Technology Evaluation for Automobile Transportation:
Electric Vehicle Energy Requirements Under Real-World Use

by

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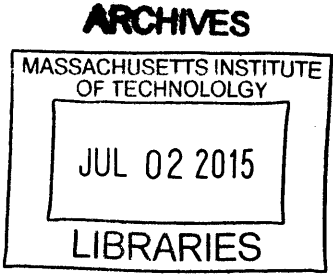Haverford College (2011)

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Abstract

In recent years, an increasing number of electric vehicles (EVs) have become available for purchase to meet personally operated vehicle (POV) travel needs for a certain sub-set of drivers. Many in the climate change mitigation research community envision EVs as a major potential tool in reducing carbon emissions from the transportation sector, as EVs do not produce direct emissions during their use. Limitations of current EV technology, specifically limited range and high production costs, are recognized as constraints on the market share of EVs, but estimates vary as to the true adoption potential of current technologies. Many suggest that EVs should be targeted to drivers in cities, where the shorter driving distances and slower speeds allow EVs to meet more existing demand, but that conclusion remains relatively untested. It is also unclear whether focus on designing EVs for city use will allow for the greatest possible emissions reduction as vehicle batteries improve. This thesis presents a detailed POV energy use model that both accurately considers driving behavior and vehicle performance on a second-by-second level and on a macroscopic regional and national level, using over 100,000 GPS velocity histories, over 1,000,000 travel survey trip records, and a national database of hourly temperature readings to inform the results. We find that existing EV technology, based on the example of the relatively affordable Nissan Leaf, is able to replace 87% of all vehicles in the US on a given day without mid-day recharging. Our results support the conclusion that current EVs are most suited for urban use, finding higher EV adoption potential and greater prospects for EV-related reductions in gasoline consumption in all of 12 cities studied than the national average, with especially good performance in sunbelt cities such as Los Angeles and Phoenix. However, we find that—under a scenario of improved batteries—reductions in gasoline consumption would be increased by focusing on rural areas rather than urban ones.

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Thanks to Jessika Trancik for all of her helpful guidance and comments. Her advice has been crucial to helping clearly frame the questions here in terms of what is important and impactful.

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Chapter 1

Introduction

1.1 Context: Driving and Emissions Targets

The transportation sector accounts for 28% of United States energy use and 34% of US carbon emissions, and the majority of those emissions come from personal vehicle trips—people commuting to work, driving to social events, and performing everyday errands in their cars and light trucks [1]. There were an estimated 131 million personally operated vehicles (POVs) registered in the United States in 2010, and they are estimated to have driven 2.6 million miles in that year [2]. The number of vehicle miles traveled (VMT) in the United States is expected to increase from 2.6 million today to 3.1 million in 2030, but despite this expected growth, the United States has committed to reducing overall carbon emissions by 30 % from 2000 levels by 2030 [3]. To reduce emissions in keeping with these and other targets, there will have to be dramatic changes in the the way personal vehicle travel needs are met.

Improving vehicle efficiency has historically been the main policy lever for reducing energy use and emissions. Beginning in the 1970s, the US imposed the Corporate Average Fuel Economy (CAFE) standards, requiring new vehicles to meet progressively higher fuel consumption standards. In 2012, the Obama administration signed stricter guidelines requiring that the fleet-wide fuel economy increase from approximately 33.4 miles per gallon (MPG) for new cars in 2012 to 54.5 in 2025 [4]. Of the model year 2012 vehicle types tested by the EPA, only 1.8% of them met this

standard, and that portion has only reached 2.8% in 2014 [5].

Reaching these goals will likely require additional technological innovation, and furthermore meeting these standards alone may not reduce carbon emissions to levels that meet climate policy targets. For instance, the U.S. Energy Information Administration predicts that, even when efficiency improvements due to CAFE standards are factored in, reference case US transportation-related greenhouse gas emissions in 2025 will reach 1.68 billion metric tons, far greater than the 1.31 billion metric tons representing a decrease of 30% from 2000 levels [1]. Even in the case of greater than expected reductions in other sectors, then, it is likely that sufficient reductions in transportation-related GHG emissions will require fundamental demand or supply side changes to the US transportation system, the comparable in scale to the beginning of the interstate highway program in the 1950s.

It is difficult to overstate how disruptive transportation system changes might need to be. Mobility has profound effects on society, and the shape those effects take is in part directly traceable to technological properties inherent in the available transportation technologies. Walking and sailing shaped old downtown areas such as Boston's, streetcars and subways allowed for the development of dense downtowns and skyscrapers, freight rail and canals allowed for vast industrial development, and cars and the interstate system have shaped the emerging sprawling and decentralized development patterns and economic growth of the past half century [6]. During this past century, the availability of POVs has had great effects on society at large, impacting land use [7], public health [8], the economy [9], and the environment [10]. While many of these changes are due to the proliferation of personal vehicles in the abstract, the effects off the car boom that began after World War II have been moderated and shaped by the specific strengths and weaknesses of available POV technology options.

Right now, the major POV technology in the United States remains the internal combustion engine, which was first invented in the late 19th century. In 2009, the majority of all person-miles and person-trips in the US were covered in personally operated vehicles, and the vast majority of those vehicles were powered by internal

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combustion engines burning fossil fuels [11]. Internal Combustion Engine Vehicles (ICEVs) are powered by the combustion of a fossil fuel, converting chemical potential energy into rotational kinetic energy, which is then converted by gears and a transmission into forward movement. The combustion of the fuel produces carbon dioxide, particulate matter, noise, and heat as byproducts, and the overall efficiency of the process is often below 30% [12]. The high energy density and relatively widespread availability of fossil fuels, mostly gasoline, means that this relatively low efficiency has not been an impediment to the ICEV's adoption and use. By and large, energy constraints have not had significant effects on POV mobility since the advent of the modern automobile.

The technological details described above are particular to the internal combustion engine—not fundamentals of POV travel—and these peculiarities have had non-trivial impacts on the way the transportation sector has shaped society over the past century. Had the first popular POVs been powered by batteries or by steam engines, for example, energy use and travel behavior in the United States would look very different.

The specific impacts of the technological properties of the internal combustion engine show up across daily life in the US. On average, people tend to devote similar proportions of their time and money budgets on travel, and so the spatial extent of cities is implicitly limited by the typical speed and cost of ICEVs [13]. Relatively cheap and efficient energy storage, in terms of gasoline stored in tanks, and relatively prevalent gas stations means that drivers rarely plan their travel behavior around energy storage constraints. Users do not need to own any dedicated infrastructure in order to fuel their vehicles, allowing for drivers to live in apartment buildings, farms, and suburban subdivisions. Indeed, the comparatively low cost of gasoline has led to a set of vehicle design standards and infrastructure systems that prioritize driving comfort and speed over energy efficiency[1]. However, while relatively low, per-mile costs of ICEV driving are closely tied to the commodity price of oil, meaning that

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[1]In most of Europe, fuel taxes and fuel prices are much higher than in the US. Although the relationship with fuel costs is not purely causal, Europeans tend to drive smaller vehicles and more of them drive diesel vehicles which are more efficient than gasoline ones. Further, Europeans (even in wealthy countries) tend to drive much less than Americans do.

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international politics can have outsized impacts on the American economy and on the ability of people to afford to take trips by car.

Additionally, ICEVs produce many types of emissions with health impacts. The localized emissions, such as asthma-causing particulate matter and smog-causing sulfur dioxide, have historically produced and continue to produce negative health effects in areas with high densities of car travel, producing inequitable and unfair outcomes [8]. The greenhouse gasses (GHGs), primarily carbon dioxide, produced by the consumption of fossil fuels have been and will continue to be a major cause of climate change.

Engineering properties of the internal combustion engine have also shaped transportation policy. The majority of federal and state highway funding comes from excise taxes on gasoline. Receipts from these taxes have not risen as fast as inflation or maintenance costs, straining the existing funding mechanism and promising further challenges if vehicles continue to become more efficient or switch to other energy sources besides gasoline. Many existing regulations on vehicle use have arisen due to features specific to the internal combustion engine. Rising worry about air pollution and smog due to driving led to Clean Air Act regulations on vehicle emissions, and worry about the resiliency of US economy under oil price shocks led to the CAFE fuel economy standards. Had vehicle technology developed differently, personal travel behavior and national transportation policy would have evolved differently as well.

But while the ICEV has done a great deal to shape American society over the past century, consumer preferences and government regulation have long influenced ICEV technology and design as well. Different sub-types of vehicles have emerged to cater to different markets—small efficient cars for those who value affordability, SUVs and minivans for those who value space, and sports cars for those who value performance and aesthetics. Quieter, more efficient, more powerful engine technology has made driving more fun and less expensive, and advances such as regenerative braking have reduced spending on gasoline. Technologies have evolved to make in-vehicle time more pleasant, from entertainment systems to heated seats to navigation systems.

Additionally, regulation has historically affected ICEV technological development.

The technological dimensions most important to policy makers and regulators have been the gasoline supply chain, the impact of particulate emissions on public health, and the effect of vehicle design on public safety, leading to regulations that have produced catalytic converters, mandatory airbags and seat belts, flex-fuel vehicles, and overall efficiencies improving to meet CAFE standards.

An understanding of this history is important for an understanding of the future of POV transportation in the United States. While the ICEV has shaped society as much as the demands of society have shaped the ICEV, its dominance as a technology may not continue indefinitely. With improvements in vehicle propulsion and energy storage technologies, along with rising prices for fossil fuels and increased awareness of the dangers of climate change, alternative vehicle technologies such as plug in electric vehicles and fuel cell electric vehicles are poised to enter the market as viable choices for personal vehicle transportation and as viable competitors to the internal combustion engine [14]. This may represent the first time in generations when a viable alternative to the ICEV is widely available to consumers. However, alternative vehicle technologies will not be competing with ICEVs on a blank slate—instead they will compete in a society and economy that has in large part been shaped according to the strengths and weaknesses of ICEV technology. This market competition, and the direction of future transportation energy requirements, will in part be determined by individual choices based on the ability of POV technologies to meet this existing demand.

1.2 The Importance of Technological Choice

Since the beginning of the automobile era, motorized personal transportation has been characterized by a lack of drivetrain technology choice. The Ford Model T was introduced in 1908 and quickly became widespread, and since then consumers in the United States have largely only been able to purchase personal vehicles powered by internal combustion engines. The differences customers perceive between vehicles have been largely limited to price, safety, comfort, and aesthetics, and these areas

have been among the primary directions of innovation in ICEV technology. Greater availability of alternative vehicle technologies will increase the degree of choice available to customers and add to the degrees of performance along which it is possible to evaluate and differentiate vehicles.

When compared to the range of currently available ICEV options, electric vehicles offer an entirely new set of strengths and weaknesses. Unlike conventional vehicles, EVs draw energy as electricity from the grid and store it in batteries within the vehicle. Even though battery technology is improving, batteries still tend to be relatively expensive and heavy, especially when compared to gas tanks that serve a comparable function in ICEVs. Cost and weight constraints limit the amount of energy storage available in EVs—and therefore the distance that can be driven in between recharging events—to a degree that is rarely an important consideration for ICEVs. Batteries also tend to be degrade in performance over time, are produced with a number of potentially dangerous chemicals, present a potential fire hazard, and perform poorly in particularly cold or hot weather. However, the electric motor that converts energy stored in the battery into movement does so at much higher efficiencies, often exceeding 90%, all without requiring expensive and difficult to maintain transmission and gearing mechanisms. This high efficiency, coupled with relatively inexpensive electricity available from the grid and lower maintenance costs, make EVs typically cheaper to operate than ICEVs [15].

Further, coupled with decarbonization of the electric grid, EVs have the potential to decrease the greenhouse gas emissions associated with personal transportation towards zero. Unsurprisingly, therefore, EVs have been proposed as a large component of the needed decarbonization of the transportation sector [14, 16, 17, 18, 19]. EVs also can reduce many other negative externalities common to ICEVs—they are quieter and produce none of the localized emissions produced by the combustion of gasoline that can cause respiratory problems and smog, giving them potential to mitigate many other of the negative externalities we associate with automobile travel. However, many of the predicted benefits of EVs—grid stabilization, lower carbon footprint, less dependence on foreign energy—are not directly perceived as benefits by consumers.

In the absence of either direct or indirect subsidy, including tax credits, carbon taxes, or free access to HOV lanes, many of the most important benefits of EV technology are divorced from the utility felt by users.

Along with this problem of externalities, electric vehicles also face challenges that are not felt by ICEVs, providing significant barriers towards widespread adoption.Two of the largest impediments to wide-ranging popular adoption of EVs are range anxiety and price [20], both of which are fundamentally related to EV, and especially battery, technology performance. Drivers are reluctant to invest in a vehicle with limited range and limited possible recharging locations, even if their typical daily commute falls well within the vehicle's expected range. Additionally, even though lower maintenance and fuel costs bring the life-cycle costs of some EVs to levels comparable to affordable small cars, the higher purchase cost of EVs likely turns away customers as well. Many of these barriers to adoption would be alleviated by the advent of cheap, light, small, high capacity batteries. Batteries do have the potential to both improve energy density and become cheaper, but the timeline is uncertain [21]. The speed at which EVs can penetrate the market depends both on the rate of progress in battery technology and in the degree to which battery improvements are perceived by consumers.

Further, the choice between ICEVs and EVs is not a binary one—there exists significant differentiation within each group that complicates the choice. EVs such as the Nissan Leaf are sold as affordable alternatives to typical internal combustion engine vehicles (ICEVs) with similar life-cycle costs [15], but the Leaf and its competitors have limited range—the Leaf has an EPA rated range of 73 miles in battery preserving mode—limiting its pool of potential users. The Tesla Model S, on the other hand, is marketed as a luxury high performance vehicle and has an advertised range of up to to 265 miles, but its most affordable configuration retails for over $80,000, more than twice as much as the Leaf. Electric vehicle manufacturers face a tradeoff between physical constraints on one hand, as batteries are bulky and heavy, and economic constraints on the other, as batteries are expensive. Manufacturers will continue to balance these tradeoffs as battery technology improves and as EVs become more widespread. Whether EVs of the future take over the POV market

quickly and decisively as the Model T did a century ago, whether they infuse more slowly as gradually expanding niche market, or whether they will only catch on with directed and costly government subsidy depends on technological progress, real-world POV use, and intermediate engineering decisions.

An understanding of the potential long-term benefits of a full or partial switch to EV technology requires an understanding of how EVs compare with other POV technologies. Properly assessing the potential costs and benefits of the adoption of new technologies requires studying both their expected performance and on the degree of disruption required to integrate them into existing systems [22]. Even though many policymakers and scientists expect that EVs will produce many systemwide benefits, especially in terms of carbon emissions, the extent of their societal benefits depends on both the performance of EV technology in the real-world and the outcome of the market competition between different vehicle technologies. The degree of eventual carbon mitigation required and the future development of alternative vehicle technologies depends closely on how consumers react to these new options, and how these new technologies perform under existing behavior that will not immediately adapt to the new technology's strengths and weaknesses.

As such, the position of the policy-maker is a difficult one, especially when funding constraints limit the amount of money that can be applied to research and development into technology improvement, subsidy towards purchase of existing technologies, and incremental improvements towards better-established technologies. The leverage of different policy options, in terms of social welfare, is a difficult question to understand and one that must be framed as a question of technology choice. The new technological option that EVs represent will be introduced into a market whose underlying paradigms have been driven by the limitations and advantages of the internal combustion engine. Our travel behavior, land use, and personal preferences have grown up around internal combustion engines and thus it is extremely important to understand how these new technological options will perform under these existing usage patterns. The performance of technologies under existing use will directly determine which technologies are widely adopted, which engineering decisions are made

as these technologies continue to mature, and which decisions are made to regulate the new challenges that these technologies have the potential to introduce.

Evaluating the tradeoffs between ICEVs and EVs is important both as a predictive measure and as a proscriptive one. For EVs to cross over from a niche market to a core one, they must continue to adapt in order to better meet the day to day needs of a typical driver at a reasonable price. The usefulness of EVs as carbon mitigation options depend on the ability of current and future technologies to meet market needs, the degree and speed to which the technology must improve in order to meet those needs, and the energy and climate impact of these vehicles and the remaining conventionally-powered ones once the transition is further along. It remains an open question how far away current EV technology is from meeting these needs and what fleetwide performance and energy use will look like as current or future technology achieves market penetration.

1.3 Research Overview

At some point in the not-too-distant future, the United States and the world will almost certainly begin to dramatically decrease their emissions of greenhouse gasses, including those from the transportation sector. Electric vehicles, combined with a less carbon intensive electric grid, present a potential mitigation option for emissions from the transportation sector. A large-scale transition from ICEVs to EVs in the POV fleet, whether accomplished entirely though market mechanisms or as a results of government regulation and incentives, would be one of the largest fundamental changes to aggregate transportation behavior in generations.

Despite great technological progress in recent years, it is unclear what changes to vehicle technology are necessary and how disruptive the changes will have to be in order to allow for this level of widespread EV adoption. It also remains unclear exactly what levels of EV adoption are consistent with proposed climate targets. Assessing the plausibility of various pathways towards transportation decarbonization, and coming up with related technology targets, requires an understanding of both the performance

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of various vehicle technologies and a detailed understanding of the energy demand of personal vehicle transportation.

The research presented in this thesis is intended to elucidate some of the key factors that influence the choice between ICEV and EV technology. It examines in detail the energy needs of existing travel behavior and evaluates the performance of both kinds of technologies under this real-world use. Such a detailed understanding of both travel energy demand and POV technology performance allows for an understanding of existing and future technology trade-offs with a degree of detail that is currently nonexistent. This type of understanding is extremely important for a realistic understanding of the potential long-lasting effects of contemporary engineering and policy decisions. After laying out the details of the POV transportation energy use model, this thesis presents some conclusions relating to variations in EV range, potential market size of current EVs, and the rate at which additional battery improvements will increase the potential share of transportation that can be electrified. This research lays a methodological framework for more in-depth evaluation of the energy use and emissions effects of policy change, technology change, and behavioral change.

The **Background** section will frame the relevant literature and research with regard to three related but separate questions. How do we better understand personal travel behavior and relate it to energy use and technological needs? How does this travel demand relate to the technological demands placed on electric vehicles, and what engineering decisions and further technological advancements will be necessary for electric vehicles to appropriately serve existing personal vehicle travel behavior? And, to what degree will electric vehicles serve the decarbonization of the United States energy system in keeping with proposed climate targets? An understanding of these three areas is important in order to evaluate the potential of electric vehicles in a context and usage specific way.

The **Methods** section will describe the trip energy distribution model. The analysis presented here relies on a bottom-up energineering model that converts distance and duration data from a National Household Travel Survey (NHTS) POV trip into

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a probability distribution of energy requirements. This model has three largely independent components. The tractive energy component estimates the amount of kinetic energy dissipated by the vehicle over the course of the trip, using a set of GPS drive cycles and an engineering model of tractive force to estimate energy requirements. The drive efficiency component estimates the total efficiency—the ratio between the tractive energy delivered to the vehicle and the amount of energy withdrawn from the energy storage device—for the trip. The auxiliary energy component uses temperature data to estimate the amount of energy required to maintain a comfortable temperature within the vehicle and to power other electric devices such as the dashboard and the lights.

The **Results** section will use the method described above to answer some questions about the strengths and weaknesses of ICEV and EV technology, the tradeoffs between the two, and the underlying structure of transportation-related energy use in the United States. It begins by examining the specific sub-question of vehicle range, both its inherent variability and from trip to trip and its dependence on local climate and local travel patterns. It then evaluates existing EV technology by looking at the suitability of one specific EV configuration for use in a large set of American cities, factoring in both differing vehicle performance and differing levels of demand to ask what portion of vehicles and what portion of gasoline use would EVs be able to displace. We then examine the surprising similarity between cities in terms of EV suitability, tracing much of the similarity to fundamental aspects of personal travel behavior. Finally we evaluate the effects of expected improvements in battery specific energy on EV performance, noting the increasing differences in expected EV use between urban and rural areas as storage technology improves.

The **Conclusion** section will re-frame the results within climate policy and transportation policy and identify directions where this model could be used to better inform public and private sector decision making.

Chapter 2

Background

2.1 Personal Travel Behavior and Energy Use

Yearly energy use due to personal vehicle transportation is estimated at 28 exajoules per year for the US and 111 exajoules per year globally [1], the majority of this energy currently coming from gasoline and diesel fuels. This energy consumption has been disaggregated many ways for many ends. Particularly relevant to this study has been research on the effects of location and technology choice on aggregate transportation-related energy consumption. This literature informs the research presented in this thesis by beginning to answer the question: what properties do we know about the distribution of personal transportation energy use *besides* simply its total, and how can we use this more detailed information in order to inform paths towards reducing this energy demand and its climate impact?

At the most abstract level, there has been a great deal of research on the nature of human mobility, drawing many parallels between human behavior and statistical phenomena observed in other natural systems. With large enough samples, individual human trajectories can begin to resemble paths drawn from simple statistical relationships. Brownian motion, during which every time step a particle takes a fixed distance step in a random direction, is a natural analogy for human motion, but Brockmann et al. [23] showed that the trajectories individually tagged dollar bills follow is much better approximated by a Lévy flight. A Lévy flight is similar to

Brownian motion, except that both the duration between steps and the distance of a step are randomly drawn from a heavy tailed distribution, such as lognormal or Weibull. Rhee et al. [24] show that this scaling behavior is consistent with human travel behavior on many distance scales over short time periods, and Gonzalez et al. [25] show that over long time periods human trajectories tend to follow similar scaling patterns. While the potential usefulness of this understanding is great, especially in fields such as epidemiology and traffic flow modeling, but they have yet to be widely applied to more macroscopic problems such as energy use and climate change.

