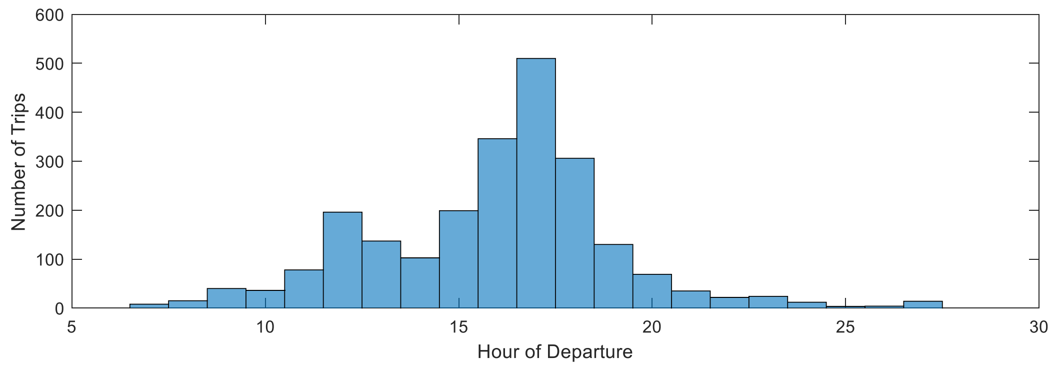

Figure III-3: Histogram of Commuter Departure Times

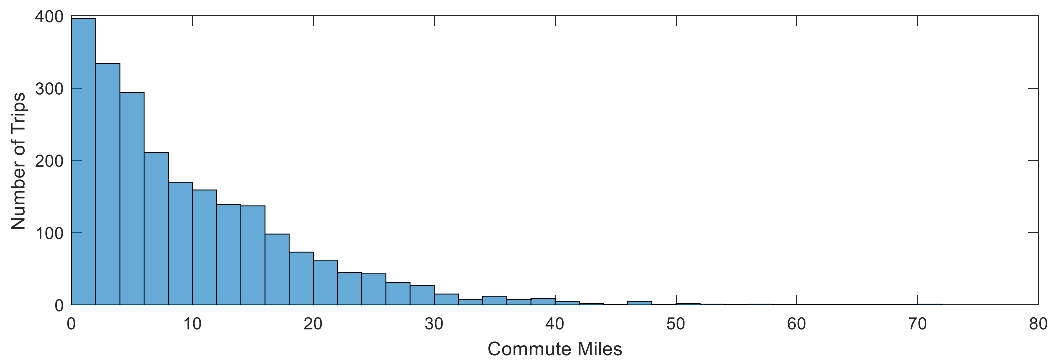

Figure III-4: Histogram of Commute Distances

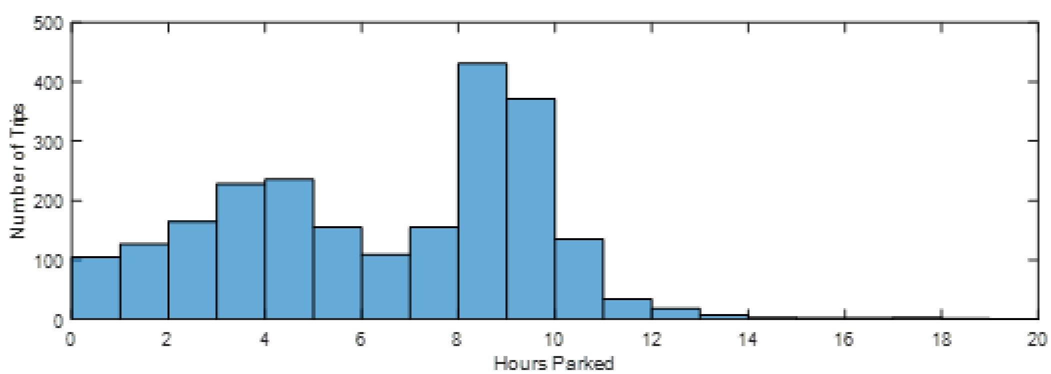

Figure III-5: Histogram of Parking Durations

King County, Washington has approximately 1,500 census block groups and commuting demand was found for about 900 of these. Distances between the census blocks were calculated from the Puget Sound Regional Councils GIS database (Norton n.d.). Manhattan distance was used — that is, the sum of the absolute value of the differences between the x and y centroids. This was used to derive the cost of walking and cost of driving. In both cases, two trips were expected every day of a 260-day work year. The cost of walking from a parking space to a destination was based upon King County's $41,700 per capita income, 2015$ (U.S. Census Bureau 2017), a 52-week year, a 40-hour work week, a 3-mph average walking speed (National Academies of Sciences, Engineering, and Medicine 2013), and a 50% assumed value of time discount for personal vehicle traveled, factored by a 220% increase for time value of walking when compared to personal vehicle travel (National Academies of Sciences, Engineering, and Medicine 2013). The walking speed, 3 mph, was taken from the Transit Capacity Manual (National Academies of Sciences, Engineering, and Medicine 2013). This leads to a yearly cost of ~ $5,400 a year per mile-spot, when diverting parking from desired zones, as shown in Equation III-2.

Equation III-2: Cost of Walking

$$7.34\frac{\$}{mi} \approx 41{,}700\frac{\$}{\mathrm{yr}} * \frac{1}{52}\frac{yr}{week} * \frac{1}{40}\frac{wk}{hr} * \frac{1}{3}\frac{hr}{mi} * 0.5 * 2.2$$

The costs of additional driving for a Level 5 EV to travel to another parking area was taken using a $0.10 per kWh electricity cost (US DOL 2017), a 35 kWh per 100 mi fuel economy (EPA n.d. X), 0.005 2015$ / mi maintenance cost (Alexander and Davis 2013), and a 0.246 2015$ / mi depreciation cost (AAA 2015), the last cost not being specific to electric vehicles. This leads to a ~ \$0.33 per mile cost a when diverting parking from desired zones, as shown in Equation III-3. This is much less than the costs of walking. In a drop-off and pick-up scenario, chargers can be expected to be further from demand. This allows significant infrastructure cost savings by traveling further than the maximum allowable walking distance. I note that the costs of automation equipment have not been included in this estimate, which represents an optimistic assumption.

Equation III-3: Cost of Driving

$$0.331\frac{\$}{mi} \approx \left(0.35\frac{kWh}{mi} * 0.1\frac{\$}{kWh} + 0.05\ \frac{\$ - maint.}{mi} + 0.246\ \frac{\$ - depr.}{mi}\right)$$

Real estate costs for parking spaces were estimated using data from King County GIS ("KCGIS Data Download" 2014). Parcel data was spatially joined and aggregated into each census block. The specific data point used was the average assessed unimproved land value per square foot of all parcels in a block. The average was taken only from parcels that had positive real estate values. Unimproved values were used in the absence of gross-square-foot values for a parcel, which would allow the value of built structure space to be used, as opposed to the value of a parking lot. Some blocks had no parcels with given positive assessed real estate values. Of these, only one was a full block. The others were pieces of census blocks, cut by the borders of the county and with small dimensions for distance calculations. The full block and two of the cut-off blocks also had travel demand. For the full census block, ID 530330211004, the average cost of the seven surrounding zones, 18.8 \$/sq-ft, was used. For block 530610507005, the average of the full two zones below it, 19.5 \$/sq-ft, was used. For block 530610509003, the average of the full two zones below it, 22.1 \$/sq-ft, was used. The few remaining blocks with no real estate and demand data were removing them from consideration for charger placement. The size of a parking space was taken as 15m^2, as defined by the Seattle city code for a standard space for "large vehicle" (City of Seattle 2017). This ignores the additional space required for navigation, which would change based upon scale.

4.2.3: Charger Selection and Infrastructure Costs

Based on a DOE report on the costs of electric vehicle infrastructure equipment (Smith and Castellano 2015), I estimated the capital costs of charging equipment to be 10,000 2015$ per charger. This is based on $4,000-6,000 single-port level 2 charger and $6,000-13,000, a mean $3,000, for installation (Smith and Castellano 2015). Level 2 chargers can charge at a rate of 6.6 kW, providing a typical vehicle about 20 miles of range per hour of charging (Smith and Castellano 2015). Given the trip distance distribution seen in Figure III-4, this will cover more than 95% of all trips considered in under 2 hours. For levels 4 and 5 automation, where one charger can fulfill multiple vehicles, DC charging would cost more per mile per hour than level 2 charging (Smith and Castellano 2015), a gap that increases as one accounts for the time to switch out vehicles. Level 1 charging requires only an outlet and a plug, provided by electric vehicles themselves. This would require little to no on the operator's side and was therefore rejected as a meaningful decision. This $10,000 capital cost was annualized over 15 years, using the City of Seattle's current 4.122% 30-year bond rate (City of Seattle n.d.) to about 900 $2015 per year. Maintenance is likely to be insignificant except in cases of vandalism or a failure not covered by warranty (Smith and Castellano 2015). Wireless communication is likely to be necessary to allow for autonomous parking, and the DOE lists current wireless infrastructure for charging costs as between $100-$900 a year (Smith and Castellano 2015). I assumed this was unnecessary in non-autonomous scenarios, but necessary, additional cost, in autonomous scenarios with a cost of $500 per year per charger.

4. 2.4: Optimization

4.2.4.1: Previous Charging Infrastructure Optimization Model

This chapter expands on Chen et al.'s (Chen et al. 2013) investigation into optimizing electric vehicle charging infrastructure for the Puget Sound area. Chen et al. (2013) used household travel-survey trip data and TAZ demographics to forecast where people would be parking for long-enough times to charge. They then used Mixed Integer Optimization to attempt to minimize the commuter cost — that is, the distance commuters would have to walk after parking — of providing public electric vehicle charging infrastructure, given a limited number of charging stations. They did not look at time-of-day effects or electric demand changes. Chen et al.'s Mixed Integer Optimization model is defined in Equation III-4 through Equation III-13.

Objective:

Equation III-4

$$\boldsymbol{min}\left[\sum_{i}\left(\sum_{j} c_{ij} y_{ij}\right)\right]$$

Constraints:

Equation III-5

$$\sum_{j}(y_{ij}) = d_i, \forall \mathrm{j} \in \mathrm{J} \text{ (parking demand constraint)}$$

Equation III-6

$$\sum_{i}(y_{ij}) \leq Mx_j, \forall \text{ i} \in \text{ I (charging supply constraint)}$$

Equation III-7

$$\sum(x_j) \leq L, \forall \text{ j} \in \text{ J (charging-station availability constraint)}$$

Equation III-8

$$\sum_{i}(\delta_{ij}x_j) \leq 1 \; \forall \text{ i} \in \text{ I (charging station spacing constraint)}$$

Equation III-9

$$y_{ij} \geq 0 \; \forall \text{ i} \in \text{ I, j} \in \text{ J (non-negativity constraint on parking demand)}$$

Equation III-10

$$x_j \in \{0,1\} \; \forall \text{ j} \in \text{ J (binary variable constraint for charging station selection)}$$

Equation III-11

$$\delta_{ij} = \begin{cases} 1 \; if \; C_{ij} < r \\ 0 \; else \end{cases} \text{(minimum inter-station spacing)}$$

Equation III-12

$$C_{ij} <= W \text{(maximum access cost)}$$

Equation III-13

$$\delta_{ij} = 0 \; if \, c_{ij} < r, \; else = 0$$

Where…

$$i, j = TAZ$$

- c = cost or distance
- W = maximum cost or distance
- M = arbitrarily large number (unlimited charger access assumption)
- L = maximum number of charging stations
- y_{ij} = parking demand of zone i met in j
- d_i = parking demand in zone i

4.2.4.2: Models Summary

This chapter makes three main additions to Chen et al.'s methods. These changes are used to attempt to model separately the effects of level 4 and level 5 automation on optimized costs and on electricity demand under an unscheduled charging scenario. First, it uses the unweighted data as a direct input rather than a travel-demand regression. Second, these models calculate operator cost in terms of a real estate component, based on assessed unimproved real estate values and the average cost to install one charging station. In our model, each charging space has a limited capacity and multiple spaces can be placed in each location. In Chen et al.'s model, operator cost was based on the number of locations, which each had unlimited capacity. I use the operator cost as a component of the objective function to find the socially optimum amount and distribution of spending. Operator cost could also be used as a constraint, either in addition to or instead of in the objective function, to find the optimum way of allocating a given operator cost, which may be possibly less than the socially optimum one. Chen et al. used operator cost solely as a constraint. In addition to these changes, I will use trip distance, time, and assigned parking data to calculate the temporal changes in electricity demand caused by vehicle charging.

In addition to a base case model, showing optimization for no or sub-level 4 automation, there are also models for level 4 and level 5 automation, individually. For level 4 and level 5 automation, demand is served in terms of miles, rather than trips, to account for the ability of vehicles to queue themselves for charging without human intervention. For level 5 automation, the maximum access cost constraint is removed and C is redefined as a function relating distance from parking to destination to the costs of energy consumption and vehicle deterioration needed to travel that distance. As with Chen et al., this chapter simplifies the solution by ignoring the increase in charging demand, but not cost, from changes in trip distance caused by parking diversions.

2.4.3: Levels 0-3 Automation Model

In Levels 0-3 automation, all chargers must be used for the full time that a vehicle is present. Demand is there taken as the peak amount of parking demanded in any census block. This model minimizes the sum of the operator cost spent building the infrastructure and the cost of commuters walking between their parking spaces and workplaces, as shown in Equation III-14. The latter is limited by a maximum 0.25-mile walking distance, Equation III-20. For the cost of distance, each peak trip is multiplied by the total number of trips per peak trip for each zone, K_{ij} . This model is defined in Equation III-14 through Equation III-23.