Instead, a great deal of research from the transportation and energy communities has gone into the determinants of total citywide energy use. Newman and Kenworthy [26] published a groundbreaking study linking city-wide transportation energy consumption to average population density. These conclusions have been challenged [27] and complicated [28] in the years since, but the general conclusions remain relatively strong—that denser, transit- and walking-oriented cities tend to have lower per-capita levels of gasoline consumption. The bulk of research on this topic attempts to understand behavior at greater detail or provide explanations for this observed behavior.

The research touching on the determinants of city-wide transportation energy consumption has been somewhat divided between studies that focus on gasoline use directly and ones that study aggregate VMT as a proxy. Of those focusing on VMT, Ewing and Cervero [29] present a thorough review of many studies on how the built environment affects travel behavior. They find that consistently increased density is found as a measure that tends to decrease VMT, but that it is a weak effect when other design variables are controlled for. Other infrastructure properties that have downward effects on VMT are job density, mixed land use, intersection density, and transit service. Zegras [30] examines data from Santiago de Chile and shows that household income has the greatest impact on household VMT—showing that it increases both the likelihood of a household owning one or multiple POVs, and that it also increases the distance driven of those vehicles. Infrastructure variables such as higher population density and proximity to mass-transit do decrease expected VMT, but the effect is secondary. While it is likely that these results hold some sort of

universality, the degree to which these conclusions hold across different countries is unknown.

A problem that is difficult to tackle empirically in these studies is self selection—the possibility that people who dislike driving will tend to locate in denser, better served areas, and therefore that these infrastructure changes as a policy instrument might not provide the significant reductions in VMT that simple elasticities or regression coefficients would suggest. Although there are many clever ways to adjust for the possibility of self selection (e.g. structured equation models such as [31]), it is difficult to show that policy solutions focusing on the supply side of transportation energy demand such as urban density and transit performance have direct, immediate, and measurable impacts on carbon emissions [32, 33], suggesting that focus on the supply side—particularly vehicle efficiency—might produce more easily measurable impacts.

Studies of aggregate gasoline demand as a measure of transportation energy use includes the additional factor of vehicle efficiency, but the research in this area has its share of complications as well. Much research in the community has been focused on the elasticity of total gasoline consumption with certain variables, often fuel price and household income. Berkowitz et al. [34], in one of the first widely-cited studies on this topic, show that aggregate demand for gasoline—a very close proxy for energy demand due to personal vehicle travel—is deeply related to demographic, economic, and environmental factors. They model citywide gasoline consumption as having two determinants at the household level—the number and type of vehicles that a household chooses to purchase, and levels of vehicle use. They find that increased costs do decrease energy use (both by incentivizing purchase of more efficient vehicles and decreasing driving distance), but that this effect is much smaller than the effect of improved vehicle efficiency on energy use, even when increased driving due to the "rebound effect" is factored in. Basso and Oum [35] provide a review of similar studies published in the years following. One finding of this sector of the literature that is cruical for our project is that demographic, infrastructure, and economic considerations impact transport energy use directly by influencing travel behavior, but they also impact it indirectly by impacting household purchasing decisions.

Dujardin et al. [36] complement much of the preceding research by showing that localized transportation energy use is an example of a Modifiable Areal Unit Problem, in which the results of a geographic analysis can change dramatically based on the scale of the geographic aggregation that is used to do the analysis. In essence, in a Belgian case study they find that while highly aggregated data shows that urban areas have less per capita energy use than ex-urban areas, there exist neighborhoods within urban boundaries that have high energy use, and there exist rural towns with low energy use.

Similarly, Gately et al. [37] present a thorough study of disaggregate roadway-level carbon emissions, looking at their results down to 1-km scales. They show that urban areas, not rural ones, are responsible for the vast majority of the growth in transportation-related carbon emissions in the past few decades. Further, they show that per capita emissions grow sub-linearly with population density, but that the relationship is not fit by a simple scaling relationship. Unlike many other studies, there results are produced by looking at traffic on each roadway link, not by person or household. This methodology elucidates the fact that even though residents of dense cities might have low levels of transportation energy use, the cities in which they live draw in many commuters from surrounding suburban areas, which tend to have disproportionately high per capita energy use. These results suggest that city-level emissions data should be aggregated at the metropolitan area, not municipality, level.

When considering the literature, it becomes apparent that personal or household vehicle energy use is a very complicated problem, and that while there are certainly regularities that can predict how a certain household's gasoline consumption might differ from another's, this is not a solved or necessarily solvable research problem. While on a project- or city- or nation-wide level, policies relating to infrastructure, built environment, and travel behavior might have the ability to significantly reduce greenhouse gas emissions and certainly to provide many other societal benefits, right now the only type of policy lever for which we have the ability to measure and quantify expected greenhouse gas reductions is with regards to technology choice and

technology switching. Hopefully, such efficiency-driven policies can be *improved* by a better understanding of all of the other determinants of POV energy use.

2.2 Electric Vehicle Performance

While efficiency improvements and technology change might be the most straightforward path to reductions in greenhouse gas emissions, the effect of these changes is certainly not *easy* to measure. The impacts produced by a technology are discussed here in terms of performance intensity—the relative efficiency of electricity generation system can be measured in terms of grams per kilowatt-hour, for example. These measure involve averaging over different operating conditions, and therefore they never produce perfect predictions[1], but for POV transportation useful performance metrics are especially difficult to produce. The two largest complexities related to producing meaningful emissions intensity metrics for POVs relate to the inherent variability in trip-to-trip energy use, and in the wide-ranging daily travel needs that different customers place on their vehicles. Information on ICEV performance is important for many types of technology development and policymaking, both to provide better scenarios with which to test and compare different technologies during development and to evaluate a technology's usefulness as a means of carbon mitigation.

The easiest to interpret measure of vehicle performance intensity is energy use per unit distance driven. In a study focused on ICEVs but relevant to all technology options, Berry [12] presents a detailed examination of how differences in moment to moment driving behavior can have large impacts on per mile energy consumption. She finds that interventions such as lowering top highway speeds or reducing maximum accelerations are capable of reducing aggregate energy consumption by approximately 5%, a non-trivial amount for a change that requires no new infrastructure or technology. The trip to trip variation of even an individual vehicle's per mile emissions

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[1]For example, for an electricity provider with a certain emissions intensity, an additional electric load plugged into the grid during the middle of the day and one plugged in overnight will likely produce different amounts of excess carbon emission, depending on which power plant is on the margin and would pick up the extra demand

intensity can be much greater, often varying by a factor of two or more. In a separate study, Ericsson [38] found similar results—that different driving behavior can lead two trips of the same distance to have dramatically different energy needs. Interestingly, a very complex model that measured sixteen different variables relating to vehicle performance, including vehicle speed, acceleration, gear ratio, and engine RPM was only able to capture 76% of the trip to trip variation in energy use, underscoring how difficult of a problem this one is to solve with limited data.

In order to produce an aggregate measure of emissions and energy intensity for new vehicles, the US Environmental Protection Agency (EPA) publishes an estimated fuel economy value for each vehicle, giving the expected amount of gasoline (or gasoline equivalent energy, for EVs) used per mile of driving in city conditions, highway conditions, or aggregate mixed driving [5]. These estimates, different than the CAFE ratings also measured by the EPA[2], are the result of a detailed testing procedure that has become increasingly complex since the beginning of the labeling program [39]. The program works by testing vehicles on a dynamometer in the laboratory, intended to mimic the demands of driving on the road but in a more controlled and reproducible setting [40]. Each vehicle is tested over a pre-determined set of "drive cycles," or second-by-second velocity histories, over which the vehicle's fuel consumption is measured. The results of these dynamometer tests are then adjusted upwards to account for auxiliary use (such as radios or climate control), more extreme driving behavior, and other factors such as under-inflated tires that can increase energy use. Currently, the program is in transition from a two-cycle model based on a city (USDDS) and highway (HWFET) drive cycle to a five-cycle one that is intended to capture more of the possible variation in vehicle performance and distill all the different factors that might affect energy use into city, highway, and combined fuel economy. Even if these numbers are perfectly accurate at an average level, it is impossible for them to capture differences in energy consumption between trips, climates, and cities.

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[2]As the CAFE standards are meant to produce and measure improvements in fleetwide fuel economy over time, the CAFE rating procedure has not changed dramatically since the program's inception in order to allow comparison between years.

For electric vehicles, because range limitations are often important considerations, trip-to-trip variations in vehicle energy consumption can be especially important. The source of this variation tends to be different for these two vehicle types. In ICEVs, a great deal of the variation in trip-to-trip energy comes from differing conversion efficiency within the powertrain. Electric motors, unlike ICEs, have roughly constant efficiency over a wide space of different torques and speeds, reducing this source of variability. However, because of their already high degree of powertrain efficiency, climate control auxiliaries contribute a much greater portion of total energy requirements for EVs. Especially in cold weather, EVs must devote a great deal of energy from the battery to maintain a comfortable internal temperature, along with overcoming higher internal resistance within the battery. This stands in contrast to ICEVs which, because they have such low thermal efficiencies, produce enough waste heat to keep the cabin warm without expending any more energy than that needed to run a radiator fan.

A number of groups have studied how temperature variations in particular effect EV performance. Bush et al. at the Argonne National Laboratory [41] present a series of studies in which actual hybrid-electric vehicles (vehicles with both ICE and electric motors) were driven through identical drive cycles in real-world conditions under different temperatures. This allowed the group to measure the cold-weather efficiency losses due to decreased battery performance and increased climate-control energy consumption. They show that in very cold weather fuel consumption can double over the same drive cycle, and they suggest that these effects can be even more dramatic in pure EVs that only rely on battery power.

Yuksel and Michalek [42] use energy consumption data from electric vehicles captured by board diagnostic devices to measure the effect of ambient temperature on energy consumption. They run a simulation model that combines this data with hourly temperature data to estimate the distribution of EV range over the course of a year across the US, finding that daily range can vary as much as 50% in one location over the course of a year, and that range on the worst day of the year can vary by more than 50% between cities with different climates. While useful, these numbers

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do not take into account variations in average driving speed and driving distance between these locations, both of which could also affect the relative performance of EVs as well. They also do not take into account typical daily driving distances, which determine whether range constraints matter to users at all.

A number of studies have sought to characterize how differences in driving behavior effect EV performance. This has included testing individual electric vehicles in the field with the intention of characterizing what a "realistic" set of behaviors might look like. Devie et al. [43] directly follow the charging and discharging behavior of a single electric vehicle over time. They find that the day to day demands on the battery can vary greatly, but that they tend to cluster into a set of similar usage scenarios, which they suggest could be used by battery developers to ensure that their products perform well under their expected real-world use patterns.

Other groups have used GPS data from other vehicles (largely ICEVs) and simulation to estimate the energy requirements of different EV technologies under real-world driving behavior. Gonder et al. [44] used multi-day GPS traces from 227 vehicles around the St. Louis area to estimate the performance and energy use of PHEVs under real-world driving. Among their many conclusions was that the standard city and highway certification drive cycles do not fully capture the range of accelerations and speeds present in actual driving. Their analysis finds that existing PHEV technology would be able to reduce gasoline use by approximately half compared to similar ICEVs, although it is unclear to what extent their results hold universally, rather than just in the St. Louis area from which their sample was taken with its specific distribution of trip lengths, trip speeds, and daily driving patterns.

Seeking to estimate the impact of different individual driving patterns on EV performance, Raykin et al. use a traffic simulation program to generate typical daily driving patterns for users in different locations in the Toronto metropolitan area. They find that per mile energy use of PHEVs is best in city driving, both because the shorter distances allow for energy from the battery to cover a higher portion of the total energy, and because the powertrain configuration is more efficient with low-speed driving [45]. These results contrast with typical performance for ICEVs, which tend

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to operate most efficiently per mile at highway speeds. Amirjamshidi and Roorda [46] take the analysis a step further, using a fully detailed microscopic traffic network model to generate synthetic drive-cycles for vehicles in the Toronto area, showing that per-mile carbon emissions were almost 20% greater under their drive cycles than the EPA highway test cycle. In their paper, they propose a general method for generating synthetic drive cycles from traffic-count data for city-wide emissions inventories, but the realism of their synthetic drive cycles, vehicle model, and behavioral model remain unvalidated.

While these results on EV emissions intensity build high-level understanding of technological performance, some researchers attempt to use a better understanding of EV performance to inform engineering decisions made by manufacturers. A common question asked by researchers relates to battery size—many researchers wonder how many users will be able to adopt existing vehicles given their travel needs, and what battery sizes will be required for this level of possible market penetration to reach a given target. Khan and Kockelman [47] consider the first question, asking what portion of households would be able to adopt current EVs with minimal disruptions to their typical driving behavior. To do so, they use a powerful dataset that gives daily mileage over the course of an entire year for 445 vehicles in the Seattle metropolitan area. Because they have longitudinal data, they are able to show that an EV with 100 mile range would be able to replace the vehicle of 50% of one-vehicle households while requiring they modify their behavior four or fewer days over the course of a year. They are also able to give results for multi-vehicle households and for plug-in hybrids, suggesting that current battery technology is able to electrify a large portion of existing miles and save fuel costs with minimal change of behavior. Two limitations of their method are that it treats EV fuel economy as a constant and that it only considers users from one metropolitan area, thus not showing whether their results are representative for different locations or for different sub-classes of drivers. Pearre [48] perform a similar analysis with one year of GPS data from drivers in Atlanta, producing roughly similar results.

Battery size can also be linked with other design variables, such as engine size,

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to allow for an optimiziation of design components. Patil et al. [49] do so, using synthetic drive cycles based on observations of real-world driving to test different powertrain configurations and to find the configuration in terms of battery size and engine size that allows for the desired performance at the minumum cost.

The general conclusions of previous work in this field are threefold. The two typical EPA drive cycles, HWFET and USDDS, do not fully capture the range of driving behavior that drivers follow in the real world. Newer EPA labeling standards are attempting to address this issue, but differences in driving behavior mean that any one "fuel economy" number is never going to entirely capture the variety of energy consumption patterns electric vehicles. Further, this variation in energy use is increased for EVs because variations in temperature have an outsized effect on on vehicle range and performance. Finally, many studies have shown that current EV technology is capable of meeting a large amount of existing driving demand, although few have disaggregated their results among regions or types of drivers, limiting potential inference that some markets might be more suitable for EVs than others. Such analysis can be used to better inform the design of EVs and to predict their market potential, but this analysis has yet to be done at a representative national level, capturing both detailed driving behavior and differences in travel patterns and vehicle performance between different locations and different drivers.

2.3 Electric Vehicles and Climate Change

For the purpose of this thesis, one of the major goals of evaluating EV technology is to better understand its potential to reduce greenhouse gas emissions, especially when compared to marginal improvements in ICEV technology. There exist many useful theoretical frameworks for the comparison of technologies. Trancik et al. compare electricity generation technologies on a cost-carbon curve, clarifying the choice between possible alternative energy technologies by comparing performance intensity and cost intensity metrics of different technologies with values needed in order to meet climate goals under different demand scenarios [50]. In order for a technology

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(or a combination of technologies) to be a plausible candidate to meet emissions goals without massive subsidy, it must fall below the required level on the emissions axis without being dramatically dominated on the cost axis by higher-emission technologies. The locations of various technologies on this curve shows the magnitude and direction of technological improvement necessary for them to be able to meet this target.

Similarly, the final mix between ICEV and low-emissions vehicles must both have low-enough life-cycle carbon emissions to meet targets and be low enough cost to compare to the base case of all ICEVs. Miotti et al. produce a similar cost carbon curve for existing vehicle technology, including ICEVs, plug in hybrid electric vehicles, and prototype hydrogen fuel cell vehicles, finding that there is no tradeoff within vehicle types—that the cheapest to own and operate tend to be the least carbon intensive as well, and that EVs with low enough lifetime emissions to fall within intermediate climate targets are only barely more expensive than even most affordable ICEVs [15]. As discussed previously, however, both the emissions intensity and the cost intensity of vehicle technologies are difficult quantities to calculate—with the true life-cycle costs and life-cycle emissions varying greatly with type of use and type of user. Additionally, because of range and cost constraints, it is very unlikely that EVs will ever fully replace ICEVs in the marketplace—thus, the best solution will likely be a mix between technology types, and it is unclear what the optimal mix will look like. As such, many different groups have tried to analyze the the cost and emissions intensities of EVs in more detailed, less universal ways.

As the climate impacts of different vehicle technologies go beyond the impacts of fuel consumption, especially including emissions due to vehicle construction and decommissioning, there has been much work in the life-cycle analysis literature analyzing different vehicle technologies. Silva et al propose a new method for assessing the life-cycle costs and emissions of different PHEV technologies [51], finding, unsurprisingly, that the overall emissions of a PHEV depend very strongly on daily commuting distance, where users whose typical daily travel falls within the limited all-electric range of the vehicle use almost no gasoline and those with longer com-

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mutes use much higher amounts. Campbell et al. [17] suggest that, with regards to transportation, EVs fed by electricity produced by bio-generation plants have more potential to reduce GHG emissions than ICEVs powered by biofuels.

Donateo et al. [52] focus on direct emissions, rather than construction and decommissioning ones. Their study uses energy use data collected directly from an electric vehicle over six months of use, capturing driving under many different traffic conditions, speeds, and external temperatures. They find that variations in conditions can affect energy use by approximately 20% over the course of different trips. They find that this variability, combined with the existing electricity generation grid mix in Europe, mean that existing EV technology can meet 2021 carbon intensity targets for most days, but not for all. Their data, while thorough, is however limited by small size, making it difficult to measure the different effects of temperature, driving style, and personal commuting habits on effectiveness of EVs.

Yuksel and Michalek, in addition to studying the effect of temperature on vehicle range, also look at the effects of temperature and local grid mix on carbon emissions [42]. They combine their vehicle range results with data on the average emissions intensity of the electricity grid in the United States and find that these two sources of variation can cause the per-mile emissions intensity of EVs to range from approximately 100 grams of carbon dioxide per mile on the west coast to over 300 in the midwest, compared to an average value of 111 grams per mile for the Toyota Prius hybrid. These results make it clear that even if EVs might be a better choice on average, there are likely some customers for whom EVs are especially good choices and some for whom ICEVs might make more sense. An optimal level of technology switching might not be complete—for some users ICEVs might make more sense financially and in terms of emissions, perhaps with very long commutes or living in very cold climates. This is a question that has been explored to some degree in the literature, but some holes remain.

To capture the possiblity that EVs might have different life-cycle carbon emissions and costs for different types of users, Karabasoglu and Michalek [53] evaluate EV and ICEV vehicles over different drive cycles representing different users' typical driving

behavior. They show that life-cycle emissions and life-cycle costs do vary greatly with driving style, with costs and emissions much lower for EVs when compared to ICEVs when they are limited to city driving. However, for primarily highway driving, ICEV and EV costs and emissions are roughly similar, with ICEVs cheaper and only having very slightly higher emissions. These results suggest that, at a policy level, the best solution might be one that favors electrification of POV travel in certain cases but prioritizes marginal improvements in ICEV emissions intensity for cases where electrification is unlikely to bring significant benefits. Karabasoglu and Michalek and others (e.g. Tran et al. [54]) suggest that a natural starting point for EV adoption would be urban users with short commutes, as they require less range and typically drive at lower speeds, behavior for which EVs tend to perform better. However, from a policy level, even if EVs do perform better for these city drivers, if city drivers drive much less than their suburban and rural counterparts, the total emissions savings from electrifying their fleet might remain small, because they represent a relatively small portion of current gasoline use. There also is a body of literature studying these questions from a macroscopic level.

Creutzig et al. [55] look at a global sample of cities and propose different pathways towards decarbonization for different types of cities. They find that EVs can represent a very important tool for decarbonization, especially with a particular sub-class of cities where driving distances are comparatively high, densities are comparatively low, and the electric grid has the potential to be relatively clean, with cities such as Los Angeles and Toronto given as examples. They suggest that for different typologies of cities, especially denser megacities such as New York City, London, and Shanghai, greater benefits can be gained by investment in high capacity public transit powered by new or imported renewable energy capacity. These results hint an underlying conflict within the literature—from a high level, EVs are a better instrument for emissions reduction in situations where they will be heavily used (or, more specifically, where they will be replacing ICEVs that would otherwise be heavily used), but from an engineering perspective EVs can best replace ICEVs that are not as heavily used. Battery improvement will likely lessen the importance of this distinction, but the

trade-off between volume of use and vehicle performance is one that has not been fully explored in the literature.

In addition to these considerations, studies have shown the importance of understanding that the interaction between vehicle emissions and the electric grid go both ways—the emissions of a vehicle depend on the vehicle's use and the local grid electric mix, but the carbon intensity and the reliability of an electricity generation and distribution system can be effected by electric vehicles as well. Some argue that, as EVs become more popular, the impact of interaction with the electric network will become comparable in importance to their mobility and emissions impact (see [56] for a review). The electric grid is already sensitive to sudden demand shocks, and it will become more sensitive if greater amounts of intermittent renewables are brought online. Electric vehicles, if plugged in to high voltage outlets during high-demand periods of the day, have the potential to seriously destabilize the electric network, demanding more electricity than the grid is able to deliver. However, electric vehicles as mobile energy storage devices, also have the ability to supply electricity back into the grid during both short term demand spikes or longer term windows of lower production from intermittent sources.

The marginal impact of EVs on emissions, as well as the stability of the electric grid as a whole, depends greatly on the timing and type of charging used by EVs. Electricity in the grid is produced by a large number of different plants using different methods to generate electricity. Plants differ both in the per-unit energy cost of generation when running at full capacity, the ramp up time needed to operate at full capacity, and efficiency penalties due to operating at partial capacity. Different fuel sources and different degrees of conversion efficiency also mean that rates of carbon emission per unit energy generated can vary greatly between plans. Different types of plants fulfill different needs of the grid. Plants that have low marginal costs but slow ramp up times, often nuclear and coal plants, tend to operate at full capacity as much as possible, whereas plants with higher marginal costs (often powered by natural gas or petroleum) tend to be dispatched only during demand peaks. As a result, the emissions impacts of an EV depend greatly on charging decisions that are

influenced by personal travel patterns.

Many have attempted to estimate the impacts of different sorts of charging patterns on the electric grid. Kelly et al. [57] use the 2009 NHTS to model the adoption potential for PHEVs across the US. They look at individual vehicle-days and model the vehicle's battery state of charge, assuming a steady discharge rate of 0.246 kWh per mile while driving, and then they aggregated these measures across the US. They find that a PHEV with a small battery with 10.4 kWh of useable energy would be able to electrify two thirds of nationwide driving distance. They used this model to evaluate total stress on the grid as well as total gasoline consumption for various charging scenarios. They find that under uncontrolled charging, where users plug in a vehicle as soon as it reaches home at the end of the day, EV charging will significantly add to the peak electric demand in the late afternoon, especially if high voltage charging is used. Modifications such as more work charging and last-minute overnight charging, on the other hand, are capable of significantly smoothing the demand curve.

Others take the modeling further and examine the effect of charging behavior on the carbon intensity of the electricity used to power EVs. Sioshansi et al [58] present perhaps the most thorough study of the carbon intensity of EV electricity, use a sample of 227 GPS drive cycles to study the time-dependent charging behavior of a group of electric vehicles. They also track vehicle battery state of charge by treatin power consumption per mile as constant, combining that with information on the time dependence of which power plants in Ohio are "on the margin" and would therefore generate the extra electricity necessary to re-charge an EV when it is plugged in. This unique setup allows them to show that EVs in Ohio will be most carbon intensive when charged overnight, as their extra electricity would be generated by base-load coal power plants. Even in this worst case, however, they find that PHEVs would represent an improvement in carbon intensity over ICEVs, and that incentives or regulations governing charge timing could reduce these emissions further.

Many also seek to model the possible positive effects that EVs, as energy storage devices, can have on the grid. In the past 10 years, a somewhat distinct subfield has emerged in the transportation energy community focusing on the potential for

vehicle to grid (V2G) interaction. A foundational paper in the field was published by Tomic and Willett in 2007 [59]. They suggest that owners of EVs could make significant annual profits, possibly over $20,000 per year, by charging the market rate for frequency regulating services that are within the technical capacity of current EV batteries. Lund and Willett [60] expand on the idea, in which they argue that vehicle batteries would be capable of not only producing a revenue stream for owners but also for making intermittent renewable energy generation more profitable by better matching generation with demand. These models, while very useful as a vision for a more beneficial EV use case, have yet to be matched with a realistic travel demand and vehicle performance model, making it difficult to predict how EVs status as grid backup and frequency regulation would complement or conflict with their status as mobility providers.

Finally, there has been some work evaluating direct emissions impact of national EV policy and technology change, although this area of the literature needs further research. Peterson and Michalek [61] ask the simple but very important question: what vehicle technologies are the most cost effective tools for reducing aggregate carbon emissions? They find that PHEVs with relatively small batteries, rather than long-range EVs, are able to mitigate carbon emissions at the least cost. They also find that, in terms of additional investment, money would be better spent on charging stations that can increase the all-electric range of small battery PHEVs rather than spent on vehicles with larger batteries. As the model they present is fairly simple, some details related to these findings remain open to further research, especially the impact of location and regional travel behavior on these findings and how technological improvement might change these results.

This thesis intends to expand on the important question—how to quantify the emissions costs and benefits of different vehicle technologies—by bringing in literature and research from other fields mentioned above. By bringing in understanding about aggregate travel behavior, EV performance, and the emissions impact of EV charging, this research is intended to fill a hole in the existing literature and begin providing concrete answers to remaining questions about EV policy and technology design.

Chapter 3

Methods

3.1 Data

Throughout the analysis presented in this thesis, care was given to ensuring that the model and results presented were based as closely as possible on simple physical laws and empirically collected data. Unlike a black-box vehicle simulation model, the vehicle performance and travel demand models described below are intended to be as transparent as possible, prioritizing interpretability and empirical grounding over detail when limitations warrant it. As such, a wide variety of publicly available data was used to inform these results. This is the first time that all of these diverse sources have been combined in order to create a uniquely detailed model of POV transportation energy use across the United States [62].

3.1.1 GPS Velocity Histories

The results presented in this thesis require an evaluation of various POV technologies under "real world" use. While there are many possible ways of defining a vehicle's use, we choose a simple one—we assume that for any given POV trip, that trip's velocity history depends on trip and user characteristics such as the trip's origin and destination, route choice, traffic conditions, and driver habit, but we assume that the velocity history is independent of vehicle choice. This simplification allows us to

GPS Data Source

	Unique Vehicles	Number of Trips
California[a]	2,899	64,358
Atlanta[b]	1,649	38,407
Texas: Houston[c]	575	3,232
Texas: Laredo	176	760
Texas: Rio Grande	357	2,515
Texas: San Antonio	526	2,853
Texas: Tyler	244	845
Texas: Wichita Falls	349	4,618
Total	6,775	117,588

Table 3.1: GPS data sets used in the energy model and the number of vehicles and trips included in each. This combined dataset is implicitly assumed to cover representative variation in driving aggressiveness and driving style across the US. Note that these numbers do not include trips that were filtered out as containing data-logger errors.

[a] From [63]   [b] From [64]   [c] All Texas data from [65]

use the same set of velocity histories to evaluate different vehicles, facilitating the comparison. Realistically, this use is not quite absolute, as the velocity history for a trip likely also depends on properties of the vehicle, particularly engine power and idling speed, but those corrections are assumed to be negligible for everyday driving.

POV velocity histories, often referred to as "drive cycles," can be captured by GPS data loggers at resolutions of 1 hz or greater. For analysis, we used a large dataset of GPS tracks that were collected as parts of travel surveys in California [63], Atlanta [64], and Texas [65]. This data was anonymized before release, so the only data available was a set of files containing vehicle speed at a series of time-steps, a vehicle identification number, and in some cases some very limited demographic information about the household—no location data or detailed household information was available.

To process the data, we broke up full-day velocity histories into distinct trips for pauses of greater than two minutes, trimming off leading and trailing zeros. In some of the GPS data, particularly from the Texas datasets, there were some problems of the GPS logger recording spurious readings of zero velocity while the vehicle was
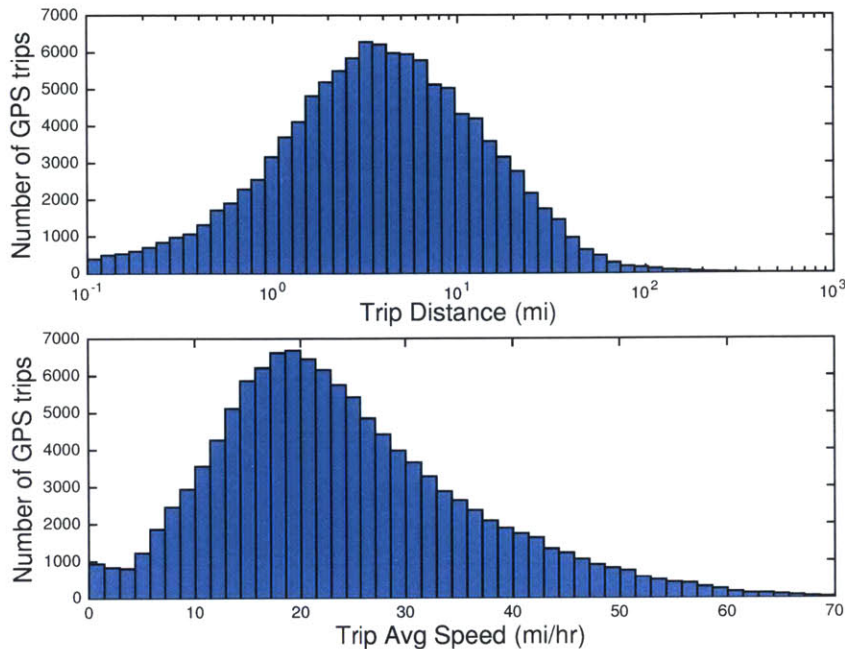
Figure 3-1: Histograms for the trip distance (top) and average speed (bottom) in units of miles and miles per hour, respectively. We expect GPS velocity histories in our dataset to span the entire plausible range of possible driving behaviors. It does not need to have a representative distribution of trip lengths, trip durations, or trip velocities in order for the model presented below to be accurate.

driving, leading to unphysical sudden stops and starts in the drive cycle. To account for this, all drive cycles with instantaneous acceleration greater in magnitude than $10 \ m/s^2$ were removed from the sample. The resulting GPS trip distance and time distributions are shown in Figure 3-1, showing that the dataset spans a wide variety of different types of trips.

The trip energy model described below uses this dataset as a pool intended to contain all of the expected variation in driving behavior across different kinds of trips. Because the travel surveys with which these data were collected were not intended to be representative of travel behavior across the United States, we cannot assume that this sample of GPS trips can be treated as a random sample of trips from across the US. However, we do assume that *locally* these distributions are identical—that for trips of a certain fixed distance and duration, the distribution of possible drive cycles represented in the GPS dataset is representative of driving behaviors anywhere in

the US. While this is a difficult assertion to prove categorically, the GPS dataset has drive cycles drawn from a wide variety of environments, and no comparisons within the dataset have shown significant differences between the drive cycles from these various locations, suggesting a degree of universality.

3.1.2 National Household Travel Survey

	NHTS Respondents	US Total
Persons	308,901	283,053,872
Households	150,147	113,101,330
Vehicles	309,163	211,501,318
Trips	1,167,321	392,022,844,961
POV Trips	1,015,749	327,117,654,775
POV Days	176,186	61,219,432,171

Table 3.2: Summary statistics for the NHTS, giving the number of each category counted in the NHTS and the number of each category that each category represents in the US when aggregated according to the NHTS weights. Note that the weighted totals for Persons, Households, and Vehicles represent the number of each present in the US in 2009, and for Trips, POV Trips, and POV Days the weighted totals represent the number of each over the course of a year.

While GPS loggers are becoming an increasingly important component in travel surveys, they are certainly not universal. To this date, there has not been a nation-wide, representative GPS survey with a large enough sample size to study communities at a sub-national level. To account for this, we combine our high-resolution but less-representative GPS dataset with the 2009 National Household Transportation Survey (NHTS) [11], a lower-resolution but nationally representative traditional travel survey.

The NHTS is produced by the US Federal Highway Administration, with a new survey every five to ten years. The NHTS picks a representative sample of households from across the US and then randomly assigns each household a travel day picked from a one year period. On that travel day, each household member keeps a detailed record of each trip he or she takes, including trip mode of transportation, distance, duration,

and purpose. The NHTS also collects data on each car owned by a household, whether or not that vehicle was driven on the travel day.

In our analysis, we limited our sample to personally operated vehicle trips, which we defined as cars, vans, sport utility vehicles, pickup trucks, and other trucks. Note that we did not include recreational vehicles (RVs) or motorcycles in our analysis, as the goal was to focus on trips that could be plausibly replaced by electric vehicles. This left a total of 1,015,749 trips in our study. Avoiding double counting by limiting the trips to ones where the survey respondent was the driver reduced the sample to 744,788. Finally, because we focused on vehicle requirements, we only analyzed trips for which the vehicle used was in the Vehicles datafile, giving a final sample size of 729,563 POV driver trips over a total of 176,186 vehicle days. This method of counting does not count trips in a vehicle that were driven on the travel day but not by a member of the household, so the results for vehicle usage are likely very small underestimates.

3.1.3 EPA Dynamometer Tests

Evaluating vehicle technologies also requires a detailed model of vehicle performance. Every year, the EPA certifies the fuel economy and levels of emissions for all vehicles sold in the United States. As part of this process, the vehicle manufacturer is required to report the results of a series of dynamometer emissions tests to the EPA, and the EPA checks the results of a portion of those tests on its own dynamometers. Dynamometer testing is intended to estimate a vehicle's fuel consumption and emissions over a pre-specified drive cycle in a controlled and replicable environment. It involves placing a vehicle with its drive wheels on a set of variable-resistance rollers, running the vehicle through a specific drive cycle, and measuring either the emissions (for an ICEV) or change in battery charge (for a BEV) to estimate fuel consumption. During the test, a driver in the vehicle uses the gas and brake pedals as a normal driver would to continuously match the vehicle's wheel speed to the drive-cycle's proscribed speed throughout the drive cycle.

The dynamometer force provided to the wheels by the rollers over the course of the

Measured Values	2013 Nissan Leaf	2014 Ford Focus
a (N)	133.8	115.3
b (Ns/m)	0.7095	1.933
c (Ns^2/m^2)	0.4910	0.3998
m (kg)	1,780	1,610
MPG Highway (Unadjusted)	146.4	50.4
MPG City (Unadjusted)	184.2	33.5

Table 3.3: Dynamometer parameters and test results for the Nissan Leaf and the Ford Focus, as published by the EPA. The coefficients a, b, and c, and m are settings used during dynamometer testing to estimate tractive force and also used by the method presented here. The unadjusted MPG ratings are based on EPA calculated emissions over the course of the Highway (HWFET) and City (UDDS) drive cycle, which are used below to calibrate vehicle efficiency parameters.

test is adjusted to match the expected tractive force—a combination of drag, rolling resistance, inertial effects, and higher order terms—that the vehicle would experience were it actually traveling at that speed on the road:

$$-F_{dyn} = a + bv + cv^2 + (1 + \epsilon)m\frac{dv}{dt}, \tag{3.1}$$

where a, b, and c relate moments of the vehicle's instantaneous velocity to the resistive force it experiences, ϵ is a parameter accounting for the rotational inertia of the vehicle's wheels and engine[1] and the dynamometer force F_{dyn} is taken to be negative because it opposes the (positive) direction of the vehicle's movement. The coefficients a, b, and c, known as the coastdown coefficients, are typically measured on a track by bringing a vehicle to a high speed and measuring its velocity as it coasts to a stop, fitting the observed deceleration to a three parameter function of instantaneous velocity [66]. A database of these coefficients is published by the EPA [40], containing information for all widely available models in the United States.

Our analysis also requires a measure of vehicle energy consumption over a set of known drive cycles. The EPA currently measures vehicle emissions and fuel economy through a detailed five-cycle procedure, but, for continuity relating to the CAFE

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[1]In practice, this value can vary depending on what gear the car is in, but it has little effect on the final results. Value from 0.05 to 0.1 are common in the literature—we take $\epsilon = 0.05$ here.

standards and the gas-guzzler tax, manufacturers continue to test and report results for the two highway and city tests. The results of these two tests are published as "unadjusted" city and highway fuel economy values [39]. These values for most widely available vehicles are available in a database from the EPA as well [5]. The parameter values and test results for the 2013 Nissan Leaf and the 2014 Ford Focus[2], the two vehicles studied in this thesis, are shown in Table 3.3.

3.1.4 Typical Meteorological Year Database

Since climate-control auxiliary energy use can be a large component of EV energy consumption, and since ambient temperatures vary greatly across the United States, it was important to accurately model the external temperatures experienced by drivers over the course of a year. As an estimate of typical temperatures across the US, we obtained hourly temperatures from the NREL "Typical Meteorological Year" database [67][3]. This dataset provides hour by hour temperatures for 1,021 weather stations located across the United States. This detailed temperature data allowed us a detailed model of the thermal load on a vehicle in any of the states or metropolitan areas given in the NHTS.

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[2]We chose the Ford Focus because it is similar to the Leaf in terms of passenger volume (90.6 cubic feet vs 93 cubic feet, and because its lifetime cost per mile is roughly similar [15]), and with a window sticker gas mileage of 30 MPG combined, it is roughly equal to the 2016 CAFE standards.

[3]This idea comes from Yuksel and Michalek [42], who use the TMY database and a different energy use model to estimate EV range for different locations.

Figure 3-2: Box plot summaries of temperature data from a set of US cities obtained from the Typical Meteorological Year database[67]. The boxes represent the middle 50% of all hourly temperature readings, the red line in the middle being the median. The dashed lines extend to the maximum and minimum reading not defined as an outlier, and the red crosses identify particularly extreme temperature readings, defined as being more extreme than 1.5 times the interquartile range. These temperature readings show that the external temperatures, and therefore auxiliary energy demands, vary greatly between cities studied in this thesis. The matching procedure designed to pair weather stations with cities is described in Section 3.2.3.

3.2 Vehicle Model

The analysis presented in this thesis makes the simplifying assumption that, for any POV trip, its energy requirements depend only on that trip's velocity history and the external temperature at the time of the trip. This is certainly a simplification, as elevation changes, cargo weight, tire air pressure, time since the previous trip, when the transmission changes gears, and weather factors beyond temperature can all influence energy use as well. However, compared to the bulk of national-scale energy use models that have been used by others—most of which take energy consumption only as a factor of vehicle choice and distance traveled—this is an unusually detailed model.

The vehicle model consists of a tractive energy component E_{tr}, representing the total amount of energy applied by the engine towards forward progress, the drive efficiency component η_{charge}, relating tractive energy to the total energy drawn from the vehicle's energy storage system going to forward motion, the auxiliary energy component E_{aux}/η_{aux}, representing the amount of energy devoted towards tasks besides movement and its associated conversion efficiency, and the charging efficiency η_{charge}, accounting for charging losses. The final equation for energy use is

$$E_{tot} = \eta_{charge} \left(\frac{E_{tr}}{\eta_{drive}} + \frac{E_{aux}}{\eta_{aux}} \right) \qquad (3.2)$$

$$= \eta_{charge} E_{use}. \qquad (3.3)$$

A schematic of these energy flows is shown in Figure 3-3, and each component is explained in more detail below.

3.2.1 Tractive Energy: E_{tr}

Our model of vehicle energy use begins with an idealized application of Newton's second law. At any point, we can identify the forces acting on a car as tractive force, resistive forces, and gravity. As before, we have defined tractive force as force actively

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applied by the vehicle's control system—namely its engine or its brakes. Resistive forces always act to lessen the vehicle's speed and are largely attributable to drag and rolling resistance. The goal of the tractive energy component of the vehicle model is to produce a time-resolved estimate for this tractive force supplied by the vehicle. Defining the positive direction as the direction of travel of the vehicle and summing these forces gives:

$$F_{tot} = F_{res} + F_{tr} - mg\sin(\theta) = (1 + \epsilon)m\frac{dv}{dt}, \qquad (3.4)$$

where θ is the incline of the road and g is the acceleration of gravity. Constants a, b, and c are the coastdown coefficients described earlier, and m is the vehicle's mass, here increased from the curb weight by 136 kg to represent typical load [39]. Rearranging to solve for tractive force gives:

$$F_{tr} = -F_{res} + (1 + \epsilon)m\frac{dv}{dt} + mg\sin(\theta) \qquad (3.5)$$

$$= a + bv + cv^2 + (1 + \epsilon)m\frac{dv}{dt} + mg\sin(\theta). \qquad (3.6)$$

Because F_{tr} is the force expended by the vehicle, the instantaneous tractive power expended by the vehicle is $P_{tr} = F_{tr}v$. Vehicle design means that when tractive force is positive, that tractive force is being applied by the vehicle's engine, and when tractive force is negative, the force is being applied by the brakes or regenerative braking system.

Thus, solving for the total work done by the vehicle's engine requires integrating the instantaneous tractive power with respect to time, but only over times where the

tractive force is positive. We define this quantity as a trip's tractive energy:

$$E_{tr} \equiv \int\limits_{F_{tr}(t)>0} F_{tr}(t)\,v(t)\,dt \tag{3.7}$$

$$= \int\limits_{F_{tr}(t)>0} \left[av + bv^2 + cv^3 + (1+\epsilon)m\frac{dv}{dt} + mg\sin(\theta) \right] dt. \tag{3.8}$$

For the work in this paper, the contributions to tractive energy use from elevation change are assumed to be negligible when compared to other sources[4]. Thus, given vehicle parameters a, b, c, m, and ϵ along with a drive cycle $v(t)$, we are able to approximate $\frac{dv}{dt}$ by finite differences, and we are able to approximate and the integral by the trapezoidal method to give an estimate for the trip's E_{tr}.

When evaluating these expressions on GPS driving histories, we often found that the net change in kinetic energy of the vehicle:

$$\Delta KE = \int F_{tr}(t)\,v(t)\,dt, \tag{3.9}$$

did not integrate to zero. This is an unphysical result, as for every trip in the GPS dataset the vehicle starts and stops at rest. To remove this numerical error, which would reach up to 4% of the total tractive energy over some trips, we integrated the velocity signal to get $x(t)$, interpolated the distance function from 1 hz to 100 hz via cubic splines, and then differentiated this function to get a new estimate for velocity and acceleration[5]. Velocity and acceleration signals were then smoothed to remove noise at frequencies greater than one hz. This interpolation reduced errors due to numerical integration by a factor of ten while still giving a signal that matched the original one when down-sampled back to 1 hz.

We used this method to calculate E_{tr} for all 117,588 GPS drive cycles in our dataset, for both the 2013 Nissan Leaf and the 2014 Ford Focus.

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[4]In terms of total energy consumption, this is a very minor simplification, as most cars will likely return to the same place where they started over the course of any vehicle day and thus the net change in elevation is zero.