Objective:

Equation III-14

$$\min\left[\sum_{i}^{I}\left(\sum_{j}^{J}\{c_{ij} * y_{ij} * K_{i}\}\right) + L\right]$$

Decisions:

- y_{ij} = peak parking demand of zone i served in location j, (stations to build in j), integer

What we Want:

Equation III-15

$$x_j = \text{\# of chargers in j} = \sum_i^I y_{ij}$$

Constraints:

Equation III-16

$$\sum_j^J (y_{ij}) = D_i, \forall \text{ I, (all parking demand served)}$$

Equation III-17

$$\sum_i^I (y_{ij}) \leq x_j, \forall \text{ j, (charging supply constraint)}$$

Equation III-18

$$y_{ij} \geq 0 \; \forall \text{ i } \forall \text{ j (non-negativity constraint on parking demand)}$$

Equation III-19

$$x_j \geq 0 \; \forall \text{ j (non negative station assignment)}$$

Equation III-20

$$d_{ij} * w_{ij} <= W \; \forall \, i \, \forall \, j \text{ (maximum walking distance)}$$

Given:

Equation III-21

$$L = \sum_{j}^{J} \left(x_j * (A_j + B) * (A|P, i) \right), \text{(operator cost)}$$

Equation III-22

$$c_{ij} = d_{ij} * E * 2 * 260, \text{(walking costs)}$$

Equation III-23

$$w_{ij} = \begin{Bmatrix} 1, & if\ y_{ij} > 0 \\ 0, & else \end{Bmatrix}, \text{(binary check if anyone walked between i and j)}$$

$$solved\ as\ \{w_{ij} * 900{,}000 \geq y_{ij}\}$$

Input Parameters:

- D_i = parking demand at zone i, peak vehicles, count
- $A_j =$ real estate cost per parking space and charger at location j, $
- $B =$ costs per charging station, equipment and installation, $
- $d_{ij} =$ walking distance between zone i and location j, miles
- $E =$ cost of walking, $ / mile
- $W =$ maximum walking distance, miles
- K_i = average number of trips per peak trip in zone i, can be fractional, count
- $(A|P, i)$ = annuity value of current lump sum, $

2.4.4: Level 4 Automation Model

With level 4 automation, vehicles can queue up to a single charger, allowing it to serve more than one vehicle at a time. To account for this, demand is redefined as the aggregate miles that commuters must drive to reach their destination in each zone. Each charger can then charge up to its 20-mph capacity times the expected utilization rate of U=31%, based upon the county's trip-length distribution. Each trip between blocks is assumed to have the average number of miles of the trips from the origin block, D_{Avg-i}. The model for level 4 automation is described in Equation III-24 through Equation III-35. Equation III-35 is a simplification, used to convert between aggregate miles, Y_{mi-ij}, and individual trips, Y_{ij}, in order to calculate commuter costs.

Objective:

Equation III-24

$$\min\left[\sum\nolimits_i^I\left(\sum\nolimits_j^J\{c_{ij} * y_{ij}\}\right) + L\right]$$

Decisions:

- y_{ij} = total trips ending in zone i served in location j, count

What we Want:

Equation III-25

$$x_j = \text{\# of chargers in j} = \frac{\left(\sum_i^I y_{ij}\right)}{U * q}, \text{ integer}$$

Constraints:

Equation III-26

$$\sum_j^J \left(y_{mi_{ij}}\right) \geq D_i, \forall \text{ I, (all parking demand served)}$$

Equation III-27

$$\sum_i^I \left(y_{mi_{ij}}\right) \leq Q_j, \forall \text{ j, (charging supply constraint)}$$

Equation III-28

$$y_{ij} \geq 0\ \forall \text{ i } \forall \text{ j (non-negativity constraint on parking demand)}$$

Equation III-29

$$x_j \geq 0\ \forall \text{ j (non-negative station assignment)}$$

Equation III-30

$$d_{ij} * w_{ij} <= W\ \forall\, i\ \forall\, j \text{ (maximum walking distance)}$$

Given:

Equation III-31

$$L = \sum_{j}^{J} \left(x_j * \left(\left(A_j + B \right) * (A|P, i) + C_w \right) \right), \text{(operator cost)}$$

Equation III-32

$$c_{ij} = d_{ij} * E * 2 * 260, \text{(walking costs)}$$

Equation III-33

$$w_{ij} = \begin{Bmatrix} 1, & if\ y_{ij} > 0 \\ 0, & else \end{Bmatrix}, \text{(binary check if anyone walked between i and j)}$$

$$solved\ as\ \{w_{ij} * 900{,}000 \geq y_{ij}\}$$

Equation III-34

$$Q_j = x_j * U * q, \text{ zone charge capacity, miles}$$

Equation III-35

$$y_{mi_{ij}} = y_{ij} * D_{avg_i}$$

Input Parameters:

- D_i = parking demand at zone i, peak commuter miles

- D_{avg_i} = mean trip distance for trips ending in zone i, miles
- $A_j =$ real estate cost per parking space and charger at location j, \$
- $B =$ costs per charging station, equipment and installation, \$
- $d_{ij} =$ walking distance between zone i and location j, miles
- $E =$ cost of walking, \$ / mile
- $W =$ maximum walking distance, miles
- U = charger utilization rate, %
- q = charger capacity, miles per shift
- $(A|P,i)$ = annuity value of current lump sum, \$
- C_w = cost of wireless AV communication equipment maintenance, \$ / year

4.2.4.5: Level 5 Automation Model

For level 5 automation, the maximum walking distance is removed to account for the ability of vehicles to drop off and pick up their passengers. The cost of walking is therefore replaced with energy and vehicle deterioration costs for this extra distance of vehicle travel, as calculated in Equation III-43. Otherwise, the model is identical to that of level 4 automation and is defined in Equation III-36 through Equation III-46.

Objective:

Equation III-36

$$\min\left[\sum_{i}^{I}\left(\sum_{j}^{J}\{c_{ij} * y_{ij}\}\right) + L\right]$$

Decisions:

- y_{ij} = total trips ending in zone i served in location j, count

What we Want:

Equation III-37

$$x_j = \text{\# of chargers in j} = \frac{\left(\sum_i^I y_{ij}\right)}{U * q}$$

Constraints:

Equation III-38

$$\sum_j^J \left(y_{mi_{ij}}\right) \geq D_i, \forall \text{ I, (all parking demand served)}$$

Equation III-39

$$\sum_i^I \left(y_{mi_{ij}}\right) \leq Q_j, \forall \text{ j, (charging supply constraint)}$$

Equation III-40

$$y_{ij} \geq 0 \;\forall \text{ i } \forall \text{ j (non-negativity constraint on parking demand)}$$

Equation III-41

$$x_j \geq 0 \;\forall \text{ j (non-negative station assignment)}$$

Given:

Equation III-42

$$L = \sum_j^J \left(x_j * \left(\left(A_j + B\right) * (A|P, i) + C_w\right)\right), \text{(operator cost)}$$

Equation III-43

$$c_{ij} = d_{ij} * F_e * P_{elc} * 2 * 260, \text{(drop-off/pick-up energy cost, \$)}$$

Equation III-44

$$w_{ij} = \begin{Bmatrix} 1, & if\ y_{ij} > 0 \\ 0, & else \end{Bmatrix}, \text{(binary check if anyone walked between i and j)}$$

$$solved\ as\ \{w_{ij} * 900{,}000 \geq y_{ij}\}$$

Equation III-45

$$Q_j = x_j * U * q, \text{ zone charge capacity, miles}$$

Equation III-46

$$y_{mi_{ij}} = y_{ij} * D_{avg_i}$$

Input Parameters:

- D_i = parking demand at zone i, peak commuter miles
- D_{avg_i} = mean trip distance for trips ending in zone i, mile
- $A_j =$ real estate cost per parking space and charger at location j, $
- $B =$ costs per charging station, equipment and installation, $
- $d_{ij} =$ walking distance between zone i and location j, miles
- U = charger utilization rate, %
- q = charger capacity, miles per shift
- F_e = fuel economy, kWh / mi
- P_{elc} = price of electricity, $ / kWh
- $(A|P, i)$ = annuity value of current lump sum, $
- C_w = cost of wireless AV communication equipment maintenance, $ / year

4.3: Results and Discussion

The optimal number of chargers given by our models for levels 0-3, level 4, and level 5 automation are of 1,900, 680, and 331 chargers, respectively. These cover a total of 2,300 trips and 1,900 peak trips. This leads to each charger covering an average of 1.2, 3.5, and 7.4 trips, with 4.4%, 13%, and 27% of the 13 hours through 6 a.m. and 6 p.m. spent charging vehicles. The maximum utilization rate that the model would assign is the 31% expected utilization rate calculated in Section 3.1. The annualized equipment and parking costs, to build upon these scenarios, for levels 0-3, level 4, and level 5 automation are $1.75 million, $932,000, and $436,000, respectively, while the total commuter and operator costs, are $1.75 million, $937,000, and $540,000, respectively.

The histograms of the distribution of chargers for levels 0-3, level 4, and level 5 automation are shown in Figure III-6 through Figure III-8. These histograms don't include the zones with zero chargers and truncate the largest groupings. Figure III-9 through Figure III-11 show the percentage decrease in number of charging stations, by census block, when increasing the level of automation. The legend groups these by equal percentile size groups. When moving from no automation to level 4 automation, roughly a quarter of the blocks keep the same number of, or no, chargers, another quarter decrease the number of chargers by as much as a third, another quarter decrease by up to two-thirds, and the final quarter decrease by up to 100%. When moving from no automation to level 5 automation, one-third of the blocks register no change, one-third decrease by up to one-half, and the remaining third decrease by up to 100%. When moving between level 4 and level 5 automation, one-third of the blocks register no change in chargers, one-third decrease by up to 93%, and the remaining third decrease by up to 100%.

The hourly electric demand from the chargers is shown in Figure III-12. Under levels 0-3 automation, peak with the arrival times, between 7 a.m. and 9 a.m., with demand at just over 2,000 kWh at 8 a.m. After this point electric demand rapidly decreases until 11 a.m., after which it continues to slowly decrease. The pattern under level 4 automation is similar, except that the 7 a.m. to 9 a.m. peak is level at just under 1,500 kWh, shaving off a fourth of the peak demand. Under level 5 automation, electric demand stays steady at just under 700 kWh until 4 p.m., when it starts decreasing as people leave their workplaces. This is a 31% decrease of the peak electrical draw under level 4 automation and a decrease of 68% under level 5 automation, when compared to no automation. This shows that simply taking advantage of the automated queueing allowed by automation can significantly smooth the demand peaks without specific consideration to grid management.

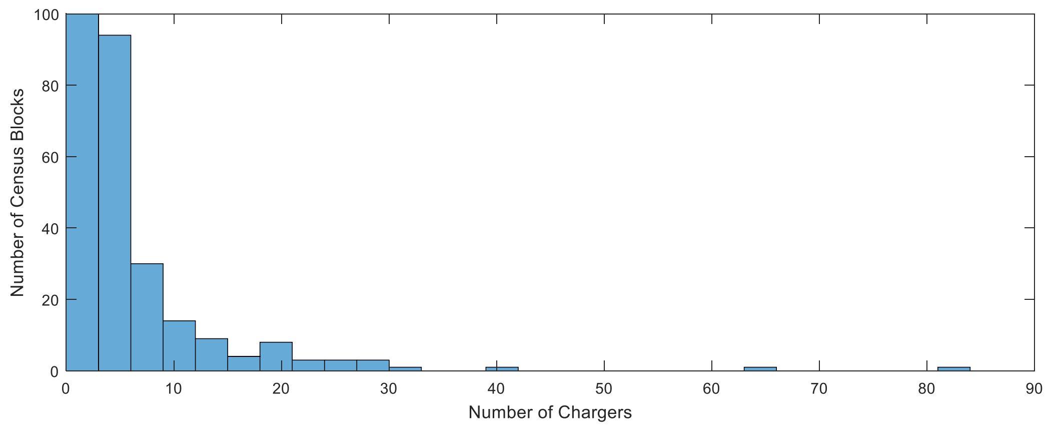

Figure III-6: Histogram of Charger Distribution for Levels 0-3 Automation, 995 Blocks with 0, 1,900 Total Chargers

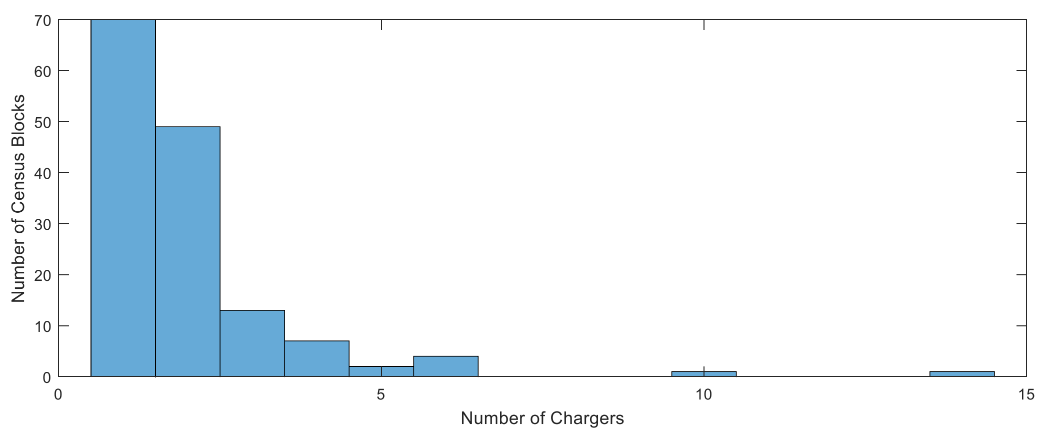

Figure III-7: Histogram of Charger Distribution for Level 4 Automation, 960 Blocks with 0, 680 Total Chargers

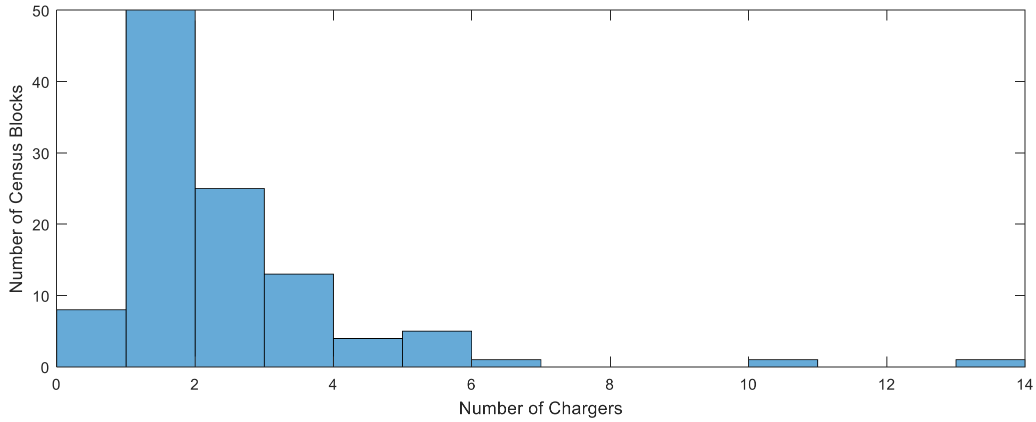

Figure III-8: Histogram of Charger Distribution for Level 5 Automation, 1.275

Blocks with 0, 331 Total Chargers

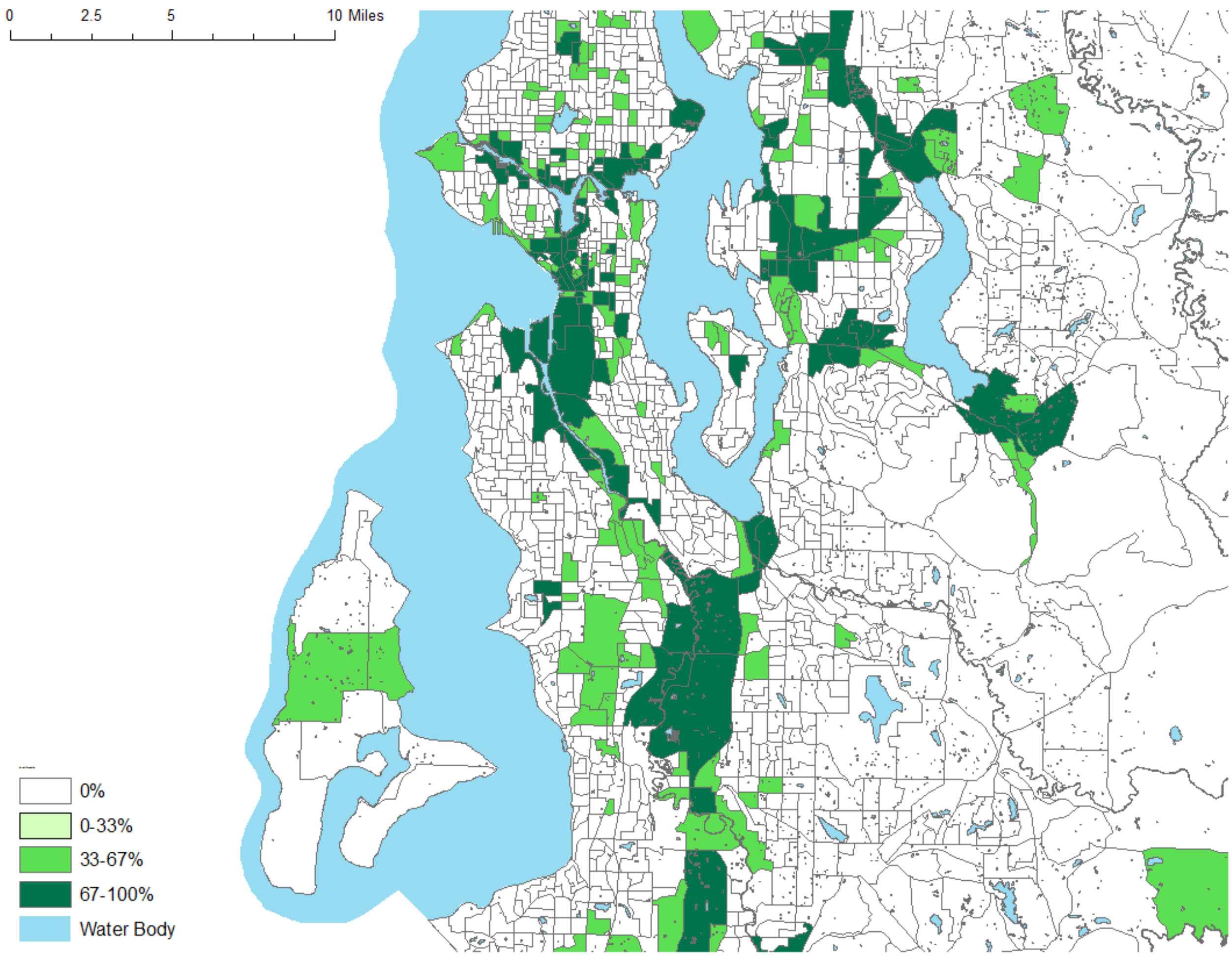

Figure III-9: Percent Decrease in Chargers from Level 0 to Level 4 Automation: Percentile Groups

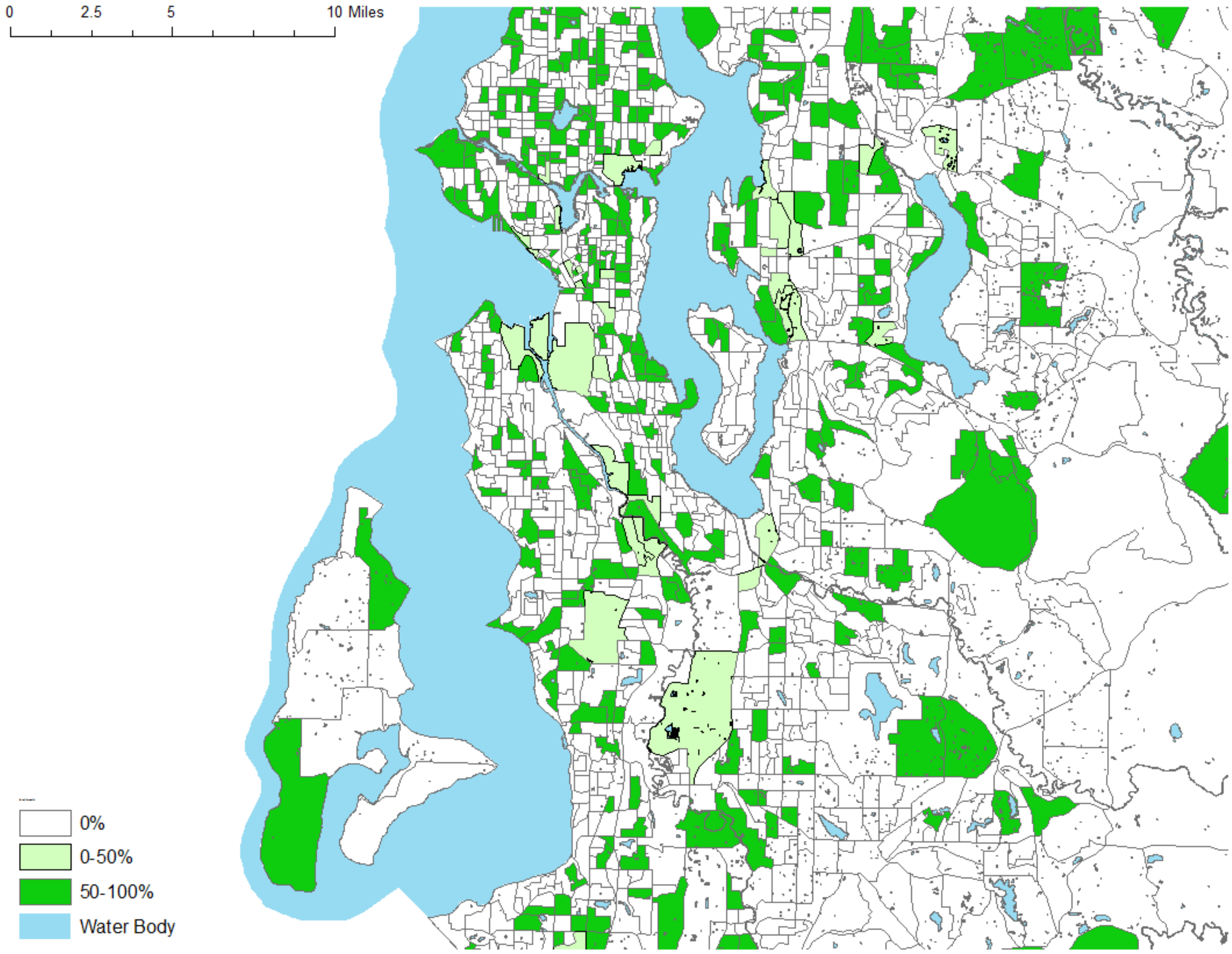

Figure III-10: Percent Decrease in Chargers from Level 4 to Level 5 Automation: Percentile Groups

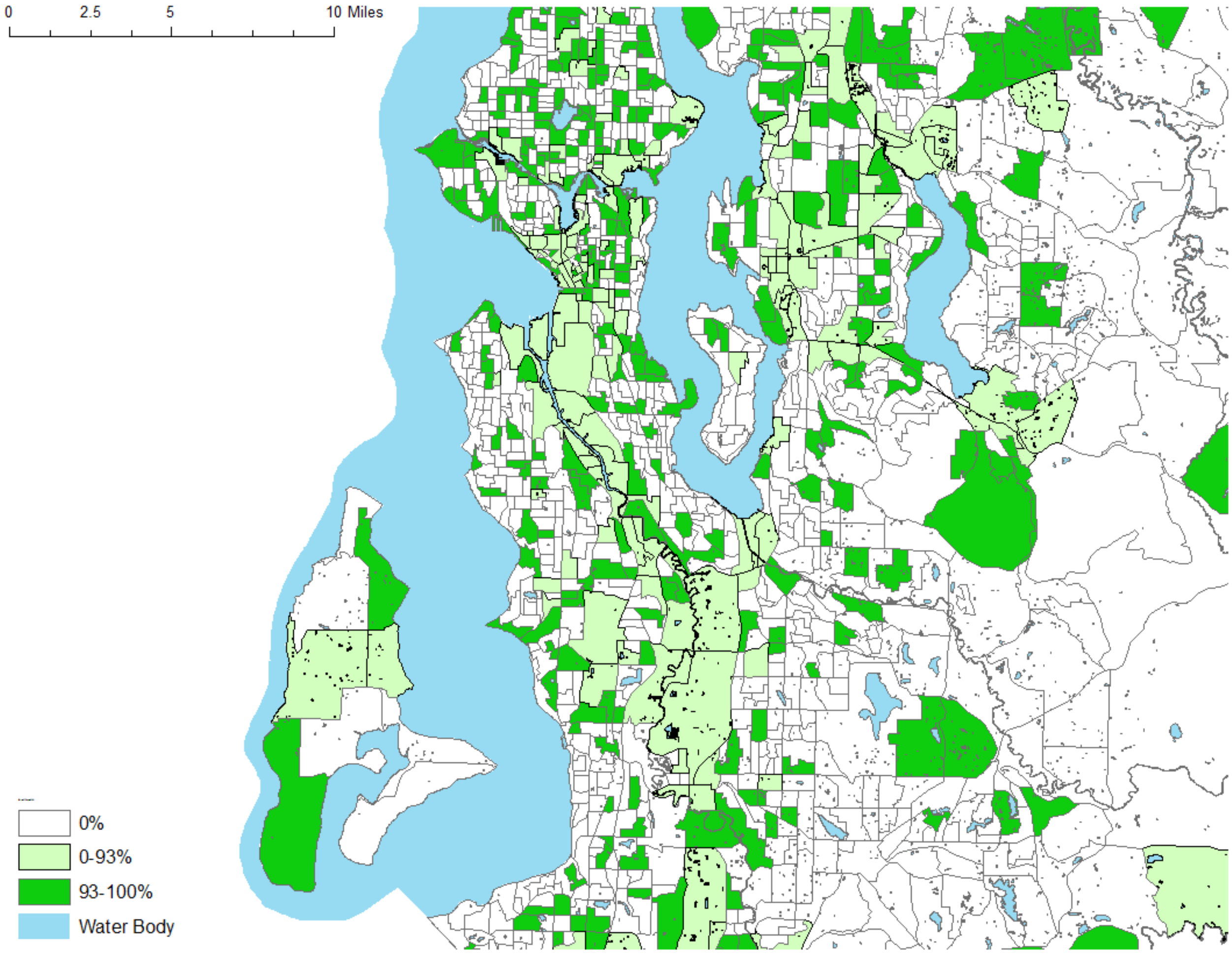

Figure III-11: Percent Decrease in Chargers from Level 0 to Level 5 Automation: Percentile Groups

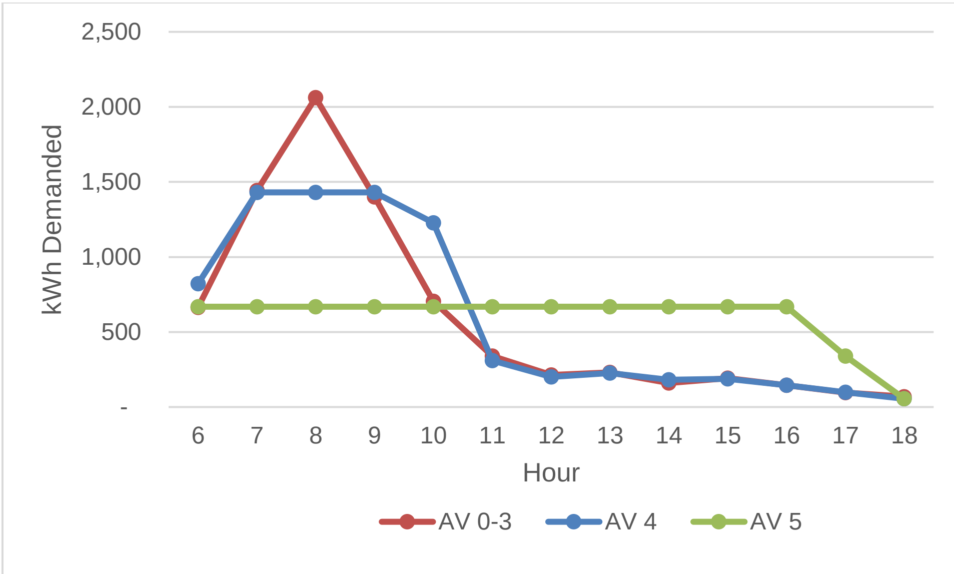

Figure III-12: Hourly Electric Demand Under Each Level of Automation

4.4: Conclusion

This chapter presented a method to optimize stationary electric vehicle charger placement and distribution when accounting for the possible effects of privately owned autonomous vehicles. This chapter optimized based on operator and commuter costs. This chapter assumed that without any automation, each vehicle would prevent the usage of a charger for the entire duration that it is parked. For level 4 automation it assumed that vehicles could vacate themselves from a charger and allow another vehicle usage of the charger, when they are fully charged, with a 1- minute delay. For no automation and level 4 automation, the commuter costs were limited by a maximum 0.25-mile walking distance. For full, level 5 automation, commuter cost was unbounded.