[5]This process, rather than just interpolating the velocity signal, was used in order to ensure that the total distance traveled over the course of the drive cycle remained constant.

3.2.2 Drive Efficiency: η_{drive}

Especially for vehicles with regenerative braking, the relationship between drive efficiency η_{drive} and more commonly discussed efficiency parameters such as the powertrain efficiency is complicated and not always intuitive. The energy pathways are shown in schematic form in Figure 3-3 and described below.

It is helpful to begin by looking at the instantaneous load on the energy storage device (called the battery for the rest of this section, but a gas tank is equivalent). The instantaneous ratio of the power entering the engine P_{drive} to the kinetic energy produced by the engine P_{tr} is the instantaneous powertrain efficiency, η'_{pt}. Of this energy, some is dissipated in the brakes, and the rest is dissipated elsewhere—largely via air resistance and rolling resistance between the tires and the road surface. Of the portion of energy dissipated in the brakes, P_{brake}, a smaller portion is returned back to the battery via regenerative braking with efficiency η'_r, at which point it can be cycled through the loop again. Finally, the ratio of energy drawn from the battery for auxiliary use to the energy used by the auxiliaries is the auxiliary efficiency η'_{aux}. The instantaneous load on the battery, then, is a the sum of the energy leaving to the auxiliaries, the energy leaving to the engine, and the engine returning from the brakes:

$$\dot{E}_{storage} = \eta'_r P_{brake} - \frac{P_{gas}}{\eta'_{pt}} - \frac{P_{aux}}{\eta'_{aux}}. \qquad (3.10)$$

As suggested by the notation, if we focus on the average rather than instantaneous efficiencies, we can simplify this equation further, defining the portion of all of the kinetic energy that is dissipated in the brakes as f_{brake}:

$$\Delta E_{storage} = \eta_r E_{brake} - \frac{E_{gas}}{\eta_{pt}} - \frac{E_{aux}}{\eta_{aux}} \qquad (3.11)$$

$$= \frac{E_{tr}}{\eta_{pt}} \left(\eta_r f_{brake} \eta_{pt} - 1 \right) - \frac{E_{aux}}{\eta_{aux}} \qquad (3.12)$$
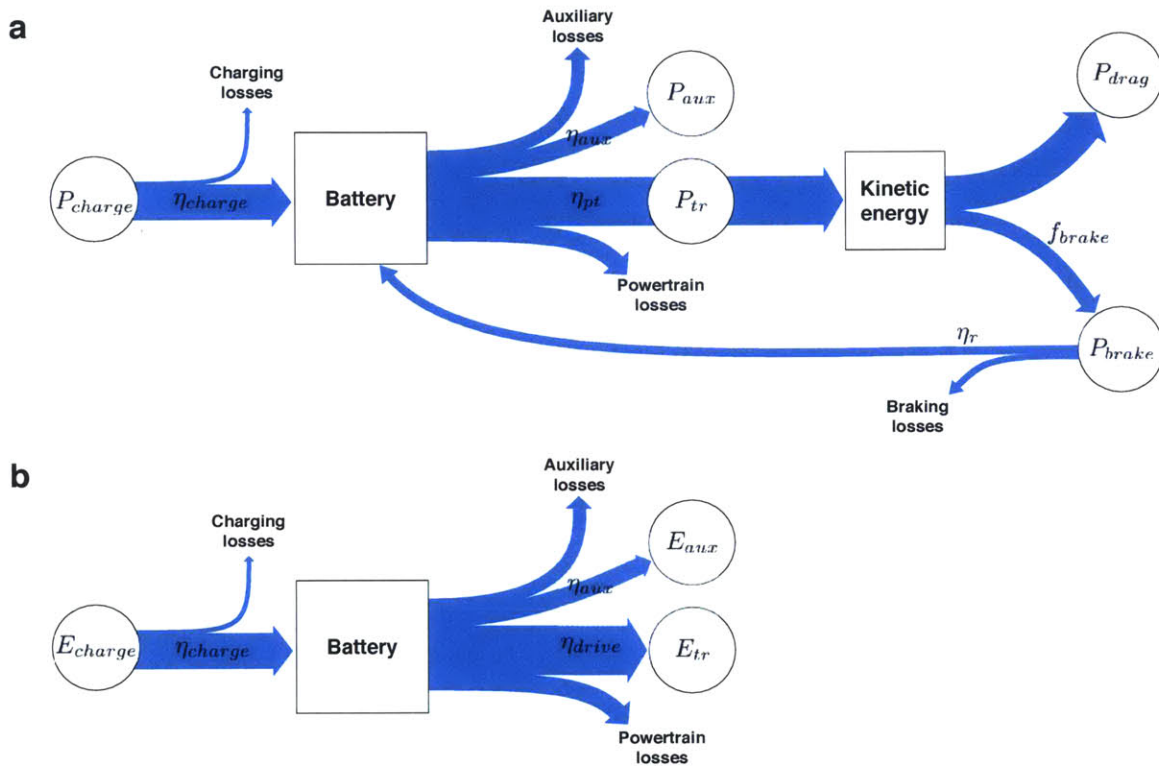
Figure 3-3: Schematic representation of evergy flows within an electric vehicle. In panel **a**, the full set of energy flows is shown: starting with the charger, energy drawn by the vehicle experiences charging losses and then enters the vehicle battery. Energy from the battery can either be devoted towards auxiliaries or towards driving, in both cases experiencing losses exiting the battery. Energy devoted towards driving gets converted, with additional losses, towards vehicle kinetic energy, which is either dissipated through resistive (mainly drag) forces or passes through the regenerative braking system. Some portion of the energy passing through the braking system is returned to the battery and can be used again. In panel **b**, the above flows are re-formulated as they are calculated in the energy model, where the drive efficiency η_{drive} captures both powertrain losses and energy returned to the battery through braking. For ICEVs without regenerative braking, the energy flow diagram looks like panel b with $\eta_{drive} = \eta_{pt}$. Credit—James McNerney for the figure

Rearranging, we can define:

$$\eta_{drive} \equiv \frac{\eta_{pt}}{1 - \eta_{pt} f_{brake} \eta_r}. \qquad (3.13)$$

This drive efficiency η_{drive} is defined as $\frac{E_{tr}}{E_{drive}}$, where E_{tr} is the tractive energy as defined above and E_{drive} is the total energy devoted to motion that is removed from the battery[6]. For vehicles without regenerative braking, such as non-hybrid ICEVs, this formulation simplifies to $\eta_{drive} = \eta_{pt}$. With this new parameter, we can simply write:

$$-\Delta E_{storage} = \frac{E_{tr}}{\eta_{drive}} + \frac{E_{aux}}{\eta_{aux}}. \qquad (3.14)$$

Given this formulation, our model attempts to estimate a trip's η_{drive} as accurately as possible given available data. The method used here is an extension of one first proposed by Lutsey [68] to estimate the conversion efficiency of a vehicle based on its EPA test results.

This method takes the EPA's unadjusted city and highway miles per gallon (MPG) ratings for a vehicle as ground truth measures of energy consumption. Lutsey has the insight to recognize that this MPG rating gives the energy consumption per unit distance over a known driving cycle $-\Delta E_{storage} = MPG \times d$, and that for the given drive cycle it is possible to calculate tractive energy requirements. Thus it should be possible to estimate a vehicle's drive efficiency over the course of an EPA drive cycle. We update his method to include auxiliary energy use and use a more precise definition of drive efficiency, giving a new equation for derived drive efficiency:

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[6]Note that this drive efficiency can be greater than 1, as energy that passes through the regenerative brakes and is returned to the battery can be put towards tractive energy again, allowing for it in effect to be double counted.

$$\eta_{drive} = \frac{E_{tr}}{d \times MPG - \frac{E_{aux}}{\eta_{aux}}}. \tag{3.15}$$

Additionally, we have assumed constant values for auxiliary power (100 Watts, see section 3.2.3) and auxiliary efficiency (0.81 for EVs and 0.185 for ICEVs, factoring in both a DC-DC conversion efficiency of 0.9 and typical powertrain efficiency) in the EPA tests, allowing for a derivation of drive efficiency that only depends on EPA test result and calculated tractive energy.

The estimated drive efficiency value is not a constant for a given vehicle—initial examination showed that it can vary greatly between the EPA highway and city tests. Therefore, the goal of the method described below is to estimate the function $\eta_{drive} = f(\text{Vehicle}, \text{Drive Cycle})$. To train this function, we only have the two data points coming from the EPA unadjusted fuel economy numbers, thus it is extremely important that the functional form include as much physical intuition and engineering knowledge as possible. To aid with this process, we used the software package ADVISOR [69] to simulate the drive efficiency of a set of GPS drive cycles and then used those values as validation data in training the model. This allowed us to both assess the plausibility of various functional relationships and derive an estimate for the precision of our estimates. While ADVISOR is used in model selection, however, it is not used in the actual fitting of the final model—that only depends on EPA test results.

Because of the fundamental technological differences between EVs and ICEVs, the underlying drive efficiency model chosen is different between the two cases:

Electric Vehicles

One of the many benefits of an electric powertrain is that, unlike an ICE, the engine maintains a relatively constant level of efficiency over a wide range of operating conditions (removing the need for a transmission, for example). Others have found that the average regenerative efficiency is also relatively constant between trips [70].

With that as guidance, it was found that the best performing functional form was one that treated powertrain and regenerative efficiency as constants and allowed them to be the fitting parameters. These parameters were chosen as the values for η_{pt} and η_r that correctly reproduced the measured energy consumption of the two EPA trips when combined with calculated values of E_{tr} and E_{aux}. Thus, the estimate for drive efficiency of a new trip, assigned subscript i, is only a function of the portion of that trip's tractive energy cycling through the brakes, $f_{brake,i}$:

$$\eta_{drive,i} = \frac{\eta_{pt}}{1 - \eta_{pt}\eta_r f_{brake,i}}, \tag{3.16}$$

η_{pt} and η_r being already-determined fit parameters. Solving for η_{pt} and η_r based on the two EPA drive cycles gives values $\eta_{pt} = 0.908$ and $\eta_r = 0.849$ for the 2013 Nissan Leaf, both of which are comparable to average values found by researchers and manufacturers [71, 66].

We tested this method with the ADVISOR model as a proxy for the real world, using it both to simulate the results of the EPA tests and to simulate the drive efficiency of a sample of 2,000 GPS trips, which is used as validation data for the method. The drive efficiency model was trained on the results of the two simulated EPA drive cycles, and that trained model was used to estimate the drive efficiency of the 2,000 trips in the training set. The results, shown in Figure 3-4, suggest that this simplified method does an acceptable job of reproducing the general behavior of drive efficiency as estimated by a much more complicated simulation model, and it does a very good job of reproducing total trip energy, which factors in both drive efficiency and tractive energy calculations. The mean square error for this estimate was 0.86% of the ADVISOR estimate[7], and this method overestimated the total energy consumption of the validation set by only approximately 1% when compared to the ADVISOR results.

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[7]This statistic was calculated ignoring the 25 out of 2000 drive cycles with tractive energy consumption of less than 10 kJ. Estimated efficiencies for these trips were much farther off the true values. However, the total energy consumption of these trips is so small compared to the rest of the sample (whose mean tractive energy consumption was 6 MJ) to render them negligible.
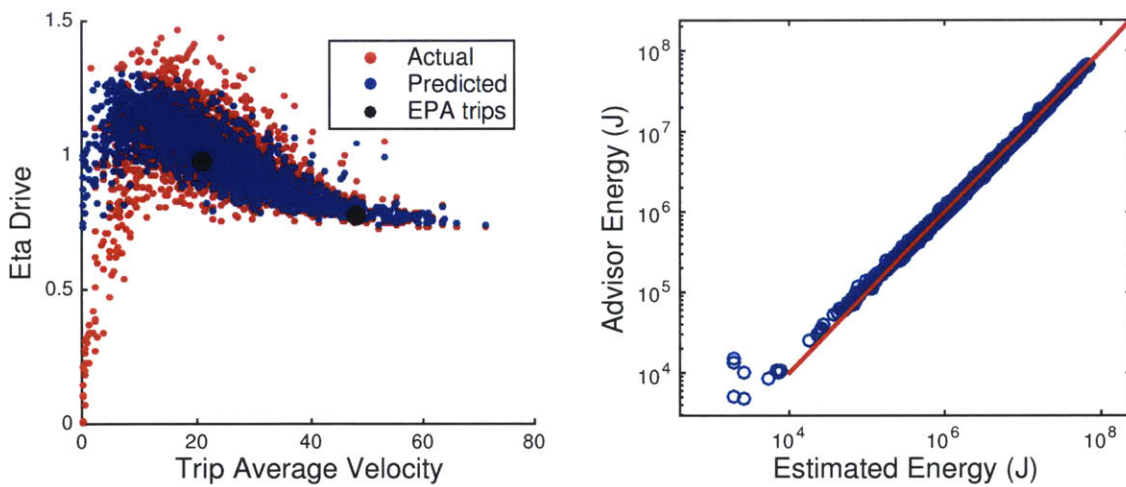
Figure 3-4: Model validation results for estimation of η_{drive} of an EV, tested against drive efficiencies calculated by ADVISOR. **Left:** drive cycle average speed versus drive cycle drive efficiency, showing that the simplified model reproduces expected behavior as a function of average speed, peaking at speeds around 20 mi/hr, decreasing sharply for lower speeds, and decreasing slowly for higher ones. **Right:** Predicted versus actual drive energy values (incorporating drive efficiency and tractive energy), taking the ADVISOR results as ground truth, showing good agreement between the two methods.

Internal Combustion Engine Vehicles

The ICEV modeled in this thesis is the Ford Focus, which does not have regenerative braking—thus the drive efficiency is equal to the powertrain efficiency. This simplification is necessary because, unlike EVs, the instantaneous powertrain efficiency of an ICEV depends very strongly on the exact operating conditions of the engine at any point in time, ranging from as high as close to 40% at high torque and moderate RPM to less than 10% for extremely high and low torque or RPM [12]. As such extremely high RPM and torque values are rarely reached during everyday driving, we had the greatest success by modeling average ICE powertrain efficiency as an increasing function of average vehicle speed and average vehicle acceleration[8]. The best performing model for drive efficiency was:

$$\eta_{drive} = \eta_{max} - \left(\frac{C_v}{v_{av} + \sqrt{\eta_{max}}} \right)^2 - \left(\frac{C_a}{a_{av} + \sqrt{\eta_{max}}} \right)^2 \qquad (3.17)$$

where v_{av} is the drive-cycle average velocity, a_{av} is the time averaged instantaneous acceleration over times when acceleration was positive, C_v and C_a are fitting parameters representing the characteristic of speeds and accelerations, and η_{max} is the maximum cycle-averaged powertrain efficiency asymptotically approached at high average speed and acceleration. There are three unknown constants in this equation, so η_{max} is chosen to be 0.35 based on physical intuition of the maximum average powertrain efficiency of an ICE [12].

The validation test results of this method are shown in Figure 3-5, producing a mean squared error of 0.3% of the actual drive efficiency, but an overestimate of the total energy by 6%. This good trip-by-trip performance but less good average performance is likely due to this method underestimating the efficiency for a small

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[8]Note that it is impossible to directly calculate engine RPM or torque from a drive cycle because gear ratio is unknown—some transmission control system must be assumed in order to do so. With no gear changes and over short time scales, RPM is roughly linearly related to velocity and torque is roughly linearly related to acceleration. However, the model presented here should be considered an entirely phenomenological model for powertrain efficiency that appears to accurately reproduce observed trends—a more accurate mechanistic model would require many more fitting parameters and thus much more data.
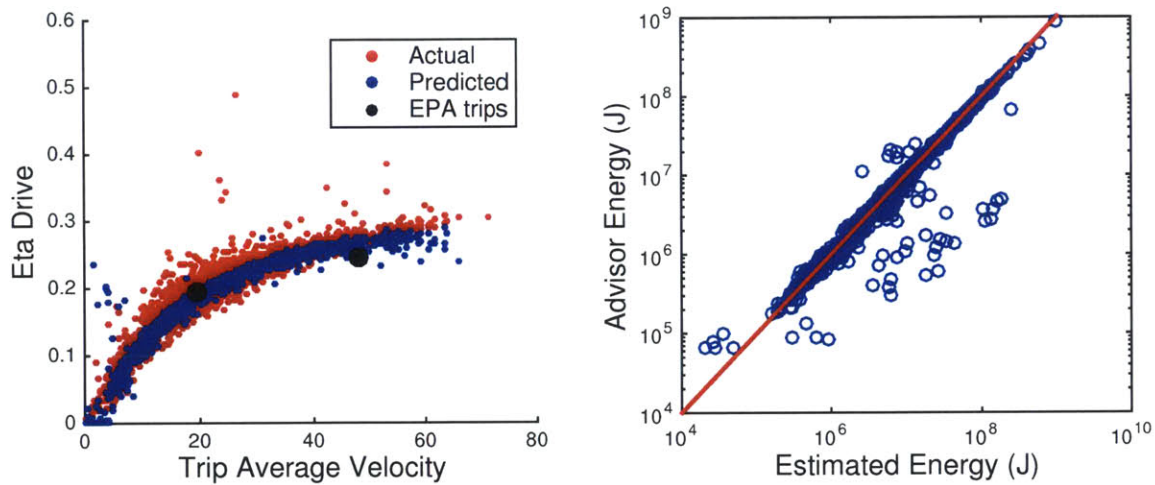
Figure 3-5: Model validation results for estimation of η_{drive} of an ICEV, tested against drive efficiencies calculated by ADVISOR. **Left:** drive cycle average speed versus drive cycle drive efficiency, showing that the simplified model reproduces expected behavior as a function of average speed, gradually increasing at higher speeds, without being overfit through the EPA highway drive cycle (right black dot), which has uncharacteristically low accelerations. **Right:** Predicted versus actual drive energy values (incorporating drive efficiency and tractive energy), taking the ADVISOR results as ground truth, showing good agreement between the two methods.

number of extremely high energy trips. For these long trips, a very small number of errors can have a large impact on the total energy. Further, these very long trips tend to capture effects, such as the engine operating more efficiently as it warms up, that are not captured in the unadjusted EPA tests and hence do not influence our predictions. Producing a better efficiency model for ICEVs should be a direction of further work, but we continue with the knowledge that our method might overestimate the energy of very long ICEV trips[9].

Trained on the EPA tests, this method produces values of $C_v = 9.89$ and $C_a = 0.0218$. We then used these best-fit constants to estimate the drive efficiency of all GPS trips in our dataset.

3.2.3   Auxiliary Energy and Efficiency: E_{aux} and η_{aux}

Auxiliary energy is energy used by a vehicle for purposes other than movement—these uses can include dashboard lights, power steering, entertainment systems, and climate control. For most vehicles, this auxiliary energy comes in the form of electricity at 12 Volts. For EVs, the electricity coming out of the battery is at a much higher voltage, so it must pass through a transformer after exiting the battery, an additional source of losses beyond simple resistive losses within the battery. For ICEVs, where stored energy is released through combustion, electricity must first be generated from the mechanical energy of the engine via an alternator before being converted to 12V and fed to the auxiliary system. These pathways lead us to estimated values for η_{aux}, which we take to be 0.81 for EVs and 0.185 for ICEVs, values that represent the much higher cost of converting mechanical energy to electricity than of drawing it from a battery.

We divide the auxiliary power into power devoted to climate control, which we assume is a function of external temperature, and power devoted to other components, which we assume is independent of all other trip properties. Geringer and Tober [72] and Del-Duce et al. [73] provide some estimates for typical auxiliary electrical loads and usage rates for various components, including the cabin air blower, lighting,

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[9]The direction of this error tends to reinforce many of the conclusions made below.

defogger, and heated seats. Based on their results, we assume a typical non-climate auxiliary load of 250 Watts, 100 Watts of which we assume to be always on and hence present in the EPA tests, the rest of which we assume to be at the discretion of the driver and hence not on in the EPA tests (see Section 3.2.2 for the importance of this quantity in estimating drive efficiency).

To estimate climate control auxiliary energy needs, we assume a simple heat balance equation for temperature inside the vehicle:

$$P_{thermal} = k|T_o - T_i| \tag{3.18}$$

where k is the thermal conductivity of the vehicle, measured in units of Watts per degree Celsius, and $|T_o - T_i|$ is the magnitude of the difference in temperatures between the inside of the vehicle and the outside of the vehicle, and $P_{thermal}$ is the magnitude of the thermal power demand on the climate control system. A value for $k = 350$ Watts per degree celsius is chosen based on various studies of air conditioning energy consumption and external temperature [74, 75, 72]. We use a simple model for internal temperature choice—we assume that the internal temperature is kept between 20 and 24 degrees celsius, with any additional difference between internal and external temperature maintained by the climate control system (this range is slightly lower than those cited in [76] because this model does not account for solar radiation or body heat, which we can expect to raise internal temperatures by a few degrees celsius). Thus, the power provided by the heating and cooling systems is:

$$P_{heat} = \begin{cases} k(20 - T_o) & \text{if } T_0 < 20 \\ 0 & \text{if } T_0 \geq 20 \end{cases} \tag{3.19}$$

$$P_{cool} = \begin{cases} k(T_o - 25) & \text{if } T_0 > 24 \\ 0 & \text{if } T_0 \leq 24. \end{cases} \tag{3.20}$$

The contribution of the climate control accessories to the total auxiliary power is a function of the thermal load on the climate control system and the various coefficients of performance (COP) of the climate control mechanisms. The COP is the ratio between the thermal power created by a device and the amount of power that the device dissipates. A radiative heater, for example, will have COP = 1 because its thermal load is equivalent to the energy it dissipates. Air conditioners and heat pumps can have COP > 1 by exploiting thermodynamics. Thus, the equation for the total auxiliary power needs of a vehicle is:

$$P_{aux} = \frac{P_{cool}}{COP_{AC}} + \frac{P_{heat}}{COP_{heat}} + P_{other}. \tag{3.21}$$

For ICEVs, the climate control heating is done with waste heat from the radiator, giving it an effectively infinite value for COP_{heat} (in other words, heating for an ICEV is 'free'). Because EVs produce so much less waste heat than ICEVs, they need other sources of heating. The 2013 Nissan Leaf has a heat pump installed, which has much better performance than the radiator that was installed on earlier versions. Both the Leaf and the Ford Focus have industry standard air conditioners installed. We take constant values of $COP_{AC} = 2.5$ for both vehicles and $COP_{heat} = 3$ for the Leaf [77, 78, 75].