The electrical demand of the optimal solution for these scenarios was also calculated. Moving from levels 0-3 to level 4 and level 5 automation reduces the peak electrical draw by 31% and 68%, respectively. This is from a peak load of about 2,000 kWh or 1 kWh per peak vehicle. If the number of peak EV trips were to be 1 per worker for the whole population, over 2 million in King county (U.S. Census Bureau 2017), then this peak would be over 1,000 MWh. Moving from no automation to level 4 automation lowered operator costs by 47% and total social costs, including both operator and commuter costs, by 46%. Moving from levels 0-3 automation to level 5 automation decreased operator costs by 75% and total social costs by 69%. Without any automation, the cost borne by commuters is insignificant as each vehicle can only serve one commuter at a time and commuters' distances between their workplace and their parking spots are limited. This cost increases in significance in the level 4 automation scenario, where a commuter can be made to walk longer to share a charger with other commuters. The total cost borne by commuters, however, is only 0.5% of the total operator cost. The cost borne by commuters is much more significant with level 5 automation, where a vehicle can balance the cost of driving over much greater distances than are possible via walking with the equipment cost savings. Here the cost borne by commuters is 24% of the total equipment and real estate costs. Due to this, increasing the relative cost born by commuters will only significantly change the level 5 automation scenario, by decreasing the movement of charging stations.

Electric vehicles are current achieving market growth and significance while autonomous technologies are being introduced to the market. This chapter has shown that these two technologies have potential synergies and a novel method to take advantage of these synergies while optimizing electric vehicle infrastructure deployment. It has also shown that taking advantage of the potential synergies between these technologies would allow for significant decreases in support infrastructure cost. This would also allow for a natural smoothing of the electric demand caused by electric vehicles.

4.5: Limitations and Future Work

The model was found to be easily computationally feasible for levels 0-3 and level 4 automation. A proven optimal solution to the level 5 automation scenario could not be found, due to computational limits. The solution reported is no more than 1.7% from the optimal solution. This reflects a possible gap of $9,000, which is under the assigned cost of a single charging station. Given more resources, the true optimal solution could likely be found, though the decrease in social cost would not be large enough to change any of the chapter's conclusions.

None of our scenarios directly accounted for the temporal aspect of parking demand in the optimization model itself. For no automation, the maximum hourly demand of each individual zone was used. This has the potential to overestimate the optimal number of stations, as neighboring zones may have different peak demand times. For the automated-vehicle scenarios, the total number of miles traveled was used. Many of these miles might be spaced close together and need to be charged in less than the full timeframe, a possibility suggested by the distribution of parking durations shown in

Figure III-5. This leads to a potential underestimation of the optimal number of stations necessary to fulfill demand. Accounting for this temporal dimension would have greatly increased computational complexity. Given the limits reached when modeling level 5 automation, this complexity was beyond the resources available to the authors for this chapter. Creating and running a time-sensitive set of models would provide more precise solutions.

This chapter used the Puget Sound Household Travel Survey's (Kilgren 2015) trips as a direct and unweighted demand input. Using the data directly provides more concentration of travel demand than reality and using the data unweighted introduces probable bias; however, the main goal of this chapter is to present the novel methodology for optimizing charging infrastructure for automation and testing the potential social gains from this technology and joint approach. These potential gains come from the ability to queue vehicles for a charger and eliminate the maximum-walking-distance constraint. The first ability is affected by magnitude and direction of social gain is affected by the trip-length distribution, which is strongly low weighted, even when accounting for data bias. The second ability is affected by the concentration of demand and by the distribution of real estate costs relative to demand. The concentration of demand is likely to be higher when directly using the survey data. The results should, therefore, still be informative on this method's potential benefit. Without a demand model, areas of no visible demand are effectively removed from the model and see no chargers in any scenario, decreasing the ability to draw spatial distribution conclusions. Adding a demand distribution model would allow for specific spatial distribution conclusions to be drawn. Additionally, by using the data directly and in its entirety, for commuters, we ignore the question of who will adopt electric vehicles and which adopters will need workplace charging. Not everyone may get EVs and some who do will have sufficient range and charging at home.

The most specific spatial data provided by Puget Sound Household Travel Survey (Kilgren 2015) was census blocks. Distance was determined using the centroids of these zones. Travel within a zone was always considered free, while travel from the border of one zone to another was counted as being equivalent to between their centroids. This is a fundamental limit of the data source. The increase of vehicle costs for level 4 and level 5 automation was not included in the model. The model only optimized for fleets that are fully level 0-3, level 4, or level 5 autonomous vehicles. Optimization models accounting for mixed fleets and/or deciding which level of automation is optimal given vehicle pricing would allow further insights.

The cost of a single parking space was taken as the space's individual physical footprint times the census block's average assessed unimproved real estate value. Parking spaces need navigational area as well, which changes as the number of spaces in a lot or garage increases. Market real estate value and usage is also affected by zoning and current built infrastructure, both of which this chapter ignores. A more accurate real estate model accounting for the value of current parking infrastructure would allow for a more accurate balance of commuter and operator costs.

Chapter IV Fuel Economy Testing of Autonomous Vehicles

This results from this chapter have been published as (Mersky and Samaras 2016).

The previous chapter discussed how to jointly optimize the placement of electric vehicle chargers for commuters and the infrastructure operators. The chapter explores how to optimize under different scenarios of automation and how this decreased the net social cost of the investment. This chapter discusses a novel method to measure and regulate the fuel economy of vehicles using autonomous technologies.

Environmental pollution and energy use in the light-duty transportation sector are currently regulated through fuel economy and emissions standards, which typically assess quantity of pollutants emitted and volume of fuel used per distance driven. In the United States, fuel economy testing consists of a vehicle on a treadmill, while a trained driver follows a fixed drive cycle. By design, the current standardized fuel economy testing system neglects differences in how individuals drive their vehicles on the road. As autonomous vehicle (AV) technology is introduced, more aspects of driving are shifted into functions of decisions made by the vehicle, rather than the human driver. Yet the current fuel economy testing procedure does not have a mechanism to evaluate the impacts of AV technology on fuel economy ratings, and subsequent regulations such as Corporate Average Fuel Economy targets. This chapter develops a method to incorporate the impacts of AV technology, for restrained car following situations, within the bounds of current fuel economy test, and simulates a range of automated following drive cycles to estimate changes in fuel economy. This algorithm simulates car following rather than unconstrained driving, however the method is consistent with and easily adaptable to the current EPA testing methods. The results show that AV car following algorithms designed without considering efficiency can degrade fuel economy by up to 3%, while efficiency-focused control strategies may equal or slightly exceed the existing EPA fuel economy test results, by up to 5%, when compared to base EPA cycle performance. This suggests the need for a new near-term approach in fuel economy testing to account for connected and autonomous vehicles. As AV technology improves and adoption increases in the future, a further reimagining of drive cycles and testing is required.

5.1: Introduction

Management of environmental pollution and energy use in the light-duty transportation sector is currently regulated through fuel economy and emissions standards. In the United States (U.S.), Japan, and the European Union these standards are in the form of quantity of pollutants emitted and volume of fuel used per distance driven (Atabani et al. 2011). Compliance with these standards is evaluated via a standardized fuel economy and emissions test. The U.S. test consists of a vehicle on a treadmill, while a trained driver follows a fixed velocity schedule, or drive cycle (EPA n.d. A). During the test all effluent from the tailpipe is tested for pollutant levels, and carbon dioxide levels are used to estimate fuel usage (Kiley n.d.). This is done for five different types of drive cycles, to simulate different conditions (EPA n.d. B). The results from each test are then aggregated to ascertain if the vehicle is complying with emissions standards. In addition, the tests are weighted four separate ways to determine fuel efficiency with respect to required standards and reporting to the consumer in the form of highway, city, and combined fuel efficiency (Kiley n.d.). This system allows for a standardized method to compare all passenger vehicles in the U.S. market, streamlining the regulatory process.

By design, the current standardized fuel economy testing system neglects differences in how individuals actually drive their vehicles on the road. As autonomous vehicle (AV) technology is introduced, more aspects of driving are shifted into functions of decisions made by the vehicle, rather than the human driver. Yet the current fuel economy testing procedure does not have a direct mechanism to evaluate the impacts of AV technology on fuel economy ratings. Autonomous and partially autonomous vehicle technology has advanced greatly over the past several years, with adaptive cruise control (ACC) with lane assist systems already reaching the market, and more advanced technologies have been announced for the coming years. While these systems may allow vehicle manufacturers to optimize their partially-autonomous vehicle control systems for fuel efficiency, these systems will not affect vehicle fuel economy ratings unless they are included in fuel economy testing. Hence, manufacturer incentives will not be aligned with improving fuel economy. Without inclusion into fuel economy ratings, autonomous technology will not help manufacturers meet their required Corporate Average Fuel Economy (CAFE) targets and manufacturers cannot advertise the increased vehicle fuel efficiency. Under such incentives, manufacturers are likely to make vehicle control decisions that increase vehicle desirability at the cost of fuel efficiency. Currently, the National Transportation Safety Board is considering if certain partially-autonomous technologies should be included as standard vehicle features for safety reasons (Mlot 2015). Requiring autonomous technologies on new vehicles for safety reasons would enhance the importance of understanding their impacts on vehicle fuel economy.

The EPA has addressed similar issues of emerging technologies through "off-cycle technology credits" for CAFE standards, and is likely to continue this practice for autonomous technology (EPA and NHTSA 2010). A manufacturer may petition for an increase in a vehicle's CAFE fuel economy rating if it can demonstrate the current two-cycle test does not capture some fuel efficiency gains that "new and innovative technologies" provide (EPA and NHTSA 2010). There are three potential challenges if this approach is used for autonomous vehicle technology. First, off-cycle technology credits only apply to new and non-standard technologies. Once other manufacturers begin to adopt them, as has already happened for many early autonomous features, they are no longer eligible. Second, the process is non-standardized. A manufacturer must submit a testing and validation method, which has to be granted preliminary approval, and go through a public review process. In addition, the EPA will not certify the method or results (EPA and NHTSA 2010), meaning that these technologies may not be tested equivalently across manufacturers. The final challenge is that this will only apply for CAFE standards and not fuel economy ratings that inform the consumer (EPA and NHTSA 2010). Hence a manufacturer still cannot reflect the impacts of this technology in its fuel economy stickers and may face restrictions when trying to advertise any fuel economy benefits to consumers.

As autonomous vehicle technologies become more prevalent, the current drive cycle system should be expanded to include drive cycles for autonomous and partially autonomous vehicles. This chapter makes a contribution to the literature by demonstrating a method to incorporate autonomous following drive cycles into the existing EPA testing regimen. This method was developed primarily for near-term conditions, where the majority of traffic is comprised of conventionally driven vehicles. This method would allow the current dynamometer testing to continue, while accounting for the introduction of AV technologies. This approach was tested on a range of possible drive behaviors, modeling different priorities that a vehicle manufacturer may wish to pursue to obtain new testing drive cycles. The fuel consumption resulting from these drive cycles were then simulated on a variety of vehicles using the Virginia Tech Comprehensive Fuel Consumption Model (Edwardes and Rakha 2014; Park et al. 2013; Rakha et al. 2011b; Saerens et al. 2013), and then compared. While the ultimate procedure adopted by EPA will have to comply with regulatory requirements, the methods outlined here demonstrate the need for a new approach and provide a starting point for discussion in the near-term. As AV technology improves and adoption increases in the future, a further reimagining of drive cycles and testing is required. This chapter is organized as follows. First, the current drive cycles used for fuel economy testing are discussed. This is followed by a review of current literature and a description of the proposed addition to the current test. Next the ACC behavior used for testing is described and the fuel consumption model discussed. Finally, the results are discussed and their sensitivity to assumptions is tested.

5.1.2: Current Drive Cycles

Currently the EPA requires five separate drive cycles for passenger vehicle fuel economy testing. These are the Urban, Highway, High Speed, Air Conditioning, and Cold Temperature tests. While the first three are permitted to be tested in any temperature between 68°F and 86°F, the latter two must be done at 95°F with the air conditioning on and 20°F, respectively (EPA n.d. B). The results of these cycles are then weighted in four different ways to find the emissions rate, urban and freeway fuel economies and combined fuel economy. This research uses the urban (FTP) and highway (HWFET) drive cycles, as the basis for the new autonomous drive cycles.

The urban drive cycle (FTP) simulates typical travel through a city with stops and acceleration changes, while the freeway drive cycle (HWFET) simulates smoother freeway travel and makes no complete stops until the end of the test. Figure IV-1 and Figure IV-2 show the velocity schedules for the FTP and HWFET drive cycles respectively, while Table

IV-1 summarizes some of the test details. Also worth noting is that the FTP calls for a cold engine start. This is important as the engine typically operates at its highest efficiency after warming up (EPA n.d. B).