As a means of illustration, the effect of this additional auxiliary energy on the range of the 2013 Nissan Leaf is shown in Figure 3-6. In our model, low temperatures can reduce the range of the Leaf almost in half.

3.2.4 Charge Efficiency: η_{charge}

Finally, we consider the energy losses due to charging the battery. It is important to make clear the distinction between energy from the battery or gas tank, which we define as E_{use}, and energy from the electric grid or gas station, which we define as E_{tot}. We define the ratio E_{use}/E_{use} as the charging efficiency η_{charge}. For ICEVs, gasoline losses due to filling the tank are practically zero, so we can simply set $\eta_{charge} = 1$. For
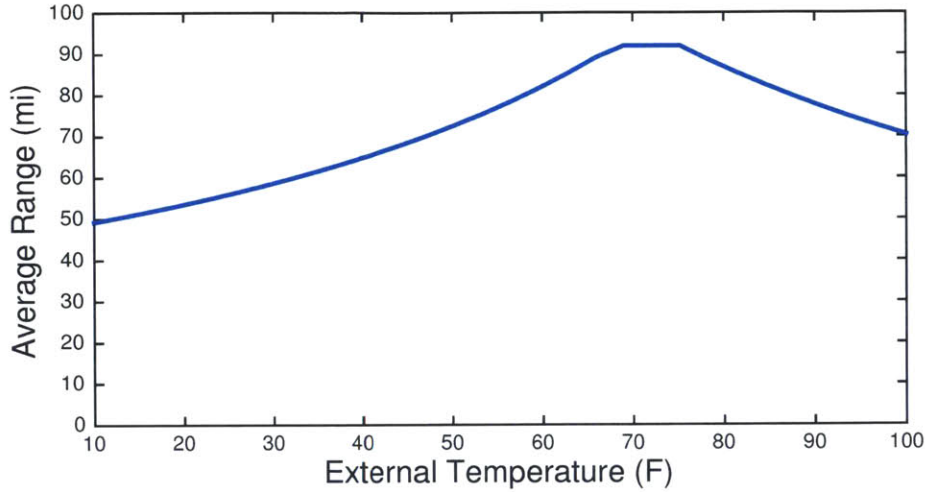
Figure 3-6: Average EV range as a function of temperature. This range is calculated by taking average values of drive energy consumption per unit distance, average values of non-climate auxiliaries, and average vehicle speeds. This simple model captures the dramatic negative effect of low temperatures on EV range observed in Yuksel and Michalek [42] and elsewhere.

EVs, there are greater losses in charging, largely due to resistive heating in the cable and battery. Typical charging efficiencies are found to be 85% - 95% (e.g. [79]), so we take a middle value of $\eta_{charge} = 0.9$ for electric vehicles.

The distinction between E_{use} and E_{tot} is very important to keep clear. Because this thesis focuses on fleetwide impacts of EV adoption, many of the results relating to EV energy use presented below are presented in terms of E_{tot}, because that is the measure of the *impacts* of the technology, on the electric grid, on the climate, and in terms of costs to the user. Many of the intermediate results, however, have to do with questions of vehicle range. Once a vehicle is charged, charging losses have already taken place. Therefore in questions of vehicle range, the meaningful comparison is between the battery's energy capacity and E_{use}, not E_{tot}.

The entire energy model, as defined by Equation 3.2, produces some insights about EV and ICEV performance when applied to the GPS dataset. Figure 3-7 shows how the various components of the vehicle energy model—tractive energy per distance, auxiliary energy per distance, drive efficiency, and total energy consumption per unit distance—vary at different trip distances and average speeds.
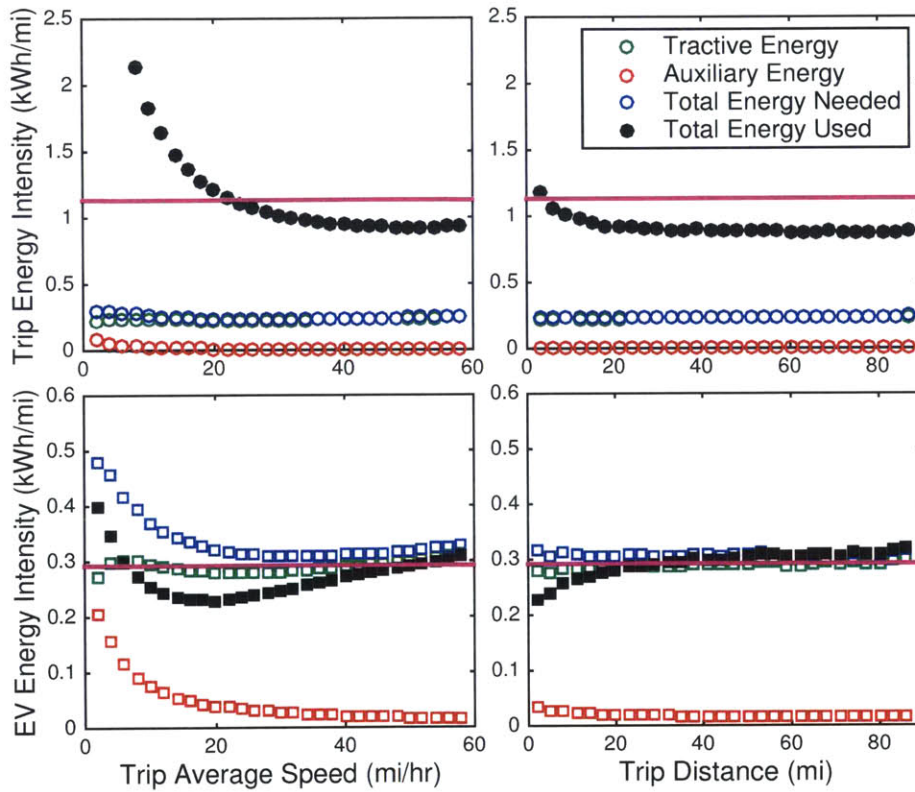
Figure 3-7: Plots of mean energy consumption for trips with different average speeds (left column) and distances (right column) for ICEVs (top row) and EVs (bottom row). Energy consumption is divided into tractive energy (green), auxiliary energy (red), drive energy (blue), and total energy (black). The horizontal lines show mean per mile energy consumption based on the EPA combined fuel economy rating for the Leaf. These results confirm many arguments about the ideal use-cases for ICEV and EV technologies. ICEVs are most efficient at high average speeds and for long distances. EVs, on the other hand, tend to be most efficient on trips whose average speed is approximately 20 mi/hr. EVs also tend to perform better for short trips when compared to longer ones.

3.3 Demand Model

The previous section describes a method to estimate a trip's total energy requirements based on a set of vehicle parameters, an external temperature, and a velocity history for the trip. Unfortunately, the best source available for nationwide driving behavior—the National Household Travel Survey [11]—does not have a GPS component or a temperature component. Indeed, the most relevant data included in the NHTS are trip distance, trip duration, trip start time, and household location. Below is described a statistical method that, by combining the NHTS with a GPS dataset and a weather dataset, is able to produce a probability distribution for the anticipated energy consumption of every trip in the NHTS. Because each trip in the NHTS in effect represents thousands of trips across the country, to the extent that the underlying datasets and methods are unbiased these probability distributions represent all of the trip-by-trip variation in POV energy use in the US.

3.3.1 De-rounding Procedure

Before proceeding further, the NHTS requires some processing to make it more suitable for analysis. Examination of the NHTS trip distances and trip durations shows dramatic evidence of rounding (Figure 3-8). Assuming that a roughly equal number of respondents round up as round down, this rounding should have little effect on derived energy use totals and averages, and hence it is rarely corrected for in studies using NHTS data. However, this research is intended to study range constraints and the effects of marginal increases in battery capacity. In studying these quantities, the "spikiness" of the raw NHTS data is liable to produce artifacts in our results. Thus, before proceeding further in the analysis, we used a simple de-rounding procedure to remove these artifacts from the distance and time distributions.

The underlying assumption behind our de-rounding method is that, when recording a trip distance or duration, a respondent can take three possible actions. The respondent can:
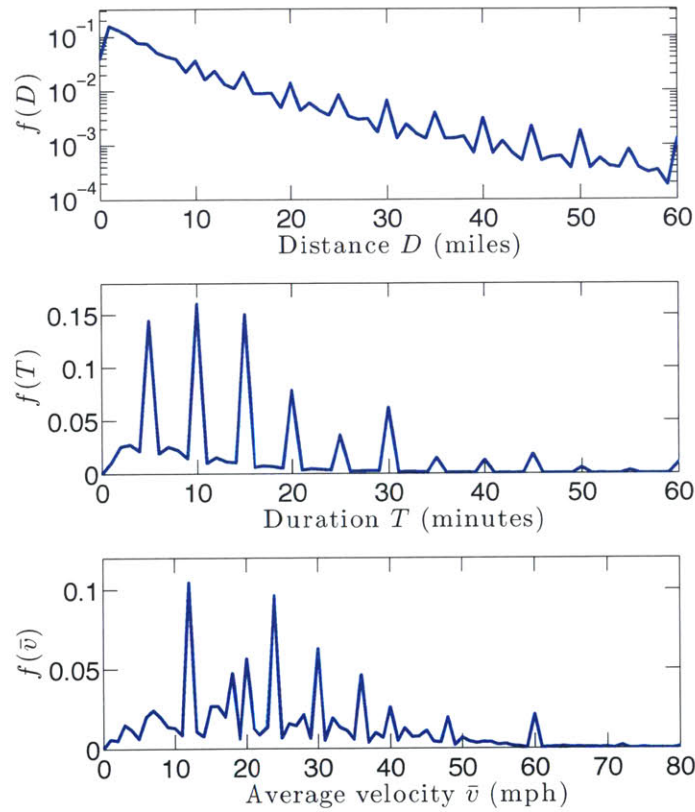
- Record the exact value.

Figure 3-8: Evidence of rounding in the NTS reported values. **Top:** Probability Distribution Function for reported trip distance, showing peaks at multiples of five. **Middle:** PDF of reported trip duration, showing strong peaks at multiples of 5 and higher ones at multiples of 15. **Bottom:** PDF of average velocity, showing artifacts of rounding in distance and duration. Credit to James McNerney for this figure.

- Round to value the nearest 1

- Round the value to the nearest 5

- Round the value to the nearest 15.

We began by using the recorded distance and time distributions to estimate the probabilities of a respondent taking each of these actions. For responses that are not a whole number, we assume that the value was recorded exactly. Limiting our data to all responses of a whole number, we define the probability of a respondent rounding to the nearest 1, 5, and 15 as P_1, P_5, and P_{15}, respectively.

We define the true value of some quantity x—in our case either a duration or a distance—and we define the recorded value $\tilde{x}$. From the data we know the probability mass function of $\tilde{x}$, $\tilde{P}(\tilde{x})$. For every trip, our goal is to estimate $p(x|\tilde{x})$, the probability density of the actual quantity given the rounded quantity.

Bayes' rule says that

$$p(x|\tilde{x}) = \frac{\tilde{P}(\tilde{x}|x)\,p(x)}{\tilde{P}(\tilde{x})}, \tag{3.22}$$

and each of these components can be approximated by looking at the distribution of the responses. $\tilde{P}(\tilde{x}|x)$ is the probability that a true value x gets rounded to a new value $\tilde{x}$. As defined before, there is a probability that x gets rounded either by 1, 5, or 15, so we can rewrite the above equation as a sum:

$$p(x|\tilde{x}) \propto \frac{P_1\,r(\tilde{x},x,1)\,p(x)}{\tilde{P}(\tilde{x})} + \frac{P_5\,r(\tilde{x},x,5)\,p(x)}{\tilde{P}(\tilde{x})} + \frac{P_{15}\,r(\tilde{x},x,15)\,p(x)}{\tilde{P}(\tilde{x})} \tag{3.23}$$

where $r(\tilde{x},x,n)$ is a function that is $1/n$ when x could be rounded to $\tilde{x}$ and 0 elsewhere.

The three parameters P_1, P_5, and P_{15} can be estimated by looking at the relative heights of the peaks at multiples of 5 and 15. We can define the height of a peak at $\tilde{x} = N$ as the mean difference between the observed probability at $\tilde{x}$, $\tilde{P}(\tilde{x})$, and the

	Distance	Time
P_1	0.82	0.27
P_5	0.11	0.55
P_{15}	0.07	0.18

Table 3.4: Rounding probabilities for trip distance (in miles) and trip duration (in minutes) estimated from the NHTS data.

observed probability at its neighbors above and below. The ratio of the heights at multiples of 15 to the heights at multiples of five (but not 15), the typical height of a peak at multiples of 5, and the constraints that the probabilities $P_1 + P_5 + P_{15} = 1$ are the three constraints required to estimate the three rounding probabilities from the survey data. The constants estimated from the NHTS data for trip distance and trip duration are shown in Table 3.4.

From here, we make the further simplifying assumption that the rounding distances are small in comparison to the values being rounded, allowing us to approximate $p(x) = \tilde{P}(\tilde{x})$. This assumption could easily be relaxed by estimating the function $p(x)$ by an appropriate smoothing of the observed probability mass function $\tilde{P}(\tilde{x})$, but we have not found reason to do so. In effect, this method produces a distribution for $p(x|\tilde{x})$ that is rectangular if $\tilde{x}$ is an integer non-multiple of 5; of width 5 with a peak of width 1 in the center if $\tilde{x}$ is a multiple of 5 but not 15; and of width 15 with two nested inner peaks if $\tilde{x}$ is a multiple of 15. This suggests that a survey response giving a multiple of 15 provides much less information about the true value of that quantity than one that is only a multiple of 5, and even less than if the response is not a multiple of 5.

3.3.2 Removal of Implausible Trips

Of the POV trips recorded in the NHTS, a number of them had invalid distances or durations, showing up as negative numbers in the datafile. For trips missing one of either trip distance or trip duration, the missing quantity was calculated from the existing quantity via an average velocity drawn randomly from the distribution of velocities of valid trips. The remaining 204 trips without valid distances or times

were treated as missing data.

Further, trips were defined as implausible if they implied an average velocity of greater than 80 miles per hour, or less than two miles per hour. For trips that were too fast, the recorded distance was treated as missing data. For trips that were too slow, the recorded duration was treated as missing data. Both of these quantities were then filled in the same manner as above. This method was chosen so as to be less likely to artificially inflate the estimated mileage, but the number of affected trips was small enough that other methods did not significantly alter the results.

3.3.3 Conditional Bootstrap

Once the NHTS has been appropriately processed, the goal becomes the estimation of a trip's tractive energy requirements based on the reported D and T values in the survey data. Because trip energy requirements are overwhelmingly dependent on trip distance, the problem becomes more tractable when it is reformulated as estimating a trip's average energy consumption per unit distance, which is equivalent to the mean positive tractive force $\bar{F}_{tr}$. Thus, the goal becomes to estimate the probability density function of $\bar{F}_{tr}$ as a function of the reported (presumably rounded) distance and time values D_r and T_r:

$$p(\bar{F}_{tr}|D_r, T_r). \tag{3.24}$$

evaluated at the specific location defined by the survey trip's distance and time. Above, we have defined a method for estimating the probability distribution for the true value D given a rounded value D_r, which we can write as $p(D|D_r)$, and similarly for T. Assuming that rounding of distances and times happens independently, and that rounding is independent of energy use, we can rewrite the above probability distribution as an integral over all possible true distance and time values:

$$p(\bar{F}_{tr}|D_r, T_r) = \iint\limits_{D_0, T_0} p(\bar{F}_{tr}|D_0, T_0)p(D_0|D_r)p(T_0|T_r)dD_0dT_0. \tag{3.25}$$

We are able to estimate this probability distribution by a series of bootstraps. The bootstrap is a statistical method for approximating a probability distribution by resampling with replacement from a finite sample of values chosen from that distribution. The procedure to estimate the distribution of $\bar{F}_{tr}$ given a pair of survey distances and times (D_r, T_r) can be best described as a series of steps:

1. Generate a possible de-rounded value the true trip distance D_0 by drawing randomly from the distribution $p(D_0|D_r)$ described in the previous section.

2. Generate a possible de-rounded value for the true trip time T_0 by drawing randomly from $p(T_0|T_r)$.

3. Use these two values to generate a possible average tractive force $\bar{F}_{tr}$ by drawing from the distribution at that de-rounded distance and time $p(\bar{F}_{tr}|D_0, T_0)$.

This process, repeated a large number of times, will reproduce a synthetic distribution that will eventually approximate the true underlying probability distribution, allowing us to estimate not only the most likely tractive energy requirements of a NHTS trip, but also the spread of the possible values we could have expected its energy requirements to take. This exact same process is used to capture drive efficiency η_{drive} as well, which is associated one-to-one with a GPS drive cycle as described above.

The hardest part of this algorithm is producing a reasonable estimate for the average tractive force of a trip whose true distance and time are known. In order to approximate this distribution, we make the assumption that our set of GPS trips is drawn from a distribution that is locally similar to the underlying distribution sampled by the NHTS. This does not assume that the underlying distributions of D and T between the GPS dataset and the NHTS are identical, only that *given* a certain pair of

D_0 and T_0 the mean tractive force distributions are similar. Additionally, we assume that the probability distribution $p(\bar{F}_{tr}|D_0, T_0)$ is relatively constant with respect to small changes in D_0 and T_0. These two small assumptions allow us to approximate $p(\bar{F}_{tr}|D_0, T_0)$ by randomly sampling GPS trips from a small window of trips that are "near" D_0 and T_0.

Results for similar applications [80] suggest that the exact shape of the window is unimportant, but that the size of it is. Choosing the size of this window is an example of the bias-variance tradeoff—a very small window runs the risk of matching too few GPS trips and hence increasing the variance of the estimate giving results that are heavily influenced by a small number of GPS trips. A large window picks up a large number of GPS trips and runs the risk of increasing the bias of the estimator by smoothing out the real shape of the underlying distribution. Because both distance and time distributions have heavy tails, the best results were found by using a logarithmic transform of the data before taking the window, and a square window of side length 0.25 in log-space was chosen as one that typically matches enough GPS trips but does not smooth out the heavy tail of the energy per distance distribution.

This bootstrapping algorithm was implemented as follows. For each NHTS trip with rounded distance and time values D_r and T_r:

1. Generate 5 possible de-rounded value the true trip distance D_i by drawing randomly from the distribution $p(D_0|D_r)$ described in the previous section.

2. Generate 5 possible de-rounded value the true trip duration T_i by drawing randomly from the distribution $p(T_0|T_r)$.

3. For each of the five pairs (D_i, T_i), generate 10 possible values for the average tractive force $\bar{F}_{tr,ij}$ by drawing from the distribution at that de-rounded distance and time $p(\bar{F}_{tr}|D_i, T_i)$.

This produces, for each NHTS trip, a population of 50 possible values $\bar{F}_{tr,ij}$ that represent the uncertainty in that trip's true energy per distance value based on both rounding of survey data and uncertainty in drive cycle. A schematic representation of
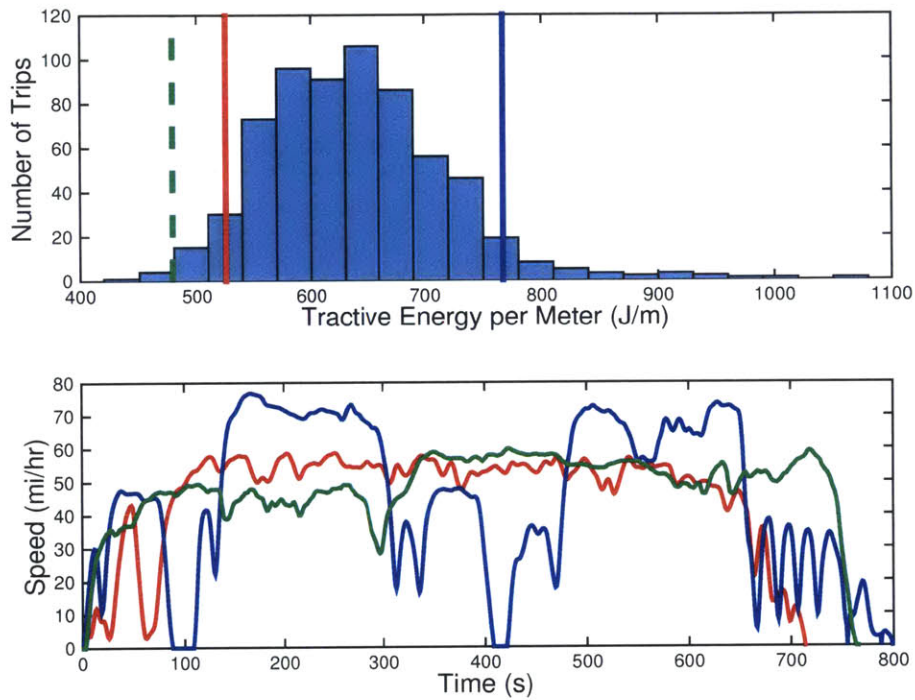
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Figure 3-9: Schematic for the GPS bootstrap procedure in the tractive energy component of the vehicle model, for the Nissan Leaf. **Top:** Tractive energy per mile distribution for trips similar in distance and duration to the HWFET (highway) drive cycle, which has a duration of 12.8 minutes and covers a distance of 10.3 miles. In our GPS dataset there were 649 drive histories within the appropriate time (11.3 to 14.4 minutes) and distance (9.0 to 11.6 miles) windows. Marked are the positions of the fifth percentile trip (red) and the ninety-fifth percentile trip (blue) in terms of tractive energy per meter. Also marked is the position of the HWFET drive cycle (green dashed line), which falls below the middle 90% range of this sample of real-world trips. **Bottom:** Velocity histories of the three trips marked on the above plot.

the final distribution generated by this process is shown in Figure 3-9. This energy per distance distribution can be turned into a tractive energy distribution by multiplying each value by its respective de-rounded trip distance.