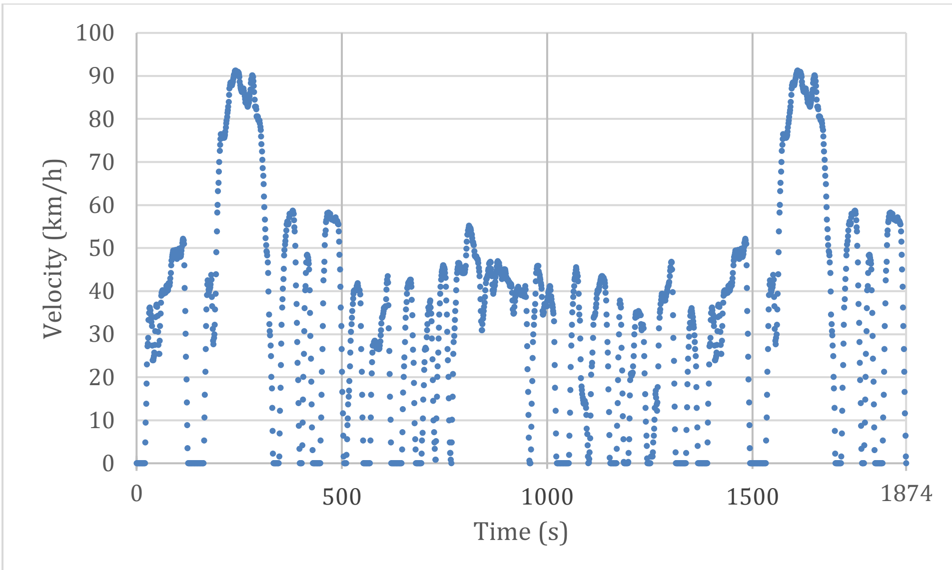

Figure IV-1: Velocity Schedule of the EPA FTP Drive Cycle (EPA, n.d. B)

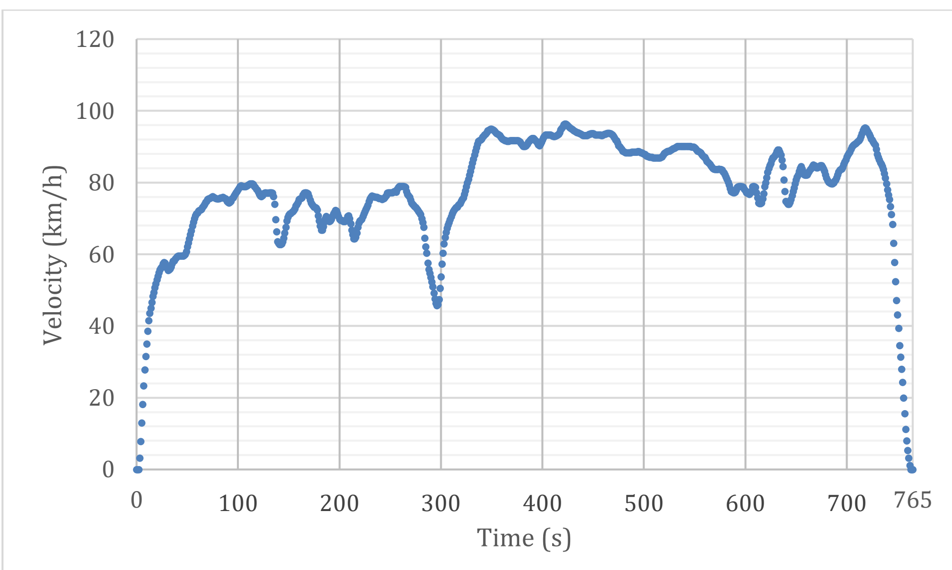

Figure IV-2: Velocity Schedule of the EPA HWFET Drive Cycle (EPA, n.d. B)

Table IV-1: U.S. EPA Drive Cycles Details (EPA, n.d. B)

Driving Schedule Attributes	**FTP**	**HWFET**
Top Speed (km/h)	90.1	96.6
Average Speed (km/h)	34.1	77.7
Maximum Acceleration (km/h/s)	5.3	5.1
Distance Covered (km)	17.7	16.6
Time Elapsed (min)	31.2	12.75
Individual Full Stops	23	0
Percentage of Time Stopped	18	0

5.1.3: Previous Research

Rakha et al. developed the Virginia Tech Comprehensive Power-Based Fuel Consumption Model (Rakha et al. 2011b). This model was produced in response to two problems found with other available fuel consumption models. The first is that many models tend to produce unrealistic optimization decisions, such as always maximizing acceleration until the target speed is reached (Rakha et al. 2011b). The second is that many require non-public or inaccessible information on vehicle and engine characteristics. Their model was designed to only require EPA or European Fuel Economy ratings and manufacturer-provided physical vehicle characteristics. Further investigations and field tests were led by Park et al. to determine the accuracy of the model for real world driving (Park et al. 2013). While errors were found, they were found to generally be relatively small and manageable. Edwardes and Rakha then expanded this model to include light duty and hybrid buses and found average errors of 4.7% and 22% for laboratory and on-road fuel consumption testing, respectively (Edwardes and Rakha 2014).

Gonder and Simpson (Gonder and Simpson 2006) investigated the Society of Automotive Engineers (SAE) J1711 testing recommendation standards for plug-in hybrid vehicles. They discussed potential improvements to the standard, some of which have since been adopted in an adapted form by the EPA. These include separately reporting petroleum product consumption and electricity consumption, per unit of distance. Additionally they recommended the assumed charging frequency be increased and a method for determining the weights for the Full, Partial, and No charge test results.

Bhavsar et al. (Bhavsar et al. 2014) investigated energy reduction strategies for connected plug-in hybrid vehicles. They tested four strategies: a base case strategy with conventional driver behavior; an optimization strategy using knowledge of the current traffic signal status of approaching intersections; a strategy using information of the headway of all leading vehicles; and a strategy using both information on the headways of all leading vehicles and any approaching light's status. Traffic behavior for these driver scenarios was simulated and used to estimate fuel consumption. They simulated results for both full and partial technology adoption. For full adoption they found fuel consumption savings of 75% for the combined strategy, 71% for the intersection only strategy and 69% for the headway only strategy (Bhavsar et al. 2014).

Wu et al. (Wu et al. 2014) investigated the performance gains that could be expected from partial vehicle automation when using information of the current traffic signal status and schedule for the approaching intersection, when compared to human drivers given the same information. In the manual drive case the dashboard would indicate target velocities when approaching an intersection and the driver would attempt to obey the advice. This was tested on a track with real drivers and their speed profiles recorded. A speed profile was then developed to show what would have happened had the advice been followed perfectly in the assumed partial automation case. Fuel consumption was simulated using the EPA's Motor Vehicle Emission Simulator. Partial automation was found to improve fuel consumption by approximately 5-7% compared to a human driver given similar instructions (Wu et al. 2014).

Rajamani and Shladover (Rajamani and Shladover 2001) investigated cooperative adaptive cruise control (CACC) systems to ascertain the highest capacity gains and decreases in headway possible. They found a decrease of headway to 1 second possible along with a near doubling of capacity from 3,000 vehicles/lane/hour for just an ACC system to 6,400 vehicles/lane/hour for CACC systems. Kesting et al. (Kesting et al. 2008) developed an ACC strategy that would adapt its behavior to different traffic patterns. The system is able to autonomously determine if traffic conditions are in 1 of 4 states, and then adjust behavior to the most capacity and flow efficient response. Through simulations they found that equipping just 5% of a vehicle fleet with this technology could significantly decrease congestion and decrease travel times. Grumert et al. (Grumert et al. 2015) investigated setting variable speed limits for cooperative and autonomous vehicles to moderate traffic patterns and decrease emissions. They found significant increases in traffic harmonization and decreases in vehicular emissions when variable speed limits were used and as the portion of cooperative autonomous vehicles increased.

Feng et al. (Feng et al. 2015) investigated using connected vehicles to decrease delays at intersections. Using connected vehicles as sensors to detect non-connected vehicles, they found that delays would decrease as more vehicle-to-infrastructure (V2I) enabled vehicles entered the road. With 100% connected vehicle penetration they found up to 16% reduction in vehicular delays at intersections.

Zloki and Themann (Zlocki and Themann 2014) estimated the fuel reduction potential of different adaptive cruise control strategies. They defined fuel reduction potential as the maximum possible in the most optimal conditions for a particular control strategy when facing a specific situation. Among the 10 different strategies they tested they found potential fuel reductions of up to 85%. On controlled track testing they found reductions of up to 70%, for one specific and short (less than 1km) scenario. It is notable that they were not including driver comfort, acceptance, or average use conditions. Finally, several recent works have bounded the energy implications from automated vehicles (Brown et al. 2014; Fagnant and Kockelman 2015; Feng et al. 2015; Folsom 2012; Gonder et al. 2012; Greenblatt and Saxena 2015; Iii et al. 2014; James M. Anderson et al. 2014; Kockelman and Fagnant 2014; Shladover, S 2012; Wadud Z et al. 2013)], but fuel economy modeling and implications remains a critical research need.

5.1.4: Proposed Addition to Current Testing for Autonomous Vehicles

In order to account for computer agency in automated vehicles, I propose the addition of "Automated Drive Cycles" to the fuel economy testing regimen. These drive cycles would be specific to the individual ruleset that a particular AV will follow, and appropriate for near-term conditions when AVs are on the road with primarily conventionally-driven vehicles. I propose that the AV cycles be generated as simply as possible, with the following method and assumptions:

- First the ruleset that the AV will follow will be abstracted to function in a one-dimensional simulation, therefore lateral control can be ignored.
- The road will be assumed to be straight, single lane, and level, with only two vehicles and no traffic control systems.
- The vehicle will be assumed to start 5 meters behind another "lead vehicle".
- At time 0 the lead vehicle will start to obey the EPA drive cycle for either FTP or HWFET conditions.

- The simulated AV will then make decisions about how to best follow the lead vehicle until the end of the test.
- The test will end at the completion of the EPA cycle, when the lead vehicle has stopped, regardless of whether or not the AV has stopped.
- The velocity profiles for both the Urban and Freeway simulations will then be recorded.
- The results can be audited and validated as necessary by physical experiments on a roadway.

The next step is to use these drive cycles in dynamometer testing to estimate fuel consumption. These results can then be either weighted in the fuel consumption and emission ratings, or used separately for advertising purposes. This method was designed to conform to the existing standards as much as possible. For more advanced automation features, such as vehicle-to-vehicle and vehicle-to-infrastructure communication, new simulations would need to be developed under future research. Should the EPA add on-road testing to emissions and fuel economy testing, on-road AV following could also be added.

One commonality that all vehicle-to-vehicle and vehicle-to-infrastructure control strategies have is enabling the connected vehicle to predict future constraints on its driving behavior. While specific simulation scenarios would be needed to capture these effects, the possible range of cumulative effects on fuel efficiency can be estimated by giving the following vehicle knowledge about the lead vehicle actions into the future for the above simulation. This would allow insight into the significance of these effects for expected future scenarios of predictive ability.

This approach relies upon manufacturers to simulate and abstract their own rulesets to derive their AV drive cycles. This however, is not significantly different than the status quo, where manufacturers perform their own fuel economy testing and are subject to auditing. Simulated drive cycles can be physically audited by having an AV follow a vehicle, driven to follow the EPA drive cycles on a test track.

5.2: Methods:

5.2.1: Autonomous Drive Cycle Simulation:

The Autonomous Drive Cycle was derived from the EPA City (FTP) and Highway (HWFET) fuel economy testing cycles; and a set of rules describing how an autonomous vehicle would react to a leading car. The EPA drive cycles provides the velocity of the vehicle on a 10 hertz cycle (EPA n.d. C). The position and acceleration used the integral and derivative of each 1/5 second's position pairs, respectively. This information was then entered into a program that would query the lead vehicle's position and velocity, in meters and m/s every 1/10 second and calculate headway, placing the lead vehicle five meters ahead at time 0. At the end of each time step the simulation would query a set of rules to obtain the velocity and acceleration for the beginning of the next time step. At the end of each time step the autonomous vehicle's position, velocity and acceleration were recorded.

5.2.2: Autonomous Driving Behavior

Car following behavior was divided into different sets of rules. These rules included basic ACC and CACC methodologies. The ACC method is meant to simulate basic ACC systems, similar to those already on the market. The CACC method is meant to simulate posited and in-development technology that would allow vehicles to communicate with each other and infrastructure to improve traffic flow. All specific methods used in this chapter are basic and generalized to run on all vehicles. They are not necessarily the most optimal for fuel efficiency. The primary contribution of this research is the process for testing the fuel economy of autonomous vehicles and deriving the autonomous drive cycles, rather than optimizing the control methods that lead to those cycles.

Two basic ACC methods were developed and tested. The first, termed HeadwayACC, follows a simple set of bounding rules and direct calculation of the exact acceleration needed to achieve minimum safe following distance or headway and the acceleration needed to achieve the desired headway. Both headway and distance measures are needed to correct for headway approaching ∞ as the velocity approaches 0. The goal of the strategy is to attempt to reach and maintain a target headway behind a lead vehicle. The rules are described in Equation IV-1 through Equation IV-5 and the variables are defined in Table IV-3.

Equation IV-1 describes the acceleration necessary to reach the minimum safe following distance by the next time step. The first two terms determine the acceleration to close the distance to 0 m and the third term is to ensure a safe distance, either in terms of a minimum distance or headway. Equation IV-2 is used to determine whether to use minimum headway or minimum space as the target in Equation IV-1. Equation IV-3 determines the acceleration necessary to reach the target headway behind the lead vehicle by the next time-step. The equation is derived from the general form equation of motion with constant acceleration, the relative velocities of the two vehicles, the current space between the two vehicles and the target headway. Equation IV-4 and Equation IV-5 are used to compare the two previous determined accelerations to the acceleration bounds and choose an acceleration. The second part of the "and" conditional in Equation IV-5 is necessary to correct for when accelerating, a_{safe} will close the gap beyond the target headway. Here a_{safe} is only used for decelerations.