Unfortunately, the GPS data is relatively sparse among the very high distance trips, along with trips with very high or low average velocities. Thus, we found the need to define an algorithm for what to do with a NHTS trips if there were not enough "nearby" GPS trips in step 3 to form a distribution. The version of this algorithm implemented in this thesis sets the minimum number of matched GPS trips at 5. If the window in log-D,T space around a de-rounded NHTS trip does not find at least 5 GPS trips, the side length of window is doubled. For trips of distance less than one mile, the window expands to cover trips with the same average speed but greater distance. For trips of greater than 50 miles, the window shifts to cover trips with the same average speed but shorted distance. For trips with distances in between, the window stays centered in the same place but simply expands in size. If after five window expansions the NHTS trip is still not matched with at least 5 GPS trips, the NHTS trip is assumed to be physically implausible and is treated as missing data.

Thus, for each physically plausible NHTS trip, this algorithm produces a set of 50 values representing the expected variation of that trip's tractive energy requirements and drive efficiency.

3.3.4 Ambient Temperature

As shown in Section 3.2, a vehicle's total energy consumption over a trip depends on both the drive energy devoted towards movement and the auxiliary energy devoted primarily towards climate control. A simple model is described there to estimate a vehicle's average rate of auxiliary energy consumption as a function of external temperature. Unfortunately, external temperature is not a quantity measured by the NHTS, so estimating this auxiliary power function requires an estimate for the external temperature when each NHTS trip was taken. Section 3.3.3 describes a prob-abilistic method for matching NHTS trips with GPS drive cycles—below is described a similar method for matching NHTS trips with local temperatures from the Typical

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City	Weather Station
New York, NY	JFK
Riverside, CA	Riverside Municipal Airport
Los Angeles, CA	LAX
Miami, FL	Miami/Kendall Tamia
Phoenix, AZ	Deer Valley/Phoenix
Washington, DC	DCA
Houston, TX	Ellington Air Force Base
San Antonio, TX	Kelly Field Air Force Base
Tampa, FL	TPA
San Francisco, CA	SFO
San Diego, CA	San Diego Miramar NAS
Dallas, TX	Dallas/Redbird Airport

Table 3.5: TMY weather stations matched with CBSA definitions found in the NHTS, for 12 of the NHTS cities with the greatest number of survey respondents. This matching, performed for each location in the NHTS, allows for ambient temperatures to be associated with NHTS trips.

Meteorological Year dataset [67].

To begin, the location of each NHTS household must be matched with a nearby weather station represented in the TMY database. To do so, we used two household location variables given in the NHTS—state and Core Based Statistical Area (CBSA) identifier[10]. First, each CBSA was matched with a weather station by name (a sample containing the cities with the most respondents is shown in Table 3.5). Trips corresponding to households within a CBSA were then matched with that CBSA's temperature profile. However, some households were not located in CBSAs. For those households, matching was based on the state—each household was randomly assigned to one of the weather stations located in its state. This procedure allowed every NHTS trip to be associated with one year's worth of hourly temperature data.

Once a NHTS trip is matched with a weather station, it is matched with an ambient temperature by taking into account the month during which the trip was

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[10] The CBSA is a geographical entity defined by the Census Bureau as the measure of a city's geographic area of influence, by their definition a CBSA consists of "one or more counties and includes the counties containing the core urban area, as well as any adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core."

taken and the trip's start time. The combination of month and time leaves, for each NHTS trip, a set of 28 to 31 possible external temperatures in the TMY dataset, depending on the number of days in the month. The bootstrap method defined in Section 3.3.3 produces a set of 50 possible trip tractive energy and drive efficiency values. Thus, for each NHTS trip, 50 temperatures are sampled with replacement for the set of possible temperatures and each is paired with a boostrap tractive energy and drive efficiency, producing an estimate for all of the components in the trip's total energy consumption defined in Equation 3.2.

3.3.5 Validation

The expected accuracy of our calculated energy totals was estimated using 10-fold cross validation. To do so, the GPS dataset was divided into 10 roughly equally sized groups. One group was chosen as the test set—a fake survey dataset was created by rounding the trip distance and time values using the same process estimated in the de-rounding procedure. The tractive energy for the trips in this test dataset was then estimated through the energy method described above, using the remaining 9 groups of GPS trips as the validation set used in the bootstrap. The comparison between these predicted energy values and their true values gives an estimate of the accuracy of the energy method. This cross validation showed that the mean square error for a trip's tractive energy was 6% of the square of the sample mean. The total energy estimate for the test set was always within 2% of the true value, typically an overestimate of 1.5%.

The bootstrap method can be compared to a method that estimates a trip's energy by taking the average energy consumption per unit distance of the validation set and multiplying that by the distance of each trip in the test set. This can be thought of as the best possible method of estimating energy consumption based on a single "Miles per gallon" equivalent value. This MPG method understandably performs slightly better at estimating the total energy consumption of the test set, with the average error being an overestimate by 0.8%, compared to 1.5% for the bootstrap method. However, the mean square error for estimating trip energy with the MPG

method is 12% of the square of the sample mean, compared to 6% for the bootstrap method. This suggests that the method proposed above sacrifices a small amount of accuracy with regard to estimating energy totals in order to gain additional accuracy in approximating variations in energy consumption between trips of the same distance.

3.4 Vehicle Trip and Vehicle Day Energy Distributions

Finally, given a probability distribution of the energy requirements of each POV trip in the NHTS, it is useful to combine those individual trip energy distributions into distributions over various combinations of trips, which allows for a better understanding of the typical energy requirements of POVs under different use conditions. The analysis presented in the remainder of this thesis often deals with one of two possible energy distributions—one over vehicle trips or one over vehicle days.

Vehicle Trip. A vehicle trip is every NHTS trip for which the survey respondent was the driver of the vehicle. This added qualification avoids double counting, as trips where multiple family members were in the vehicle show up in the NHTS once for each family member. The total energy consumption for the US or some geographical subset of it, for example, is the expected value of the weighted sum of the various vehicle trip energy distributions.

Vehicle Day. A vehicle day is the set of all vehicle trips taken by an individual vehicle over the course of its household's travel day, and thus the distribution of vehicle day energy consumption is the distribution of the sum of the energies of all of a vehicle's trips. Not every vehicle trip in the NHTS belongs to a vehicle day— about 2% of all vehicle trips in the NHTS are not assigned a unique vehicle number, either in error or because it was taken in a vehicle not associated with that household.

In an effort to correct for sampling bias, the NHTS provides a set of weights for each person and household in the survey, with the intention that all sums and

distributions calculated from the NHTS data include these weights. These weights are calculated in order to account for the fact that some populations are sampled heavier than others and to ensure that population-level demographic information, such as age, income, and location distribution, all match observed quantities. Thus, in order to come up with a vehicle trip or vehicle day energy distribution for some sub-population of the NHTS data, we let each trip or day count for a number of trips or days defined by its NHTS weight and then divide by the total NHTS weight of all of the population studied.

3.5 Performance Metrics

While the vehicle trip and vehicle day energy distributions are often interesting in their own right, here we propose three metrics based on these distributions that allow for a better understanding of a vehicle's performance under real-world use. These three metrics can be evaluated over all US driving behavior as well as any subset of it. In the next section, we often divide up travel behavior into residents of different cities, examining how EVs compare to ICEVs for locations that differ in both climate and travel behavior. Similar comparisons are possible for many other classifications of drivers—by income, by typical commute, by distance from work. These metrics are chosen in order to illustrate the most important current constraints facing EV adoption and how successfully different technologies would be able to overcome these barriers.

Because these are fundamentally questions of technology choice, it is helpful to define that choice precisely. To that end, in producing these metrics, we consider only two vehicles—the 2013 Nissan Leaf and the 2014 Ford Focus—and we model the technological choice between EVs and ICEVs as a choice between those two vehicles. While this simplification is certainly an unrealistic one, it helps distill all of the variables defining POV choice, many of which have nothing do to do with the underlying technologies, into a simplified framework where the costs and benefits of EV and ICEV technology can be compared independent of other factors such as

aesthetics, design, and price. These two vehicles are chosen because they both are designed in order to meet a mass-market audience, of relatively affordable relatively small everyday vehicles.

All of these metrics are calculated based on vehicle day energy distributions, as, with limited charging infrastructure, a vehicle day is the closest possible measurement for the amount of energy consumption between charging events. The vehicle day energy distribution, then, is more closely tied to range requirements that still are a barrier to EV adoption. In the limiting case where fast charging infrastructure was available everywhere, metrics based on vehicle trip energy distributions would be more appropriate.

In defining these metrics below, we look at the predicted EV and ICEV energy requirements for a set of N vehicle days (subscript i) and a set of k bootstrap 'worlds' (subscript j). We define the EV use energy requirements of a certain bootstrap vehicle day as E_{ij}^{EV}, and the ICEV use energy requirements of that same bootstrap vehicle day as E_{ij}^{ICEV}.

Adoption Fraction. We define the Adoption Fraction as the portion of vehicle days that an EV could replace on one charge:

$$AF = \frac{1}{kW_{tot}} \sum_{i=1}^{N} \sum_{j=1}^{k} \delta(E_{ij}^{EV} < E_{charge})W_i \qquad (3.26)$$

where E_{charge} is the usable energy in the EV's battery and the delta function $\delta(E_{ij}^{EV} < E_{charge}$ is one when the trip's energy requirements are less than the usable battery capacity and zero otherwise. The usable energy is typically less than the total capacity of the battery, as fully charging and discharging a battery tends to degrade its performance over time. Thus, many vehicles, including the Nissan Leaf, include a state of charge (SOC) window with the vehicle software, limiting the possible depth of discharge to 80% to 90% of the total battery capacity. We choose a SOC window of 80% of the battery capacity, as that is the value used in the EPA range estimates.

This estimate is not intended to be a direct measurement of the number of EVs that could be sold—because we do not have longitudinal data, it is impossible to say that just because a vehicle did not exceed the battery capacity on its NHTS travel day does not mean that it never would. However, this measure is still a valid measure of the possible technological market size for EVs, especially in a world where car-sharing and ride-sharing make it easier to base vehicle choice on the needs of its daily use.

Expected Energy Use. Another useful measure of the expected impact of increasing adoption of EVs is how much energy they can be expected on a day to day basis. This measure can be useful in understanding the impacts of EVs on the electric grid and on power plant emissions, for example. Understanding expected EV energy use is not a trivial question—range-limited EVs can be expected to be preferentially used on shorter distance vehicle days, and EVs tend to perform differently on shorter trips than longer trips. Thus, a complete understanding of expected EV energy consumption requires a detailed coupled vehicle and demand model as presented above. We define an EV's expected energy use as:

$$\bar{E} = \eta_{charge} \frac{\sum\limits_{i=1}^{N} \sum\limits_{j=1}^{k} E_{ij}^{EV} W_i \delta(E_{ij}^{EV} < E_{charge})}{\sum\limits_{i=1}^{N} \sum\limits_{j=1}^{k} W_i \delta(E_{ij}^{EV} < E_{charge})} \tag{3.27}$$

which is the average value of the vehicle day energy consumption over all vehicle days where the vehicle is driven. This is different than the average daily energy consumption of a vehicle over the course of a year, because vehicles are driven on average approximately 300 days a year.

Potential Gasoline Displacement. Finally, one of the major proposed benefits of a switch to EV technology is that they will decrease gasoline consumption, which is not only associated with greenhouse gas emissions but also many other localized pollutants. This motivates a metric that measures the potential reduction in gasoline

consumption if all vehicle days that could be covered with an EV were covered with an EV:

$$GDP = \frac{\sum\limits_{i=1}^{N} \sum\limits_{j=1}^{k} E_{ij}^{ICEV} W_i \, \delta(E_{ij}^{EV} < E_{charge})}{\sum\limits_{i=1}^{N} \sum\limits_{j=1}^{k} E_{ij}^{ICEV} W_i}. \qquad (3.28)$$

Again, this is not intended to be a simulation, or a plausible scenario of the eventual adoption of electric vehicles. Instead, it is intended to outline a contingency scenario capturing both the effects of EV market size potential and of ICEV performance. For instance, increasing EV battery capacity will increase the potential gasoline displacement by allowing a larger portion of vehicle days to be covered by EVs. However, if those newly-covered trips tend to be mostly high-speed highway trips, trips over which EVs operate inefficiently and ICEVs operate efficiently, improvements to the GDP will be less dramatic than if the newly-covered trips were stop and go city trips with better EV performance. This metric is intended to both capture the potential of EVs as mitigators for gasoline consumption, but also the potential for diminishing returns of increased battery capacity.

The combination of these three metrics paints a uniquely complete picture of the adoption potential, energy impacts, and gasoline mitigation potential of EV technologies in a way that is usage-specific but agnostic of technological inertia. By presenting the real-world performance of POV technologies in this way, we intend to clarify the fundamental technological choice between EV and ICEV technology.

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Chapter 4

Results

The POV trip energy model presented above turns a set of travel survey trip records into a probability distribution of vehicle trip and vehicle day energy requirements, calibrated to match data independently collected on vehicle performance, GPS velocity history, and historical weather. In the following section, this model is applied to the National Household Travel Survey—a large scale and nationally representative dataset on US travel behavior. We seek to answer fundamental questions about the ability of electric vehicle technology to meet existing POV travel needs and how EVs should fit within larger pathways to decarbonization of the transport sector. A selection of these results are also presented in [62].

The questions raised below fall into four major categories—EV performance, EV adoption potential, the variations in technological requirements between cities, and the benefits of continued improvement in vehicle battery capacity. In looking at EV performance, we combine a detailed vehicle model with detailed climate data and nationally-representative trip histories to examine how and to what extent vehicle range and energy consumption are effected by weather, driving behavior, and commuting patterns. Nation-wide estimates of EV adoption potential suggest that current EV technology, embodied in the 2013 Nissan Leaf, is already able to replace approximately 87% of ICEVs on a given day—reducing gasoline consumption by approximately 61% compared to a similarly sized and priced ICEV. Examination of EV performance across a large sample of US cities shows that, even though local climate

and travel behavior can vary greatly, EV adoption potential remains remarkably constant and remarkably high across cities. For EVs to offset a much greater portion of gasoline consumption, however, we find that both dramatic increases to battery storage capacity and a shift from short urban trips to longer suburban and rural ones are required.

4.1   Real World Vehicle Performance

Range anxiety—the worry of unexpectedly running out of battery charge—has often been cited as a barrier to widespread EV adoption [20]. To better inform potential customers of these limitations, the US EPA publishes an expected range for each tested EV based on the results of their dynamometer testing. For example, given a battery size of 24 kWh (86.4 MJ), and an allowed depth of discharge of 80%, the EPA predicts 2013 Nissan Leaf to have an all electric range of 73 miles in keeping with its rated equivalent fuel economy of 115 MPGe. The EPA warns that this range is only an average value, however, and indeed a vehicle's true range—the distance driven on one charge—can vary significantly based on factors such as driving aggressiveness, use of auxiliary electronics, and amount of regenerative braking. There have been a great number of studies of EV and PHEV all-electric range [81, 45, 42, 76], studying the effects of driving style and weather on range experienced during realistic driving. These studies typically focus exclusively on one particular issue—looking at variations in auxiliary energy use while keeping drive energy use constant or vice-versa—and none look at sources for regional variations in range beyond temperature.

The trip energy model presented in this paper is able to add to this understanding by of vehicle range incorporating more detailed data on national commuting patterns. Most studies estimating EV range calculate range based on the vehicle's mean energy consumption per unit distance, with that average taken over all trips. This method can lead to biased results if that metric is used to calculate whether a given vehicle day will exceed a battery's energy capacity. For instance, simple differences in trip characteristics can have dramatic impacts on vehicle auxiliary energy use—increasing
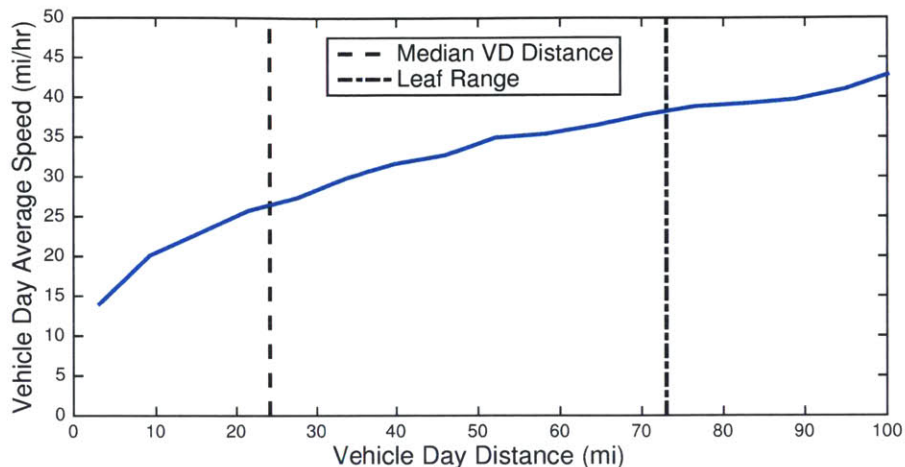
Figure 4-1: Relationship between mean vehicle day speed (mi/hr) and vehicle day distance (mi), showing that longer vehicle days tend to involve higher speed driving. In terms of auxiliary use, this means that all else equal the per mile auxiliary energy consumption of longer trips will be less than for shorter trips.

a car's average velocity over the course be 50% of a trip will decrease its auxiliary energy consumption by one third if auxiliary power remains constant, because those climate auxiliaries are using energy for less time during the trip. This phenomenon can have significant effects on vehicle range that are not captured in common models.

More than half of vehicles driven over the course of a day in the United States travel less than 25 miles in that day. For a vehicle with typical range of over 70 miles, that vehicle's performance over these much shorter vehicle days should have little to no bearing on the vehicle's estimated one-day range. The NHTS shows that trips of 73 miles average approximately 38 miles per hour, while trips of the median vehicle day distance of 24 miles average approximately 26 miles per hour. Thus, we would expect vehicle days for which the range constraint becomes relevant to devote comparatively less energy to auxiliary use per mile traveled than the typical vehicle day.

If the goal of publishing a vehicle range is to estimate the vehicle day distance around which a user should expect a range constraint to become binding, then, taking average per mile energy consumption over all vehicle days biases range estimates for vehicle days near the cutoff range value. This phenomenon of decreasing auxiliary
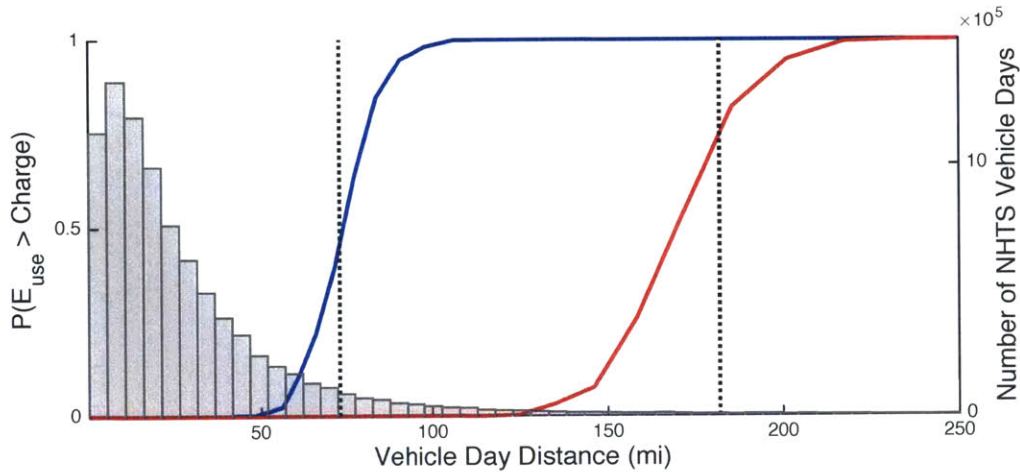
Figure 4-2: Probability that a vehicle day of a given distance exceeds a battery energy threshold, given the 2013 Nissan Leaf power train. The results are shown for the Leaf with two battery sizes, corresponding to current battery capacity of 24 kW (blue) and a 60 kW battery and current battery mass (red). The background is the vehicle day length distribution. The results show that increasing the capacity of the battery by 150% in the Leaf would increase its median range from 74 miles to 173 miles. This median range of 173 is less than 2.5 times the current median range of 74 miles because longer vehicle days, where the improved maximum range becomes relevant, have a higher portion of high speed highway driving, over which the Leaf performs less well than on stop and go driving.

energy consumption with increasing vehicle day distance, however, must be tempered with the fact that EVs tend to perform less efficiently during highway driving, which likely accounts for a greater proportion of driving on long vehicle days. Our energy model is the only way of accurately weighing these competing effects.