Equation IV-1

$$a_{safe} \geq \frac{space}{step^2} + \frac{v_{lead} - v_{self}}{step} - \frac{buffer}{step^2}$$

Equation IV-2

$$buffer = \max\left(1\, meter, \frac{v_{self}}{headway_{min}}\right)$$

Equation IV-3

$$a_{target} = \frac{-space + headway_{target} * v_{self} + v_{self} * step - v_{lead} * step}{step^2 - headway_{target} * step}$$

Equation IV-4

$$bound(x, y, z) = \max(\min(x, y)\,, z)$$

Equation IV-5

$$if\ a_{safe} \leq a_{target}\ and\ a_{safe} \leq 0:$$

$$then\ a_{new} = bound(a_{safe}, a_{max}, a_{min})$$

$$else: a_{new} = bound(a_{target}, a_{max}, a_{min})$$

Table IV-2: Variable Definitions for Control Functions

Variable Name	**Definition**
a_{safe}	$acceleration\ to\ reach\ minimum\ safe\ headway$
a_{target}	$acceleration\ to\ reach\ desired\ headway$
v_{self}	$current\ follower\ velocity$
a_{new}	$decided\ acceleration$
$a_{max,min}$	$min\ \&\ max\ acceleration/deceleration$
v_{lead}	$current\ leader\ velocity$
$s = space$	$current\ space$
$headway$	$current\ headway$
$headway_{min}$	$minimum\ safe\ headway = 3\ s$
$T_d = headway_{target}$	$target\ headway$
$buffer$	$minimum\ safe\ spatial\ distance$ (m)
$step$	$timestep\ duration = 0.1\ s$
v_d	$desired\ speed$
v_e	$speed\ error, difference\ between\ current\ and\ desired\ velocities$
a_{sc}	$acceration\ by\ speed\ control$
s_d	$desired\ spacing$
s_e	$spacing\ error$
$t_{horizon}$	$planning\ horizon$
$t_{interval}$	$planning\ interval$
p_{lead}	$absolute\ position\ of\ the\ lead\ vehicle$
p_{self}	$absolute\ position\ of\ the\ following\ vehicle$

Additionally, the vehicle will not start moving if currently stopped and the lead vehicle is also stopped and less than 10 meters ahead. The vehicle will also adjust its acceleration to never exceed 60 mph or go into reverse. This ruleset was tested with acceleration bounds of +/-2, 1.5/-2 and +1/-2 m/s^2.

The second ACC method used, VelocityACC, is a modified form of that used in Shladover et al.'s (Shladover et al. 2012b) CACC platoon simulation. VelocityACC's rules are similar to those used by Shladover et al., but with additions to account for the more dynamic driving conditions of urban streets. The goal of this method is to attempt to reach a target speed and maintain that speed, if feasible. This is opposed to the HeadwayACC method where the goal is to reach a target headway. According to Shladover et al.'s original rules the vehicle can be in either speed control or gap control. If in speed control the new acceleration is described by Equation IV-6 and Equation IV-7.

Equation IV-6 calculates the difference between the vehicle's current speed and the predefined desired speed. Equation IV-7 then sets the control acceleration at 40% of the speed error, or the acceleration bounds. The 40% constant comes from Shladover et al.'s (2012) original control scheme and functions to smooth out acceleration changes.

Equation IV-6

$$v_e = v_{self} - v_d$$

Equation IV-7

$$a = a_{sc} = bound(-0.4 * v_e, a_{Max}, a_{Min})$$

In gap control Equation IV-8 through Equation IV-10 also apply. Equation IV-8 defines the desired spacing gap as the product of the desired headway time and the current speed. Equation IV-9 defines the spacing error as the difference between the current gap and the desired spacing gap calculated in Equation IV-8. Finally, Equation IV-10 sets the acceleration with regard to the possible acceleration bounds and a desired acceleration of the sum of the current gap and a quarter of the spacing error.

Equation IV-8

$$s_d = T_d * v_{self}$$

Equation IV-9

$$s_e = s - s_d$$

Equation IV-10

$$a = bound(s + 0.25 * s_e, a_{sc}, a_{Min})$$

Further inclusions were that the vehicle will not start if the lead vehicle is close and stationary, as in the previous control scheme, and that the vehicle will check to see what is the acceleration needed for minimum safe following distance, as in the previous set, and follow that if the car chooses to decelerate inadequately, up to -2 m/s^2.

For this study the desired speed was set as 60 mph and the desired headway as 3 seconds. The vehicle will enter speed control when spacing is greater than a "speed space" and gap control when under a "gap space" and, when between, will use the last used control set, defaulting to gap control. These spaces are dependent on speed: above 40 mph, freeway speeds, the spaces are 120 and 100 meters respectively: between 25 mph and 40 mph, urban speeds, the spaces are 80 and 65 meters; and under 25 mph, local speeds, the spaces are 50 and 42 meters. The spacing for highway speeds is that used by Shladover et al. (Shladover et al. 2012b) and the others are based upon a 3.7 second headway at maximum speed cutoff, which is roughly what the freeway speed settings use. As with the previous ruleset these rules were tested with acceleration bounds of +/-2, 1.5 and 1 m/s^2.

Another control method tested was based upon connected-autonomous features. Greater improvements in acceleration and velocity stability, and therefore fuel economy, can be gained if vehicles communicate information about their current positions, velocities, and future plans with each other. The amount of information that will be shared is currently unknown and the gains from using this information will be influenced by the percentage of vehicles on the road and roadway infrastructure using the technology. A bounding case is a vehicle having perfect information on what conditions will be in front of it for a defined period of time into the future. This can be used as a proxy to estimate the effects the near future of connected vehicle technology may bring to fuel economy of an individual vehicle. The following control method, PlannedACC, was developed to simulate a control strategy under such conditions.

The rules for this PlannedACC cruise control strategy are as follows:

Starting at time 0, the following vehicle will query the lead vehicle's planned position, for the next $t_{horizon}$ and run Algorithm 1.

Algorithm 1: PlannedACC Overview

$$a_{try} = a_{max}$$

$$if\ v_{Self} = 0\ and\ v_{Lead} = 0\ and\ space\ <\ 10\text{:}$$

$$then\text{: } a_{new} = 0, \qquad break\ \#\#the\ following\ lines\ are\ not\ executed$$

$$for\ t \leq t_{horizon}\text{:}$$

$$if\ a_{try} < a_{min}\text{: } break\ \#\#crash\ is\ unavoidable\ trial\ is\ a\ failure$$

$$v_{try} = v_{self} + a_{try} * step$$

$$p_{try} = p_{self} + v_{try} * step$$

$$space_{try} = p_{lead}(t) - p_{try}$$

$$if\ space_{try} < 5\ meters\ or\ space_{try} < hedway_{min}\text{:}$$

$$then\text{: } t = t + step, \qquad a_{try} = a_{try} - 0.1$$

$$else\text{: } a_{new} = a_{try}$$

This process is then repeated every $t_{interval}$ seconds. Additionally the vehicle will ensure that it does not exceed the speed limit or reverse. The 5-meter absolute space minimum was found through trial and error to be the point where gains in safety dropped off considerably. These rules are explained verbally below.

- The following vehicle will query the lead vehicle's position, in relationship to the following vehicle's current position, every 1/10 second for the following X seconds. Various values of X are tested.
- The following vehicle will then determine if it can accelerate at a user defined maximum acceleration for the following X seconds.
  - If the vehicle falls within a user specified minimum buffer of absolute space or time headway, then the vehicle will then try again at a lower acceleration, continuing until it finds a solution or reaches and uses a user defined minimum (de)acceleration.
    - If the vehicle is ever assumed to exceed the speed limit or reverse, the software will replace the velocity for that time-step with either the speed limit or a stop, respectively.
- The vehicle will then travel for the next Y seconds at the decided upon acceleration, after which it will start the process again.
  - With Y always being less than X
    - $X - Y$ must be greater the minimum headway
- In addition the vehicle will not start from a stop if the lead vehicle is also stopped and within a user defined buffer space.

This method is designed to stabilize the acceleration curve, minimizing the number of times acceleration changes. This would be expected to reduce fuel consumption. This was tested 4 times, with acceleration bounds of +/-1 and 2 m/s^2 and X-Y pairs of 3-2 and 5-3 seconds. This allows testing of what the possible gains from connected vehicle features may be as their predictive ability increases. This method is not appropriate to measure any specific connected vehicle control function. Rather it models how far into the future a vehicle following a similar control strategy would need to be able to confidently predict the state of the road, in order to deliver fuel efficiency gains. This then acts as an initial proxy for the near- and mid-term feasibility of such a method and technology. Noticeable gains in efficiency at a few seconds of predictive power could be meaningful, but if several minutes of predictive ability are necessary to see changes, one might conclude that it will not be feasible to implement. The parameters for each of the rulesets are summarized in Table IV-3, with a common maximum speed of 26.8 m/s (60 mph).

Table IV-3: Rulesets' Parameters ("N/A" indicates an unused parameter)

Rule Set	**Normal Acceleration Bounds (m/s^2)**	**Maximum Deceleration for Safety (m/s^2)**	**Plan Ahead Time (s)**	**Planning Interval (s)**	**Target Headway (s)**	**Minimum Headway (s)**	**Minimum Safe Distance (m)**
HeadwayACC 1	+/- 2	-2	N/A	N/A	3	N/A	1
HeadwayACC 2	+1.5 / -2	-2	N/A	N/A	3	N/A	1
HeadwayACC 3	+1 /- 2	-2	N/A	N/A	3	N/A	1
VelocityACC 1	+/- 2	- 2	N/A	N/A	3	N/A	1
VelocityACC 2	+/- 1.5	- 2	N/A	N/A	3	N/A	1
VelocityACC 3	+/- 1	- 2	N/A	N/A	3	N/A	1
PlannedACC 1	+/- 2	N/A	3	2	N/A	1	5
PlannedACC 2	+/- 2	N/A	5	3	N/A	1	5

5.2.4: Fuel Economy Estimation

Fuel Economy was estimated using the Virginia Tech Comprehensive Fuel Consumption Model (Edwardes and Rakha 2014; Park et al. 2013; Rakha et al. 2011b; Saerens et al. 2013). This model relies upon publicly available vehicle and engine characteristics, as well as the official EPA fuel economy ratings for commercially available vehicles. This model has been validated in two separate papers. In a 2011 paper (Rakha et al. 2011b) three passenger vehicles, the Ford Explorer, Saturn SL and Honda Accord were put on a dynamometer and run for the Arterial Level of Service (LOS) A cycle, the LA92 cycle and the New York cycle. The instantaneous fuel consumption physically measured was then compared to the model's estimated consumption. They were all highly correlated, with R-squared values exceeding 0.9 and had slopes varying between 1 and 1.3, averaging at 1.1, suggesting slight overestimates in fuel consumption and varying good predicting power (Rakha et al. 2011b).

Park et al.'s 2013 follow-up paper (Park et al. 2013) validates the model against on-road driving, specifically on U.S. Interstate 81 between miles 118 and 132. Notably, unlike a dynamometer, this roadway section includes positive and negative grades. Six light duty vehicles, four passenger vehicles and two SUVs, were tested; a 2001 SAAB 95, a 2006 Mercedes R350, a 2008 Chevrolet Tahoe, a 2007 Chevy Malibu, a 2008 Hybrid Chevy Malibu, and a 2011 Toyota Camry. A DashDAQ unit was used to record speed and fuel consumption and cruise control was both used and not used an equal number of iterations for each vehicle. Using the default model calibration settings, the averaged R-squared values for each vehicle's instantaneous fuel consumption, measured and estimated, were found to be between 0.90 and 0.98, while the slopes were between 0.97 and 1.02, showing consistent goodness of fit, in aggregate (Park et al. 2013). Individual tests were not as good, with R-squared values as low as 0.8 and slopes between 0.72 and 1.62, showing somewhat less goodness of fit (Park et al. 2013). For overall fuel economy this led to a difference of up to +/- 36% between measured and estimated values (Park et al. 2013). However, what is most important is that the Virginia Tech Comprehensive Fuel Consumption Model correctly states whether a certain driving pattern is more or less efficient than another one. In terms of cruise control versus manual driving and driving northbound or southbound both the measured data and the modeled results showed the same trends in either direction (Park et al. 2013).

The Virginia Tech Comprehensive Fuel Consumption Model, was therefore seen as appropriate for this research. I only used vehicles that at least one of the two validating papers had used. I used the 2010 Honda accord used in (Rakha et al. 2011b) and the 2011 Toyota Camry, the 2007 Chevy Malibu and 2008 Chevy Malibu Hybrid, used in (Park et al. 2013). The vehicle parameters I used are identical to the ones used in these validating papers. This gives a comparison of three different manufacturers and a separate test for hybrid vs. conventional vehicles.

The model requires certain vehicle characteristics as inputs and a 1 hertz velocity schedule. As the vehicle following simulation used 10 hertz, every 10th point of velocity was used. While the greater precision was necessary for the control function, it was determined that it would not considerably increase accuracy for fuel economy estimation. The vehicle characteristics used are listed in Table IV-4. The program outputs a file containing the instantaneous consumption of fuel, in liters per second. This was summed to find the total fuel consumption for each control strategy and cycle combination. The total distance that the automated vehicle traveled was then computed and divided over the fuel consumption to find the fuel economy, which was then converted to miles per gallon (mpg).

Table IV-4: Vehicle characteristics for Virginia Tech Comprehensive Fuel Consumption Model (VTCFCM) (Edwardes and Rakha 2014; Park et al. 2013; Rakha et al. 2011b; Saerens et al. 2013)

Description	**Accord**	**Camry**	**Malibu**	**Malibu Hybrid**
Model Year	2010	2011	2007	2008
Wheel Radius (m)	0.3322	0.3322	0.32375	0.3322
Redline RPM	6800	6300	6000	6000
Drag Coefficient	0.30	0.28	0.34	0.34
Frontal Area (m^2)	2.32	2.424	2.318	2.313
Wheel Slippage	0.035	0.035	0.035	0.035
Cylinders	4	4	4	4
Engine Liters	2.354	2.5	2.2	2.4
Gears	5	6	4	4
1st Gear Ratio	2.652	3.54	2.96	2.96
2nd Gear Ratio	1.517	2.05	1.62	1.62
3rd Gear Ratio	1.037	1.38	1	1
4th Gear Ratio	0.738	0.98	6.8	6.8
5th Gear Ratio	0.566	0.74	0	0
6th Gear Ratio	0	0.66	0	0
Final Drive Ratio	4.44	3.82	3.63	3.63
Mass (kg)	1453	1500	1440	1604
Urban Rating (mpg)	22	22	24	24
Freeway Rating (mpg)	31	33	34	32
Rolling Coefficient	1.75	1.75	1.75	1.75
C1	0.0328	0.0328	0.0328	0.0328
C2	4.575	4.575	4.575	4.575
Driveline Efficiency	0.92	0.92	0.92	0.92
Idling Speed (rpm)	700	660	680	660

5.3: Results

5.3.1: Drive Cycles

The purpose of developing the automated driving rules and cycles was to enable comparison of the plausible differences in fuel efficiencies for autonomous and human driving. One of the methods that an autonomous vehicle can use to improve fuel economy is to lower the magnitudes of its acceleration and deceleration and how quickly it changes acceleration and deceleration. It can be expected in most cases that a drive cycle where these are moderated would be more efficient than another, all else being equal. This study used the FTP and HWFET drive cycles as the basis for a representative human driver and assumes that an automated vehicle would be following a human-driven car. Therefore improvements will come from the vehicle deciding to lower the amplitudes of accelerations and decelerations, which is directly set by the rules, and the smoothness of changes in accelerations and decelerations.