Figure 4-2 shows a more nuanced picture of EV range based on outputs of our vehicle energy model. To create it, all trips were combined into bins of similar distance, and the likelihood of a vehicle day's energy consumption exceeding the Leaf's battery capacity was calculated separately for each bin. These results show that an EV's "range" can only be expressed with very limited precision. Our model predicts 74 miles as the distance for which half of all vehicle days could be covered on one charge and half could not. However, given the variation in actual driving behavior, our model as shown in Figure 4-2 predicts that 5% vehicle days of 58 miles could not be covered by existing batteries, and 5% of vehicle days of 90 miles could. The

predicted median range of 74 miles roughly matches the EPA's range estimate of 73 miles, suggesting agreement between the two methods for vehicle performance under average use. Interestingly, the electric equivalent miles per gallon rating for the Leaf averaged over all vehicle days in our study was 109.7, lower than the Leaf's EPA-rated MPGe of 115. A MPGe rating of 109.7 would suggest a range of approximately 71 miles, which implies that the vehicle days falling near the current range constraint tend to be less energy intensive per mile than vehicle days on average.

Our model also allows an understanding of the tradeoffs inherent in the engineering decisions behind battery size. The Tesla Model S offers a version with a battery capacity of 60 kWh, 150% greater than that of the 2013 Leaf. If the Leaf's battery capacity were increased to 60 kWh, keeping the overall specific energy of the battery system constant (and thus increasing the initial battery mass of 275 kg to 687.5 kg [82]), we would expect a median range of 166 miles, with 90% of range values falling between 135 to 200 miles. If battery specific energy were improved and the battery capacity could be increased to 60 kW while keeping total mass the same, we would expect the median range to increase again to 173 miles. This relatively small negative impact on range owing to the added battery mass is an indication that battery specific energy is likely not the most important constraint limiting electric vehicle range—instead, manufacturers are limited by the desire to keep costs low and volume constraints limiting battery size, suggesting that increases in specific energy and decreases in cost must come with increases in battery energy density for them to be truly impactful.

We also see that increasing the battery's energy capacity by 150% without increasing its mass would only increase median range by approximately 130%, highlighting the nonlinear relation between vehicle range and energy capacity. Longer vehicle days tend to include greater proportions of high-speed highway driving, trips over which EVs tend to be less efficient. Our finding illustrates the value of having a model based in real drive cycles and on using observed trip-chaining to combine vehicle trips into vehicle days. A purely MPG based energy method will not capture the expected variation in range, nor will it capture the decrease in vehicle performance on long distance

days. When considering vehicle range, our results highlight the general conclusion that increasing a vehicle's battery capacity will allow it to perform a wider range of functions, including functions, such as highway driving, over which it performs comparatively poorly. Assessments of the impact of technology change should not only account for the functions that the technology is currently serving, but also for the functions that the improvements will allow the technology to serve.

4.2 Energy Use Across the US

The three performance metrics defined in the Section 3.5 are helpful in understanding the expected adoption potential, energy consumption, and gasoline displacement potential of existing EV technology. Despite all of its current drawbacks and barriers to adoption, we find that the current market for the Nissan Leaf is surprisingly large. The Adoption Fraction calculated from the national EV vehicle day energy distributions suggest that, on any given day, 87% of vehicles that are driven could be replaced by a Leaf without needing mid-day charging. Of those vehicles, we would expect them to draw an average of 7 kWh of energy from the electric grid over the course of the day. If all vehicles that could be replaced with EVs on one charge were, we would expect typical additional electricity demand of approximately one billion kilowatt hours per day, approximately 10% of current US electricity demand for all sectors [1], although that demand would likely not be spread evenly over the course of the day. Further, we would expect this level of EV adoption to reduce daily gasoline consumption by 60%, amounting to a savings of 220 million gallons of gasoline per day.

While these adoption levels are an entirely unrealistic short term policy goal, they do provide an order of magnitude estimate of the adoption limits of current technology and the effects of widespread adoption might look like. Examining these scenarios in detail can help inform how to craft policies and develop technologies that are able to replace the largest number of ICEVs and the largest portion of existing gasoline consumption with the smallest possible additional energy impact.

To do so, it is helpful to look at EV performance and adoption potential in different sub-regions of the United States. By looking at variations in performance, it will be helpful to identify what potentially reproducible aspects of certain metropolitan areas make them particularly ripe for EV technology adoption, and it will also be helpful to identify what are the main root causes of the additional barriers to adoption in locations where EVs do not perform well. Further, as urban populations continue to grow and as contemporary technology and policy choices will likely shape the direction of this future growth, these comparisons are useful not only in understanding static technology performance, but also the potential impacts of long-term policies that prioritize certain types of or locations for urban growth.

EV energy consumption related to climate auxiliaries is a natural place to start this analysis. As the US contains many different climates, and as temperature can greatly effect EV energy consumption, it is plausible that differences in climate can be a large driver in differences in EV adoption potential and hence an important target for technological improvement. Others have studied the effect of location on EV range and energy consumption [42, 76]. However, these models have treated per mile drive energy consumption and trip average velocities as constants across regions, neither of which is necessarily the case, and both of which could have competing effects on energy consumption. The model presented here allows the weighing of climate effects on regional variations in EV range with effects arising from differing travel behavior.

In looking at variations in EV range between US cities, we end up with results that are roughly similar to Yuksel and Michalek [42] but differ from those presented by Kambly and Bradley [76]. The results in the work of Kambly and Bradley tend to penalize areas with hot weather, finding the highest range values in Alaska and Michigan, two very cold states. These results are in conflict with results presented here and elsewhere, which find that cold climates are less suitable for EV adoption. In looking at differences in mean range between cities, we tend to find lower ranges in cities such as New York, Buffalo, and Chicago that experience colder winters, compared to cities such as Miami and Tampa, which are temperate for most of the year. Yuksel and Michalek present a model based on mean energy consumption
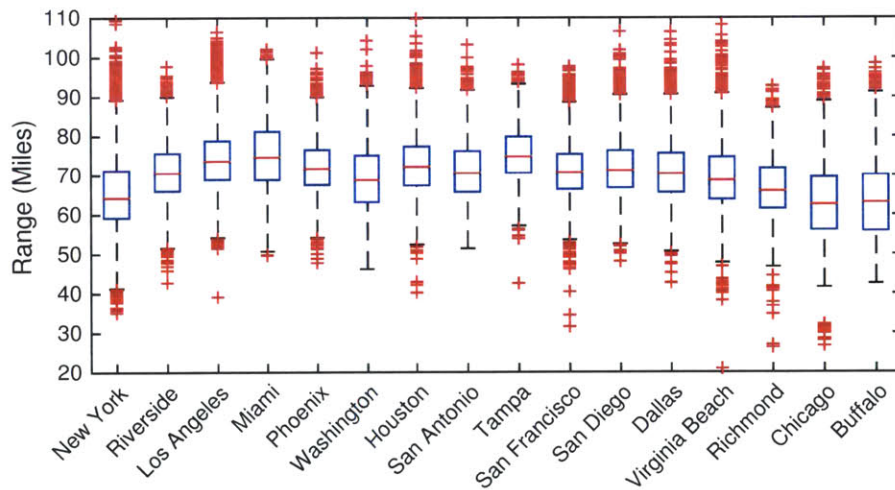
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Figure 4-3: Average range within study metro areas, showing the negative effects of hot or, especially, cold climates on EV range. Here range is estimated by taking average per mile energy consumption for trips with energy needs within 25% of the cutoff value. The cities Chicago and Buffalo were added to the sample despite having comparatively lower representation in the NHTS in order to include a larger number of cities that experience a significant amount of cold weather. These cities, along with cities such as New York and Washington, DC, that also experience some cold weather during the year, tended to have lower typical vehicle ranges.

per unit distance as a function of external temperature captured by onboard data loggers in the Nissan Leaf and find qualitatively similar patterns and quantitatively similar ranges for the medians and the 25 to 75 percentile range of their data. While their findings support the general findings presented here, their results show much less variability captured in the trips with the highest and lowest 25% of the range values. This difference is likely because our model captures differences in trip-to-trip energy consumption due to factors other than temperature as well as purely temperature-based ones. Comparison of results suggest that these variations do not have a dramatic effect on typical vehicle performance, marked by the medians of the range distributions, but it can have significant effects on behavior at the tails of the distributions. While the medians might be more relevant to measuring aggregate performance, the outliers might be more important to individual consumers interested in vehicle range on atypically inefficient days.

While EV range can vary significantly between cities, however, that is only one component in understanding the suitability of current EV technology to meet travel needs. Independent of vehicle performance, travel behavior and the resultant demand it places on POVs varies greatly between cities as well. Even in a city where climate provides significant limitations to EV range, if typical driving distances in that city tend to be shorter than average, EVs could potentially replace a greater than average portion of vehicle days, even though they perform comparatively poorly on them. To better understand this tradeoff, and to better understand how the demand placed on a vehicle can vary—or not vary—from city to city, we consider in detail the comparison between New York City, NY, and Houston, TX, as a case study. In doing so, and for the rest of the analysis presented here, we define a city's metropolitan area as the Core Based Statistical Area (CBSA) surrounding the city proper. Because these CBSAs are generous definitions of the city's boundaries, often extending far into the suburbs, we limit the following analysis to areas with population density of over 1,000 persons per square mile—a limitation that keeps approximately all inhabited areas within a city's boundaries but removes many low density far off suburbs whose travel
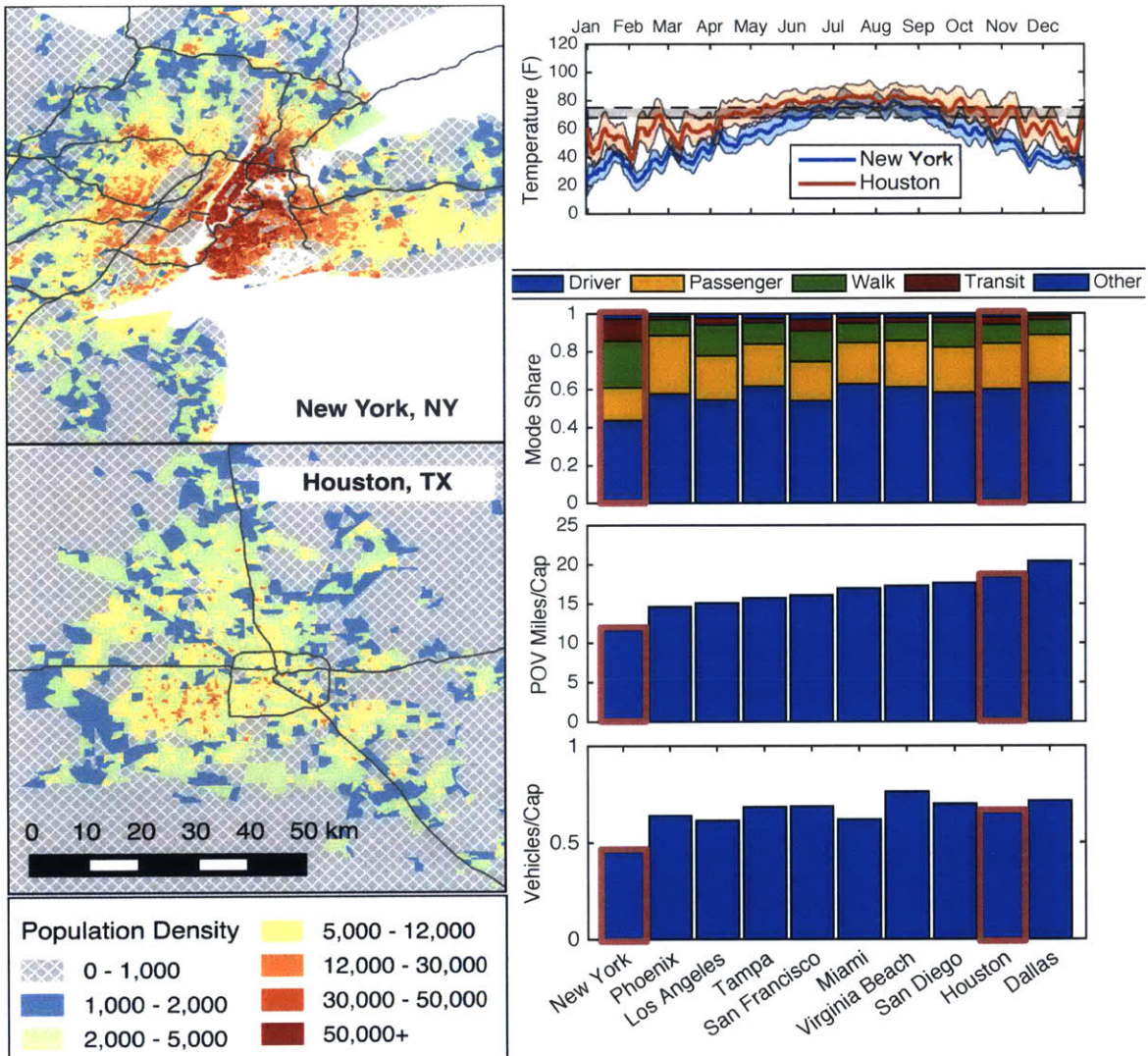
Figure 4-4: Left: Population density maps of New York (top) and Houston (bottom). Both maps are to the same scale and have the same color scheme, with the units of population density persons per square mile. Right, top: Temperature histories in New York and Houston, with the shaded range 7 day averages for daily high and low temperatures and the middle line a moving average of daily mean temperature. Right top middle: mode split for cities POV miles per capita, showing the portion of total trips taken by each mode of transportation. Right middle bottom: POV miles per capita across cities. Right bottom: Vehicles per capita across cities, as contained in the NHTS vehicles data file. Population density data from [83].

behavior likely has little to do with that of residents in the center city[1].

By most conceivable metrics, travel behavior and technological demand is as different between New York and Houston as it can be for any pair of major cities in the United States. The comparison is illustrated in Figure 4-4. Houston is a fast growing city in the sunbelt region of the US. With its surrounding metropolitan area, Houston had a population of just under six million during the 2010 census. Its population drew dramatically in the middle of the 20th century, coinciding with the growth of the Interstate Highway system and the rise of the POV as the primary mode of transportation in the United States. As a result, Houston is a very sprawling city, with vast areas of land built up at a moderate population density but few clusters of dense urban development. Approximately 80% of all trips taken in the Houston area are by car, and the average person in Houston drives approximately 18 miles a day. Both of these totals are among the highest of the NHTS metropolitan areas studied here.

In almost every way, New York City is a very different sort of city from Houston. Its surrounding metropolitan area housed almost twenty million people in 2010, over eight million of whom lived in New York City proper. Unlike Houston, New York's population boomed in the 19th and early 20th centuries, a time before POVs were widespread as a means of transportation. As such, its development patterns are much denser, focused around walking, horse cars, and, eventually, the most widely used subway system in the United States as primary means of transportation. Still, in the New York metropolitan area, approximately 60% of trips are taken by car. This is in part due to the inclusion of suburbs in New Jersey, Connecitcut, and Long Island within the CBSA boundaries, but it belies the fact that even in New York, cars play a very important role in daily travel behavior. Still, when compared to other cities in the United States, New York is among the least car reliant metropolitan areas, with the lowest value of daily POV miles per capita and vehicles owned per capita of all the major metro areas studied. Like the rest of the coastal eastern United States, New York experiences strong seasonal weather, with hot and humid conditions during the

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[1]These low population density regions are shown as the cross-hatched areas in the maps in Figure 4-4.
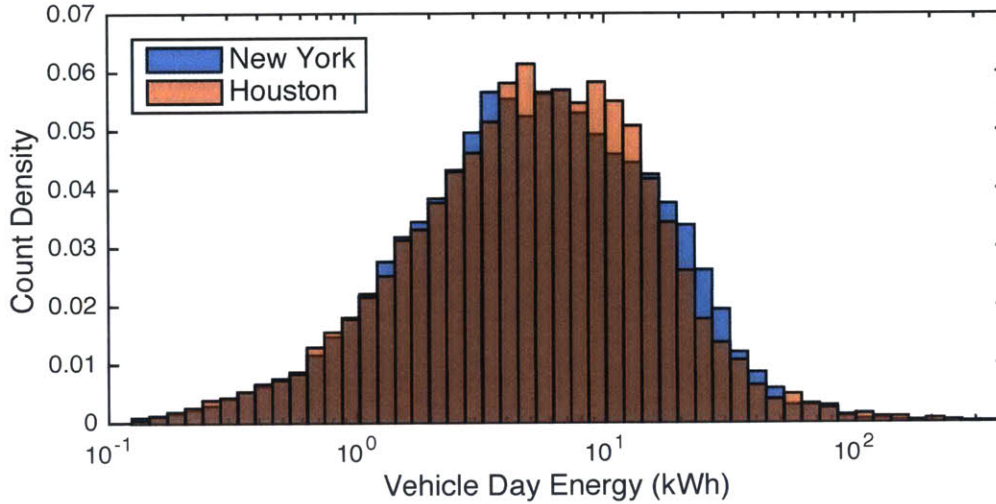
Figure 4-5: Vehicle day energy distributions for the metropolitan areas of New York, NY, and Houston, TX. Despite great differences in climate and travel demand between the two cities, the energy requirements placed on EVs are remarkably similar.

summer and stretches of weather at or below freezing during the winter, providing plenty of opportunity for both air conditioner and heater use. When compared to a set of other major US cities, as is done in the right portion of Figure 4-4, Houston and New York fall towards the extremes of most measures of car dependence.

Despite all of these dramatic differences in city form, travel behavior, and weather, the actual vehicle day energy distributions of New York and Houston are remarkably similar. Histograms of these distributions are shown in Figure 4-5. At first glance, one might expect residents of Houston, a much more auto-oriented city, with much more driving per capita, to place much more demand per day on a POV. Indeed, Newman and Kenworthy [26] and many others have shown that per capita dense cities such as New York have much lower rates of energy consumption than sprawling low density cities such as Houston, a fact that is supported (if complicated) by a wide body of research [26, 28, 34, 55, 29, 13]. Our results do not contradict previous because our results are not per-capita but instead per vehicle day. This behavior is likely in part because, as in [30], vehicle use and vehicle ownership is a choice that households make based on their transportation needs and the options available to them. In a city such as New York, where much of the population has easy access to very good
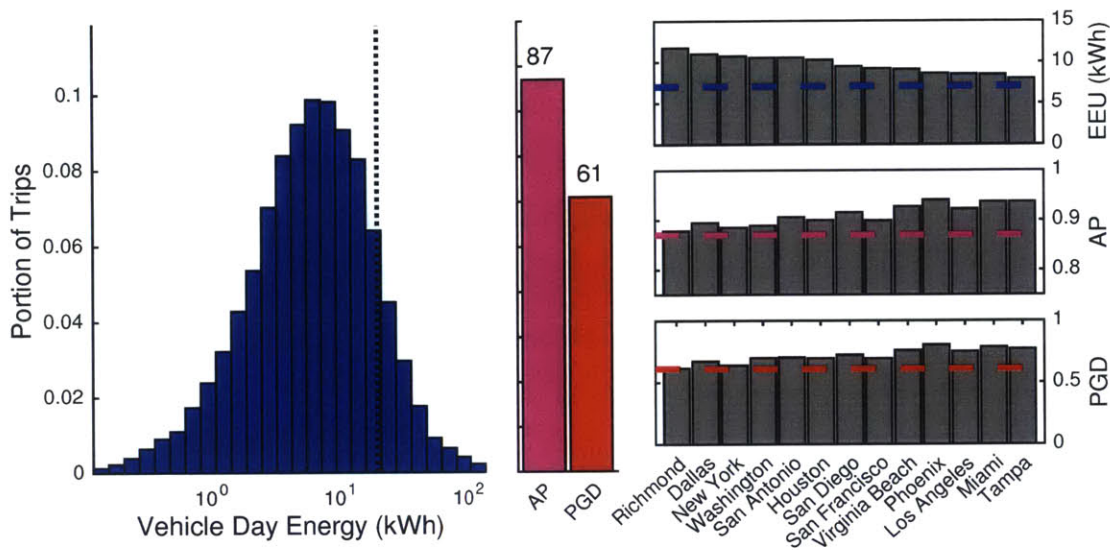
Figure 4-6: Left Main: Histogram of EV vehicle day energy consumption for the entire US. Center: Adoption potential (purple) and Gasoline Displacement Potential (Red) across the US. Right: Values of these three quantities in different cities across the US. All twelve cities shown here perform equally well or better than the US average by these three metrics of EV performance.

public transit and where owning a car can be both inconvenient and expensive, a family will typically only own a car if its circumstances demand that the car will be used relatively heavily. Further, New York, with its immense areas of dense, walkable neighborhoods, is surrounded by similarly immense sprawling suburbs. In general, we see that the differences in per-capita energy use between Houston and New York arise from differences in vehicle ownership, vehicle occupancy, and travel mode split, rather than in differences in the energy consumption of individual vehicles.

Looking at a larger set of cities, we continue to see similarities in per vehicle energy consumption. But, while the differences between cities are small, comparing a larger sample of cities draws out some patterns in the variations in EV performance and adoption potential. For instance, we see that for all three metrics discussed—adoption potential, expected energy use, and gasoline displacement potential—all cities in our sample perform equivalently or better than the US on average, suggesting that there is some truth to the arguments that current EVs will be most effective in cities for early adopters. Further, among the cities studied, different measures of EV suitability

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tend to align with each other. We predict that electric vehicles in Richmond, VA, for example will be able to replace the lowest portion of ICEVs, will do so with the highest electricity expenditures per vehicle, and will be the least effective at displacing gasoline consumption. On the other hand, EVs in Phoenix, AZ, would be able to replace the highest portion of ICEV days, with the third lowest per vehicle electricity use, and with the third highest reduction in gasoline consumption.