The HeadwayACC method performs similarly to the PlannedACC method. Both have similar acceleration bounds and similar rates of change in acceleration as compared to the EPA's cycles, even when allowed more. The PlannedACC does keep acceleration constant for longer periods than the HeadwayACC method. The VelocityACC method has larger acceleration bounds, when allowed, and switches accelerations much quicker than the other methods and the EPA's cycles. On the basis of acceleration bounds and changes alaone, it is expected that the VelocityACC method would have a lower fuel economy, the HeadwayACC method a slightly higher fuel economy and the PlannedACC ruleset an even higher fuel economy than the car following the EPA's drive cycles.

5.3.2: Fuel Economy

Table IV-5 though Table IV-8 shows the fuel economies of the drive cycles for the simulated vehicles* and the percentage change from the modeled fuel economy for the EPA's drive cycles. Rated fuel economies are notably lower than simulated EPA cycles, due to usage of the extra 3 cycles for the rated fuel economies. The HeadwayACC control method was better than the EPA's cycle, for urban driving, with improvements varying from 3 to 4%. For freeway conditions the HeadwayACC cycles had fuel economies gaiuns of roughly half those in urban settings, normally about 2%. The VelocityACC control strategy performed consistently delivered decreases in fuel economy. These were 2-3% for urban cycles and under 1% for freeway driving. The PlannedACC method always showed improvement in fuel economy, for both the urban and freeway cycles. For the city cycles fuel economy gains were greater than HeadwayACC, and varied between 2% and 4%. PlannedACC for freeway cycles improved fuel economy between 1% and 2%. PlannedACC, surprisingly, performed worse than HeadwayACC. This seems to suggest that focusing on constant acceleration alone is not an optimal control strategy. Note that VelocityACC and was not stable when acceleration bounds were decreased and crashed for ruleset 3, in urban conditions. This result was not reported.

Table IV-5: Simulated Fuel Economy Results for 2010 Honda Accord

2010 Honda Accord	**Fuel Economy (mpg)**	**Percent Change from EPA**
EPA Urban (FTP)	25.9	
EPA Freeway (HWFET)	43.2	
HeadwayACC Urban 1	26.8	3.7%
HeadwayACC Freeway 1	44.1	2.0%
HeadwayACC Urban 2	26.8	3.7%
HeadwayACC Freeway 2	44.1	2.0%
HeadwayACC Urban 3	26.6	3.0%
HeadwayACC Freeway 3	44.1	2.0%
VelocityACC Urban 1	25.7	-0.7%
VelocityACC Freeway 1	43.0	-0.6%
VelocityACC Urban 2	25.3	-2.3%
VelocityACC Freeway 2	43.0	-0.6%
VelocityACC Freeway 3	42.4	-2.0%
PlannedACC Urban 1	26.4	2.0%
PlannedACC Freeway 1	43.6	0.9%
PlannedACC Urban 2	26.6	2.7%
PlannedACC Freeway 2	43.9	1.4%

Table IV-6: Simulated Fuel Economy Results for 2011 Toyota Camry

2011 Toyota Camry	**Fuel Economy (mpg)**	**Percent Change from EPA**
EPA Urban (FTP)	26.8	
EPA Freeway (HWFET)	46.2	
HeadwayACC Urban 1	27.8	3.6%
HeadwayACC Freeway 1	47.1	2.0%
HeadwayACC Urban 2	27.8	3.6%
HeadwayACC Freeway 2	47.1	2.0%
HeadwayACC Urban 3	27.6	2.9%
HeadwayACC Freeway 3	47.1	2.0%
VelocityACC Urban 1	26.6	-0.7%
VelocityACC Freeway 1	45.9	-0.6%
VelocityACC Urban 2	26.2	-2.3%
VelocityACC Freeway 2	45.9	-0.5%
VelocityACC Freeway 3	45.2	-2.1%
PlannedACC Urban 1	27.3	2.0%
PlannedACC Freeway 1	46.6	0.9%
PlannedACC Urban 2	27.5	2.7%
PlannedACC Freeway 2	46.9	1.5%

Table IV-7: Simulated Fuel Economy Results 2007 Chevy Malibu Conventional

2007 Chevy Malibu Conventional	**Fuel Economy (mpg)**	**Percent Change from EPA**
EPA Urban (FTP)	23.0	
EPA Freeway (HWFET)	33.7	
HeadwayACC Urban 1	24.0	4.5%
HeadwayACC Freeway 1	34.3	2.0%
HeadwayACC Urban 2	24.0	4.5%
HeadwayACC Freeway 2	34.3	2.0%
HeadwayACC Urban 3	23.9	3.8%
HeadwayACC Freeway 3	34.3	2.0%
VelocityACC Urban 1	22.8	-0.9%
VelocityACC Freeway 1	33.5	-0.6%
VelocityACC Urban 2	22.4	-2.6%
VelocityACC Freeway 2	33.5	-0.5%
VelocityACC Freeway 3	33.0	-2.1%
PlannedACC Urban 1	23.6	2.4%
PlannedACC Freeway 1	34.0	0.9%
PlannedACC Urban 2	23.8	3.4%
PlannedACC Freeway 2	34.2	1.5%

Table IV-8: Simulated Fuel Economy Results 2008 Chevy Malibu Hybrid

2008 Chevy Malibu Hybrid	**Fuel Economy (mpg)**	**Percent Change from EPA**
EPA Urban (FTP)	26.9	
EPA Freeway (HWFET)	44.7	
HeadwayACC Urban 1	27.9	4.0%
HeadwayACC Freeway 1	45.7	2.2%
HeadwayACC Urban 2	27.9	4.0%
HeadwayACC Freeway 2	45.7	2.2%
HeadwayACC Urban 3	27.7	3.2%
HeadwayACC Freeway 3	45.7	2.2%
VelocityACC Urban 1	26.6	-0.8%
VelocityACC Freeway 1	44.4	-0.6%
VelocityACC Urban 2	26.2	-2.6%
VelocityACC Freeway 2	44.4	-0.6%
VelocityACC Freeway 3	43.7	-2.2%
PlannedACC Urban 1	27.4	2.2%
PlannedACC Freeway 1	45.1	0.9%
PlannedACC Urban 2	27.7	3.0%
PlannedACC Freeway 2	45.4	1.5%

All percentage changes were calculated from simulated fuel economies for both the EPA and Automated cycles, to ensure trends in simulated uncertainty are constant. Calibration research on the Virginia Tech Comprehensive fuel consumption model showed that directions and relative magnitudes in fuel consumption changes were accurate, even if absolute values were not perfect (Park et al. 2013) (Rakha et al. 2011b) (Park et al. 2013), ensuring the relative integrity of the results. The losses in fuel economy in VelocityACC appear to be due to temporary stability losses caused by an inability of these methods to predict the future and plan ahead.

If the 2010 Accord were equipped with the necessary technology for the above automated control strategies, one could then use the results above to envision what the proposed process would look like. First the process can be simplified to only include the derived autonomous tests and original Urban and Freeway cycles, each weighted evenly with their counterpart, for the urban and freeway rating, respectively. The combined fuel economy rating would follow the current 55% urban 45% freeway split (EPA 2014a). Honda would abstract their vehicle control rules to run on a level straight road and work with complete knowledge of the location of the vehicle in front of it. Honda would then record the velocity schedules and run dynamometer testing, using 4 test cycles, the original 2 FTP and HWFET cycles and their 2 derived ones. The results of both freeway and both urban tests would then be averaged to find the new fuel economy sticker ratings, so for the VelocityACC control method urban fuel economy would decrease 0.2, freeway 0.3 mpg, while with HeadwayACC they would both rise 0.9 mpg. Possible blended fuel economies for other weighting methods are shown in Table IV-9. This shows a definite benefit for autonomous features, as a ~1-mpg gain may well improve sales, help with compliance, and reduce emissions. The fully autonomous features could still help or hurt CAFE requirements for different manufacturers. This is especially important as automation is becoming much more common. A 1-3% gain or loss across a full fleet would be considerable. Additionally any fleet gains and losses in fuel economy directly limit or enable increased sales of larger, less fuel efficient, and more profitable vehicles.

Table IV-9: Blended Fuel Economies for 2010 Honda Accord

ACC Ruleset	Traditional Cycle Weight (%)	Autonomous Cycle Weight (%)	Simulated Weighted Fuel Economy (MPG)	Weighted % change from EPA
FTP Urban Cycle (22)*	100	0	25.9	N/A
HWFET Freeway Cycle (31)*	100	0	43.2	N/A
EPA Combined (25)*	100 (55% City / 45% Highway)	0	33.7	N/A
HeadwayACC City 1	80	20	26.1	0.7%
HeadwayACC Freeway 1	80	20	43.4	0.4%
Headway ACC Combined 1	80	20	33.9	0.5%
HeadwayACC City 1	60	40	26.2	1.5%
HeadwayACC Freeway 1	60	40	43.6	0.8%
Headway ACC Combined 1	60	40	34.0	1.1%
HeadwayACC City 1	40	60	26.4	2.2%
HeadwayACC Freeway 1	40	60	43.8	1.2%
Headway ACC Combined 1	40	60	34.2	1.6%
HeadwayACC City 1	20	80	26.6	2.9%
HeadwayACC Freeway 1	20	80	43.9	1.6%
Headway ACC Combined 1	20	80	34.4	2.1%
VelocityACC City 1	80	20	25.8	-0.1%
VelocityACC Freeway 1	80	20	43.2	-0.1%
VelocityACC Combined 1	80	20	33.6	-0.1%
VelocityACC City 1	60	40	25.8	-0.3%
VelocityACC Freeway 1	60	40	43.1	-0.2%
VelocityACC Combined 1	60	40	33.6	-0.3%
VelocityACC City 1	40	60	25.7	-0.4%
VelocityACC Freeway 1	40	60	43.1	-0.3%

ACC Ruleset	Traditional Cycle Weight (%)	Autonomous Cycle Weight (%)	Simulated Weighted Fuel Economy (MPG)	Weighted % change from EPA
VelocityACC Combined 1	40	60	33.6	-0.4%
VelocityACC City 1	20	80	25.7	-0.6%
VelocityACC Freeway 1	20	80	43.0	-0.5%
VelocityACC Combined 1	20	80	33.5	-0.5%
PlannedACC City 2	80	20	26.0	0.5%
PlannedACC Freeway 2	80	20	43.4	0.3%
PlannedACC Combined 1	80	20	33.8	0.4%
PlannedACC City 2	60	40	26.1	1.1%
PlannedACC Freeway 2	60	40	43.5	0.6%
PlannedACC Combined 1	60	40	33.9	0.8%
PlannedACC City 2	40	60	26.3	1.6%
PlannedACC Freeway 2	40	60	43.6	0.8%
PlannedACC Combined 1	40	60	34.1	1.2%
PlannedACC City 2	20	80	26.4	2.2%
PlannedACC Freeway 2	20	80	43.7	1.1%
PlannedACC Combined 2	20	80	34.2	1.6%

*Rated fuel economies are notably lower than simulated, due to usage of the extra 3 cycles for the rated fuel economies

5.3.3: Parameter Sensitivity

Both HeadwayACC and VelocityACC are sensitive to desired headway. HeadwayACC increases fuel economy by 0.8-1.1% and 0.4-0.5% for each second of headway, from 2 to 6 seconds for freeway and urban conditions, respectively. VelocityACC increases fuel economy by 0.4-0.9% and 0.3-0.6% for each second of headway, from 2 to 6 seconds for freeway and urban conditions, respectively. The increases in headway serve to guard from instability, limiting the need to brake using the safety override, Equation IV-1. However, increasing headway excessively would decrease effective lane capacity, in aggregate. This leads to questions on how to balance fleet fuel economy and individual fuel economy. This paper only investigates the latter, as does current testing methods. In addition, in real world conditions, it would allow and encourage vehicle to merge in front of the vehicle, which may require unplanned breaking. This could lead to decreases in real world performance, when increasing headway. The proposed methodology would not capture this effect.

For the PlannedACC control strategy desired headway was not a parameter. Instead, the plan ahead and re-planning intervals were modified to vary between 1 and 6 seconds for each. As expected, the longer the vehicle plans into the future, the greater the fuel economy benefits. The interval between changes in acceleration however, must be smaller than the time the vehicle plans for. Equal plan ahead and re-plan intervals almost always lead to decreased fuel efficiency and are always less efficient than if they were different, for a given planning interval. The buffer between these two intervals ensures the smoother acceleration pattern, which allows for the efficiency gains. Overall fuel economy gains were shown at all times where the time between restarting the planning algorithm was shorter than the time it could look ahead, suggesting fuel economy gains are possible with any level of predicative ability from connected features.

Decreasing the difference between the planning times, in addition to being less efficient, is also not always safe. For both 2 seconds and 6 seconds of planning time vehicles crash when the re-planning time is equal. This is due to the limited headway emphasis and simplifications that ignored rules that would be necessary for safety outside normal operation. Crashes can occur in this method when the speed at which the vehicle is traveling at the end of each re-planning interval is high enough to cover the distance between the vehicles in the time between the re-plan and planning intervals. As the minimum headway is 1 second, any difference less than that can lead to a crash. For example, if over the next 6 seconds it is found safe to accelerate to 60 mph and the vehicle accelerates for the full 6 seconds while the lead vehicle is stopped, there will be at least 27 meters between the two vehicles before the next decision is made. The maximum 2 m/s^2 will not allow the following vehicle to safely stop within this distance. In reality, all control methodologies would have contingency rules that would allow uncomfortably fast decelerations. This was ignored here, both for simplicity and because the test cycles are not meant to examine extreme situations. Additionally one of the main predicted advantages of connected-autonomous vehicles is the ability to safely reduce headway. Therefore, modifying the control rules to increase headway, rather than maintain a difference between the two planning intervals would not represent ultimate likely conditions.

5.4: Summary and Conclusions

Autonomous vehicle driving behavior can have a considerable effect on fuel economy. Here I proposed a standardized method for testing the fuel economy effects of autonomous vehicle behavior when following another vehicle. The method consists of two steps, and is applicable in the near-term, when AVs will travel in traffic with primarily conventional vehicles. First the driverless vehicle's control strategy is abstracted for simulation to a simple one lane and one dimensional road, with only one leading vehicle and perfect visibility; it is then run following a vehicle obeying the EPA's FTP and HWFET drive cycles. These derived drive cycles are then to be tested with a dynamometer, similar to current testing. A series of simplified rulesets was then developed for ACC behavior and their car following behavior was simulated for the EPA's drive cycles. Fuel economy was estimated using the Virginia Tech Comprehensive Fuel Consumption model. Results showed considerable variation in fuel economy, with the simplest ruleset showing decreases in performance, and a slightly more complicated and less-aggressive ruleset showing both minor improvements and decreases in fuel economy. Another control algorithm, relying upon an assumption of predictive ability provided by connected autonomous vehicles was shown to consistently provide improvements in fuel economy.

The results of this study have shown that following control algorithms designed without considering fuel economy performance can perform significantly worse, while more intelligently designed control schemes may equal or exceed the base driver performance assumed by the EPA fuel economy tests. At present, with no incentive to design more fuel efficient autonomous rulesets, manufacturers may not design for increased fuel economy. They may design a system to maximize speed and/or acceleration, by default or as an option. This would be similar to the poor performing VelocityACC ruleset we tested, which often had worse fuel economy than the EPA fuel cycle. In addition, this study found more advanced connected features can improve performance consistently and significantly, by improving the amount of time a vehicle can predict actions in the future. While the basic testing method outlined here would have to be expanded to meet U.S. regulatory requirements in order to test automated vehicles, it does show the need for a new testing procedure. This chapter also only tested an AV's performance when following another vehicle following specific rules, not unconstrained or able to pass. Therefore, this chapter only compares fuel economy changes when compared against the EPA cycles, which may be different than how a human driver would perform under similar restrictions. The fuel consumption model used precluded any testing of grade-based optimization. This study demonstrated that simulations of a car with autonomous features following another vehicle obeying the EPA drive cycle can be used as a standardized method to create a drive cycle to test fuel economy.

The results suggest that this method can be used to demonstrate how AV behavior may affect fuel economy in vehicles following similar traffic patterns to those currently assumed by the EPA. These results are limited by: the simplification of control strategies; the accuracy of the fuel consumption model used; and the usage of the EPA Urban and Freeway drive cycles, which likely do not reflect the real conditions in which the initial AVs may be operating. With these factors noted, I found a range of possible automation outcomes from fuel economy losses of up to 3% to gains of up to 5%.

This study used the current EPA Urban and Freeway fuel economy drive cycles as the base for the automated following cycles. This may not be appropriate for the expected future of NHSTA Levels 2 and 3 AVs (NHTSA 2013). These vehicles are not expected to be able to drive themselves in all conditions. Instead they are to have a limited subset of conditions in which they may enter an autonomous mode. Therefore, the leader drive cycle should be designed to account for these situations. In addition, the approach used here is for the near-term evaluation of AV technologies. As technology and adoption increases and the system becomes more efficient, the driving behavior of the lead vehicle as well as the entire system will change. Hence, car following algorithms will have less predictive power. What is clear is that rapid progress is being made in the development of and market for autonomous and connected vehicles and that AV technology affects individual vehicle fuel economy. Given this, stakeholders can use the methods outlined here as a starting point in the discussions for the best path forward.

Chapter V Conclusions, Contributions, Policy Implications, and Future Work

6.1 Summary

New technologies such as vehicle electrification and automation offer the potential to greatly reduce the externalities associated with mobility and transport. Chapter I discussed some of the many externalities currently associated with transport and travel and how vehicle electrification and automation might affect them. Under the predominantly petroleum-fueled status quo, these externalities include oil security, air pollution, climate change, congestion, traffic accidents, and noise. The estimated per gallon of gasoline values of these externalities are shown in Chapter I, Figure 0-1. Some of these externalities have been decreasing; crashes, for example, have been decreasing since 1990. Total crashes only increased for the first time in 2015 (US DOT 2017b). Oil consumption has been decreasing per mile traveled for the past decade and is projected to decrease over the coming decades (EIA n.d.; USDOT FHA 2017).

Autonomous and electric vehicle technologies have the potential to drastically reduce the externalities associated with passenger travel. Driver error and impairment are estimated to be contributing factors in about 90% of all U.S. roadway crashes (Dingus et al. 2016) and current autonomous technology could mitigate one-third of U.S. crashes (Harper et al. 2016b; US DOT 2017b), but could potentially raise VMT (Harper et al. 2016a; James M. Anderson et al. 2014). Electrification removes the oil security costs by changing the fuel type, while also increasing an individual vehicle's efficiency (Chae et al. 2011; Gautam et al. 2011; Miller et al. 2011; US DOE n.d.). Automation may increase, or decrease, vehicle efficiency and network performance (Asadi and Vahidi 2011; James M. Anderson et al. 2014; Mersky and Samaras 2016; Park et al. 2011; Rakha et al. 2011a). Automation also has the potential to either increase, or decrease, VMT (Childress et al. 2015; Fagnant and Kockelman 2015; Harper et al. 2016a; James M. Anderson et al. 2014; Martin et al. 2010).

This dissertation contributes to the literature by addressing four components necessary to ensure that these new technologies contribute to a socially optimal outcome. These four components are: being able to determine if adopting new technologies, for a specific locality and purpose, would provide a social benefit; knowing how to encourage adoption of a technology; knowing how to optimally construct necessary infrastructure for the new technologies; and being able to effectively regulate technologies so that their future development increases social value. This dissertation addressed each issue in a chapter focusing on specific novel applications and case studies.

6.2 Contributions

Chapter II focused on the issue of determining the social value of implementing a new technology with a case study of the City of Pittsburgh's municipal vehicle fleet, and also potentially adding solar power or renewable-energy credits. A municipality evaluating a potential transition to an electrified vehicle fleet has its own set of decision criteria. Several cities have been exploring ways to simultaneously increase both distributed solar photovoltaic (PV) generation and electric vehicle (EV) charging infrastructure. While most PV installations would not directly charge an electric vehicle, PV installations would start to change the emissions from electricity purchased by municipalities, which would influence their decisions and performance metrics. Chapter II contributed to the literature by conducting a life-cycle assessment and cost-benefit analysis for municipal fleet electrification decisions, using Pittsburgh, Pennsylvania, as a case study. The analysis included Pittsburgh's municipal permitting vehicle fleet over several electricity grid scenarios, and it assessed the use of PV installations at city-owned parking facilities. Costs were included while comparing vehicle options, as were the emissions and externality costs of GHGs, SO_2, and NO_x from both direct and upstream effects. For Pittsburgh's municipal fleet BEVs, but not PHEVs, were found to have lower life cycle GHG emissions than HEVs. However, vehicle electrification was found likely to have higher total social emissions costs than conventional options. As the electricity grid transitions to lower-polluting sources, EVs likely have clear advantages over conventional vehicles. PV systems built over city parking facilities could power the equivalent of more than 30 times the yearly travel of the municipal vehicle fleet. The necessary structures to preserve parking spaces, while providing PV, make this system cost-prohibitive. By providing a comprehensive life-cycle assessment and analysis, this chapter provided a method for municipalities, counties, states, and other stakeholders to evaluate the potential benefits and costs of vehicle electrification.

Chapter III focused on how predict the adoption of a technology by investigating the predictive power of demographics and incentives on EV sales in Norway. Current EVs tend to be more expensive and have shorter range, which can hinder public adoption. Norway has a long history of incentivizing BEV adoption, including measures such as exemption from roadway tolls, access to charging infrastructure, point of sale tax incentives, and usage of public bus use limited lanes. Chapter III contributed to the literature by analyzing the sales of electric vehicles on a regional and municipal basis in Norway and then cross-analyzed these with the corresponding local demographic data and incentive measures to attempt to ascertain which factors lead to higher BEV adoption. Chapter III showed that access to BEV charging infrastructure, being adjacent to major cities, and regional incomes had the greatest and most significant predictive power for the growth of BEV sales. It showed that short-range vehicles showed somewhat more income and unemployment sensitivity than long-range vehicles. Toll exemptions and the right to use bus-designated lanes did not appear to have statistically significant predictive power for BEV sales in the linear municipal-level models, but this could be due to neighboring major cities, another variable, containing those incentive features. As this chapter does not test for causation, it cannot be determined from this chapter if correlation of per capita sales with charging stations is purely due to the consumer incentive effect of the charging stations, or if the charging stations are being built in response to local EV demand. This correlation, however, was shown to be non-random. Regardless of the direction of causation, or the presence of any confounding variables, charging stations act as an effective predictor for electric vehicle adoption, given the conditions in Norway. This infrastructure is also a physical requirement for EV adoption, when residential charging is unavailable. It is therefore prudent to plan for increased charger construction when planning for increased AV adoption as the factors that lead to this correlation are likely to be present in US as well.

Chapter IV focused on how to optimally construct necessary infrastructure for new technologies using the joint application of electric vehicle chargers and vehicle automation in King County, Washington, as a case study. Chapter IV contributed to the literature by optimizing EV charging station placement based on operator cost, commuter cost, and level of automation. Moving from levels 0-3 to level 4 and level 5 automation reduced the peak electrical load from EV charging by approximately 31% and 68%, respectively. Moving from no automation to level 4 automation lowered the optimal number of chargers by 65% and the total costs by 46%. Moving from levels 0-3 automation to level 5 automation decreased the optimal number of chargers by 84% and total costs by 69%. The cost borne by commuters was only significant with level 5 automation, where the cost borne by commuters was 24% of the operator's cost.

Chapter V focused on how to effectively regulate technologies so that their future development increases social value, focusing on the specific problem of measuring autonomous vehicle fuel economy. Environmental pollution and energy use in the light-duty transportation sector are currently regulated through fuel economy and emissions standards. These standards assess quantity of pollutants emitted and volume of fuel used per distance driven. The U.S. fuel economy tests, by design, neglect the differences in how individuals drive their vehicles on the road. As autonomous vehicle (AV) technology is introduced, more aspects of driving shift into functions of decisions made by the vehicle, rather than by the human driver. Yet the current fuel economy testing procedure does not have a mechanism to evaluate the impacts of AV technology on fuel economy ratings and on regulations such as Corporate Average Fuel Economy targets. Chapter V contributed to the literature by developing a method to incorporate the impacts of AV technology within the bounds of current fuel economy tests, and it simulated a range of automated vehicle drive cycles to estimate changes in fuel economy. The results showed that AVs following algorithms designed without considering efficiency could degrade fuel economy by up to 3%, while efficiency-focused control strategies may equal or slightly exceed the existing EPA fuel economy test results by up to 5%. This suggested the need for a new near-term approach in fuel economy testing to account for connected and autonomous vehicles.

6.3 Policy Implications

The chapters' contributions, individually and as a group, lead to distinct policy implications. Chapter II showcased the importance of understanding actor motivations, emissions accounting frameworks and spatial effects when considering the net social value of adopting a new technology, specifically electric vehicles. Chapter III suggested that major metropolitan areas are the most likely to quickly adopt electric vehicles and that charging infrastructure needs to be built or likely will be built for electric vehicles. Chapter IV complemented this by showing that planning jointly for autonomous vehicles and electric vehicles allows for significant savings in operator and net social costs and reduced amounts of EV charging infrastructure. It also enables the smoothing of the peak electric demand from electric vehicles. Chapter V showed that it is necessary to measure the effect of automation on driving patterns to ensure that the technology does not decrease fuel economy.

This last conclusion is important when discussing or assessing policies for transportation for the future. Electric vehicles and autonomous vehicle technology are undergoing development and commercialization concurrently. These technologies have potential interactions, some positive and some negative. Assessing whether and how to adopt and regulate either technology is a matter not only of assessing the technology in isolation along each of the four listed components, but also of investigating how the technologies could and should interact. Building for EVs may be more expensive than necessary, unless one considers automation. Rules for optimally controlling conventional AVs will be different than rules for electric ones. Ensuring that these technologies work to achieve the optimal social benefit possible requires considering them in unison through regulation, adoption, and support.

6.4 Future Work

Each of the chapters suggest questions to be investigated in follow-up work. Chapter II addressed the question of adoption of EVs for one specific municipality. The spatial differences in answering this question across municipalities is significant. Exploring these differences while still accounting for the combined social value and municipal motivations is a natural next step. Chapter III showed a causal uncertainty in the correlation between charging infrastructure and electric vehicle adoption. Investigating the exact cause of this correlation is necessary to design effective incentive policy. Chapter IV showed significant and large synergies when optimizing EV charging infrastructure with autonomous technology. However, the results are noisy, due to the lack of an underlying demand model and the lack of a time component in the optimization model. Chapter V suggested a methodology for accounting for autonomous technology in fuel economy rating. It does not, however, come up with a comprehensive methodology for accounting for the individual or system-wide gains possible with connected autonomous vehicle technology.

The results of this dissertation suggest future lines of investigation. Chapter IV showed that the effective costs of electric vehicles can decrease with the addition of autonomous technology as the costs of the required infrastructure decrease. Combining this result with Chapter II's investigation would show improvements in the performance of EVs. Chapter V showed a potential weakness when accounting for the fuel consumption of AVs. This introduces errors into the results of Chapter IV's infrastructure optimization model. Accounting for this would improve the veracity of the results. Chapter III suggested the potential acceptance of shorter-range EVs. Accounting for the potential savings this would introduce and how charging infrastructure would enable it would allow for Chapter IV's model to include another cost component of social value, currently ignored.

Ensuring social value from a new technology's adoption requires considering four components: determining whether adopting new technologies, for a specific locality and purpose, would provide a social benefit; knowing how to effectively encourage adoption of a technology; knowing how to optimally construct necessary infrastructure for the new technologies; and being able to effectively regulate technologies so that its future development increases social value. No technology, however, is born in a vacuum. This dissertation has contributed to the literature by showing that these four components must account for the possible interactions of the new technology when paired with other, plausible market entrants. This is clear when looking at electric and autonomous vehicle technologies, which are simultaneously and concurrently undergoing development and market introduction.

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