Indeed, the fact that some of these measures appear to be related should not come as much of a surprise. Vehicles with a fixed range will tend to be able to cover fewer vehicle days and replace less gasoline in cities with longer typical travel distances, and cities with longer typical travel distances likely have more miles driven in a typical day beyond the range of an EV that therefore most be covered by ICEVs.

Perhaps conveniently for EV adoption, many of the best performing cities are among the fast-growing, sprawling, car oriented cities located in the sun belt region of the southern and western United States, including cities such as Phoenix, Miami, and Los Angeles. This corresponds with the findings of Creutzig [55], who suggested for focus on EVs in warmer cities with already large amounts of driving. The direct causes for these phenomena, in terms of travel patterns and expected EV performance, appear to rooted as much or more in EV performance than in travel behavior. Table 4.1 show various measures of both POV performance and demand for the 13 cities with the greatest number of NHTS respondents. Some patterns of travel demand appear to make cities less suitable for EV adoption, as Dallas, TX, and Richmond, VA— the cities with two of the three highest average POV distances per vehicle day—also measured the lowest in terms of potential EV adoption fraction. Vehicle performance also appeared to play a role, as the two cities with the highest fuel economy MPGe rating, Miami, FL, and Los Angeles, CA, also scored among the highest in terms of adoption potential and gasoline displacement potential.

It is not directly obvious, however, whether these variations are due to underlying differences in travel patterns or due to specifics of EV technological performance. Figure 4-7 shows mean EV vehicle day energy consumption plotted against mean ICEV energy consumption for the 12 cities with the most NHTS respondents. This
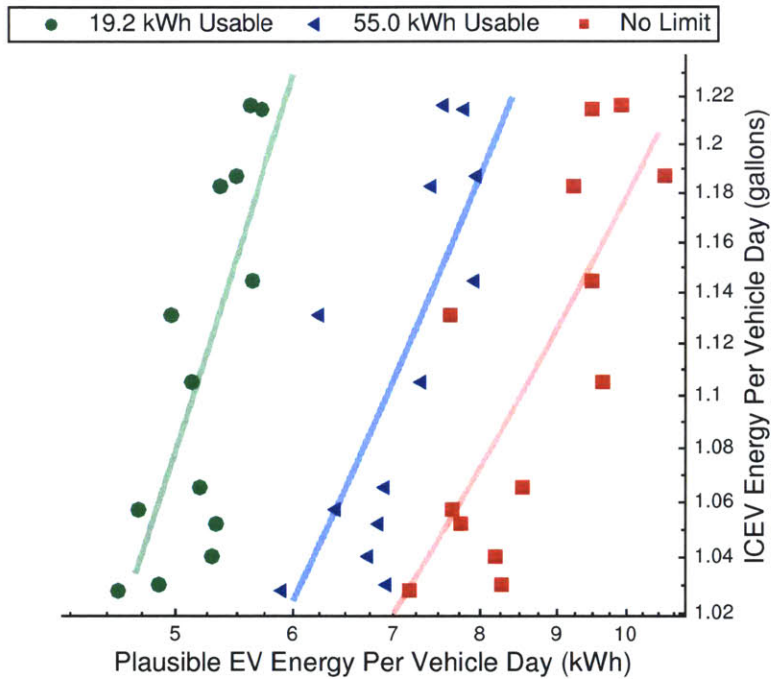
Figure 4-7: Mean per vehicle day energy consumption by vehicle technology under different assumptions of EV adoption. The y-axis shows average gasoline consumption per vehicle day in various cities, assuming an equivalent vehicle (a 2014 Ford Focus) is used for all trips. The x-axis shows the expected EV energy consumption per vehicle day of different cities, assuming only vehicle days where the 2013 Leaf would not require recharging (green circles), where a Leaf with improved battery capacity would not require recharging (blue triangles), and where the Leaf replaced all POV driving (red squares).

Metro Area	Sample	$\bar{D}$ (mi)	$\bar{V}$ ($\frac{mi}{h}$)	MPGe	AP	EEU	PGD	Veh/Cap
San Diego	6,339	33.7	28.7	120.4	91.5%	6.65	72.4%	.701
Dallas	5,681	37.3	29.5	114.4	89.5%	7.24	67.2%	.717
Los Angeles	5,200	32.0	24.8	126.3	92.2%	6.07	75.0%	.615
Phoenix	4,746	30.2	26.7	118.3	94.0%	6.78	80.4%	.640
Miami	4,185	32.4	24.2	128.5	93.7%	6.35	78.8%	.620
New York	4,143	33.4	25.3	104.8	88.5%	6.70	63.9%	.459
Houston	3,872	38.4	36.2	118.8	89.0%	6.95	69.7%	.664
Virginia Beach	3,051	31.8	26.6	117.7	92.7%	6.79	76.0%	.764
San Francisco	2,375	32.3	26.7	117.8	89.9%	6.29	69.4%	.689
Tampa	1,931	30.3	25.5	127.1	93.7%	5.85	77.2%	.685
Richmond	1,771	37.9	30.4	108.5	87.8%	7.10	61.7%	.772
San Antonio	1,718	36.7	28.9	117.2	90.6%	7.29	70.3%	.684
Washington	1,679	34.3	25.3	109.0	88.9%	7.22	69.9%	.644
Urban	123,202	35.0	28.1	110.6	89.1%	6.67	64.5%	.700
Rural	52,985	46.5	35.3	107.8	80.8%	8.27	52.2%	.900
All US	176,186	37.9	30.0	109.7	87.0%	7.04	60.9%	.747

Table 4.1: Vehicle day statistics for eight metropolitan regions in the United States. Sample is the number of vehicle days observed in the NHTS, $\bar{D}$ is the average vehicle day distance, $\bar{V}$ is average velocity, MPGe is the electricity equivalent gas mileage (including charging losses). AP, EEU, and GDP are the metrics described in the previous section: AP is the adoption potential—the portion of vehicle days that could be covered by the vehicle on one charge, EEU is the expected energy use, the mean energy consumption (in kWh) of all vehicle days that could be covered by the Leaf, and GDP is gasoline displacement potential, the portion of gasoline consumption that could be replaced by the Leaf, assuming a Ford Focus as the comparable ICEV. Veh/Cap is the number of vehicles per resident of the metropolitan area.

relationship is shown under three EV energy use assumptions—that EVs only cover vehicle days that could be taken on one charge with current battery capacity (green circles), that they only cover vehicle days requiring less than 55 kWh of energy[2], and that EVs cover all vehicle days. The plots show that, for current battery capacities, there does exist a weak relationship between ICEV energy consumption and EV energy consumption, showing that some of the differences in EV energy use are due to underlying technology-agnostic aspects of local travel behavior. The deviations from the trend can be attributed to differences in technology-specific vehicle performance between cities, either due to range constraints masking the effects of longer vehicle

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[2]This number corresponds to the leaf having a battery with the ARPA-E target specific energy of 200 W/kg and its current mass [84, 82].

days on average energy consumption or differing efficiency between ICEVs and EVs driving up or down energy consumption across the same set of days.

As battery capacity increases, both the relationship between EV and ICEV energy consumption and the deviations from the trend become stronger. For the case where EVs are able to cover all vehicle days, deviations from the trend are due only to differences in EV and ICEV performance within cities, because the underlying travel demand met between the two technologies is identical. Thus, cities to the far left of the trend line—notably Miami, Houston, and San Antonio, are cities where ICEVs can meet existing travel demand using comparatively less energy when compared to ICEVs. Cities to the far right of the trend line, such as San Francisco, Virginia Beach, and New York. These results suggest that, as EVs become able to cover higher portions of travel needs, variations in EV energy consumption relating both to vehicle performance and underlying travel demand will become more important. The reasons for this behavior can be found by examining in greater detail the underlying vehicle day energy distributions.

4.3   Importance of Scaling Behavior

The heavy-tailed nature of the vehicle day energy distribution is both precedented in the literature and has in itself implications for EV adoption and energy use, especially as EVs with greater storage capacities become available. It has been shown that individual travel patterns tend to follow heavy-tailed distributions [23]. Particularly, it has been found that the distribution of trip lengths tends to decrease as a power law for large distances [25, 24]. We see in Figure 4-8 that vehicle day energy use also tends to follow a heavy tailed distribution. The left panel of Figure 4-8 shows the probability density functions for vehicle day energy for fifteen US cities on a log-log scale. Towards the right side of the plot, the tails of the PDF become linear, a result of a power law tail of high-energy vehicle days.

However, the right panel of Figure 4-8 shows that at current battery sizes (depicted by the left dashed line), the PDF of vehicle day energies is still decreasing roughly
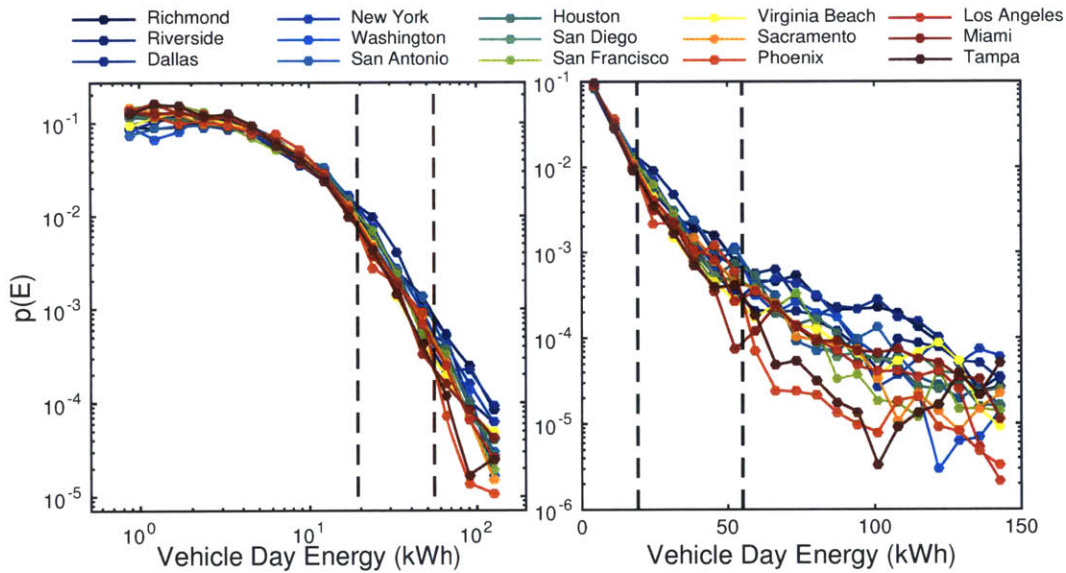
Figure 4-8: Left: Probability Distribution Function for vehicle day energies on a log-linear scale, with the straight line representing an exponential decrease of $p(E) \propto e^{-E/2.5}$ (with E in GJ). **Right:** Same plot on a log-log scale, with a straight line representing power law decrease $p(E) \propto E^{-2.8}$. The dotted lines on the plot show current Leaf available battery energy (left) and target battery energy (right). These plots show a crossover to power law scaling behavior, where the heavy tail has strong influence on the mean of the distribution, from an exponential tail, where the tail has less of an influence on the mean. This crossover happens within the range of expected battery capacities.

exponentially, showing linear behavior on a plot with a logarithmic y axis. This linear regime ends around the right dashed line, depicting battery storage capacity ARPA-E target specific energy and current mass [84, 82]. This behavior suggests that the "plausible" vehicle days are much more homogeneous than the sample as a whole and that a large portion of the variation in energy use per vehicle day between cities comes from vehicle days that are too energy intensive to be covered on one charge with current technology.

These functional forms help explain why the EV energy demand between cities is so similar. In the Figure 4-7, we see that ignoring these high energy vehicle days further decreases in the variation in mean vehicle day energies between cities. The relative similarity of mean expected EV energy consumption between cities is also to be expected, as introducing an energy cutoff truncates the positive tail of the energy distribution, removing high energy vehicle days with outsized influence on the mean energy consumption of the set of trips. Indeed, when compared to potential EV usage in rural areas *outside* of cities, the variation in these metrics appears much smaller. For instance, our model predicts that current EVs would be able to replace 87% to 94% of vehicle days in our sample of cities, but in rural areas we would expect this value to be as low as 80%. We would expect EVs to be able to reduce gasoline consumption by between 60% and 75% for the cities studied, but in rural areas this value is approximately 50%, pointing to a fundamental difference in aggregate personal vehicle energy demands between cities and rural areas that is significantly greater in degree than variations due to driving behavior, infrastructure, and climate.

To some degree, the remarkable consistency between cities is due to the battery capacity constraint turning the plausible vehicle day energy distribution from a heavy tailed one into a weak tailed one. The means of heavy tailed distributions tend to be influenced heavily by a small number of observations coming from the tail, and thus a small number of very energy intensive vehicle days drive a disproportionate amount of the variation in between city energy consumption. The crossover between the exponential and power law regime, while different between cities, tends to happen within the range of plausible battery sizes given expected technological improvement,

suggesting that improved battery capacity will increase the differentiation and variability in expected use between cities, and it will allow variations in EV performance and total EV energy consumption to be driven much more heavily by very high energy vehicle days in the tail of the distribution.

4.4 Technological Evaluation

The vehicle energy model presented above allows for direct quantification of the marginal benefits of improvements in EV battery specific energy, using metrics that incorporate realistic user behavior and choices. To do so, we set up a simple technological choice between the Nissan Leaf and the Ford Focus, two vehicles that are relatively comparable in size and lifetime price. The scenarios presented assume that all vehicle days that can be covered in one charge are driven by the Leaf, and that the remaining ones are driven by the Focus. This is compared to a baseline where all trips are taken in the Focus. This is not intended to be a predictive adoption scenario but rather a contingency scenario to understand the technical potential and limitations of EV technology.

This exercise allows for a quantitative comparison of the tradeoffs between EV and ICEV technology, and how technological change will alter that tradeoff. In Figure 4-9, we show the effects of increases in usable battery capacity on various measures of technology performance. These calculations can clarify the effects of technological change, both for the US as a whole and for different types of household location. Doing so allows for quantitative answers to simple questions about what technological improvements are needed in order to meet adoption goals. For example, a nationwide adoption potential of 99% would require usable battery capacity of approximately 70 kWh. Increases to that degree would allow for the replacement of almost 90% of gasoline consumption with EV technology, amounting to slightly over one gallon of gasoline per vehicle day.

This model also allows for a more detailed understanding of the benefits of technological progress. In Figure 4-9, we disaggregate expected EV performance between
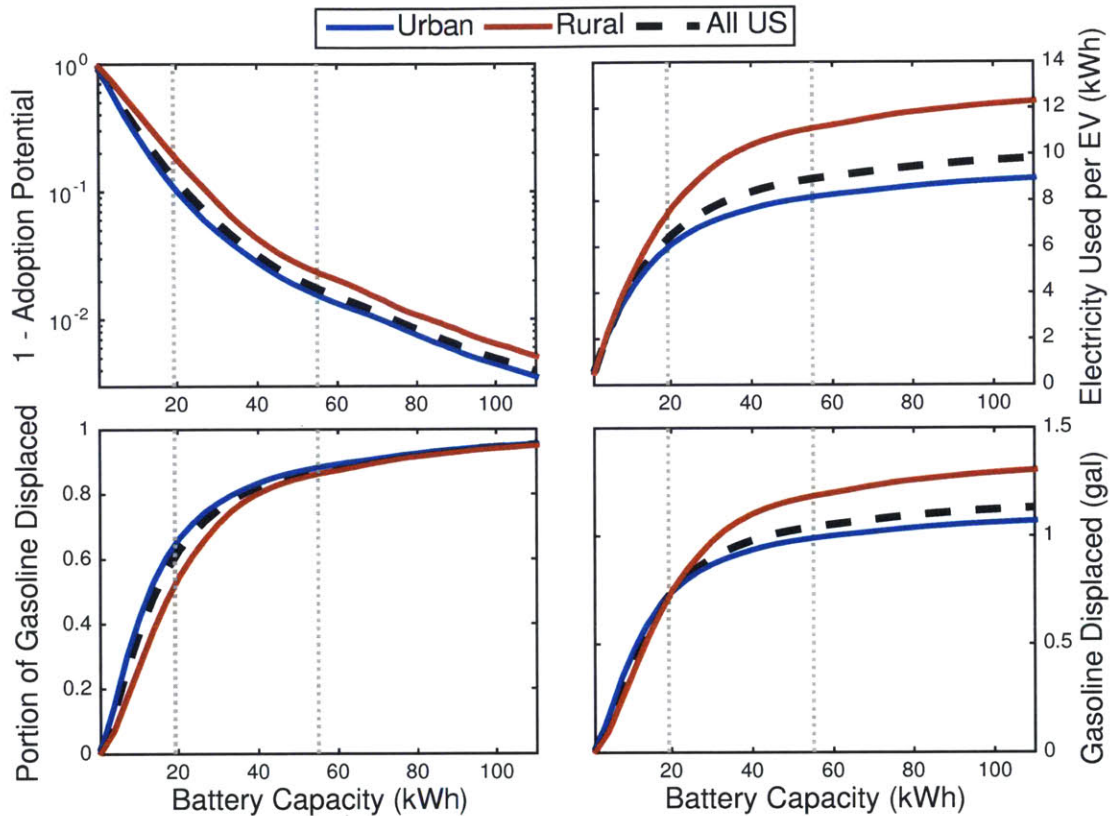
Figure 4-9: Marginal benefits to the electrification potential of EVs due to increasing battery specific energy, disaggregated by household location. Red lines represent values for vehicles belonging to households defined by the census as "rural," blue lines represent values for "urban" households, and black dotted lines represent values for the US as a whole. **Top Left:** Effect of increased battery capacity on the "tail fraction," or the portion of vehicle days whose energy use exceeds that of one full charge. Vertical grey dotted line is the position of the ARPA-E target specific energy of 200 Wh per kg, showing diminishing returns in terms of adoption potential with greater energies. **Bottom Left:** Effect of changes in battery capacity on PGD, the portion of gasoline use displaced by EVs over a typical vehicle day. **Top Right:** Effects on per vehicle day EV energy use. **Bottom Right:** Amount of gasoline displaced per vehicle if all possible vehicle days are switched to EVs. Note that the amount of electricity used increases faster than the amount of gasoline displaced, especially for rural drivers.

rural locations and urban ones, as that appears to be the single distinction that has the most effect on the measures shown. In terms of adoption potential, expected EV energy use, and in potential to displace gasoline consumption, there exist fundamental differences as to the impacts of technological improvement for vehicles used in urban versus rural areas.

Results above have shown that the option to switch to a 2013 Nissan Leaf could reduce gasoline consumption in the United States by over 60% compared to a base case of the 2014 Ford Focus. This value shows strong differentiation between urban and rural regions, with that number being 65% in urban areas and approximately 50% in rural ones, suggesting that current EV technology is much more effective as a mitigator of gasoline consumption in urban rather than rural environments. With battery specific energy increased to ARPA-E targets, however, we would predict that the Nissan Leaf could displace over 85% of the Focus's gasoline consumption, and we would expect that result to be roughly similar between urban and rural areas. Thus, at some point between usable battery sizes of 20 kWh and 55 kWh, EVs transition over from being an emissions reduction tool primarily for cities to one that is equally suited for use in rural areas.

However, just because EVs with greater storage capacity would be able to displace similar portions of gasoline consumption in urban and rural areas does not mean that either EV energy use or the resultant emissions reductions would be similar in these two areas. With current battery capacity, we would expect EVs and ICEVs to be able to displace similar amounts of gasoline consumption in urban and rural areas, with the lower adoption potential in rural areas cancelled out by the increased energy consumption in rural areas coming from what days can be covered by EVs (indeed, a lower capacity EV would be able to replace more absolute gasoline emissions in cities than in rural areas because it would be able to cover such a small portion of rural driving). Increasing battery capacity to the ARPA-E target would increase the total amount of gasoline reduction potential by less than a third in urban areas while almost doubling it in rural areas. While current EV performance is best in urban areas, the greatest vehicle for vehicle potential for large scale reductions in gasoline usage comes

from rural areas. The potential reduction from rural areas is so high because typical driving distances are so far, the exact reason why adoption potentials there are lower with current technology, a constraint that will become less with battery improvement.

However, gasoline consumption is not the only useful metric for evaluating EV technology improvements. Mean energy consumption of an EV for the Nissan Leaf is expected to be slightly higher in a rural environment than an urban one. However, this difference increases greatly at higher battery capacities, when EVs in rural areas are able to cover a greater portion of days and the days that they do cover tend to be longer. At these higher battery capacities, the difference in average EV energy consumption between rural and urban areas is greater proportionally than the difference in gasoline savings between these two areas. In effect, increasing battery capacity will allow for decreases in gasoline consumption in rural areas but create proportionally larger increases in EV electricity consumption. This phenomenon is likely largely due to the fact that these high energy rural vehicle days involve long, high speed, highway trips, trips over which EVs tend to operate inefficiently. Depending on the price and carbon intensity of electricity, this may or may not pose a problem to potential consumers and climate-change policy makers.

By all metrics, increasing EV battery capacity will allow for EVs to transition from a more niche, urban market to one that encompasses all regions and climates across the United States. While battery capacity currently limits the portion of vehicle days that could be covered by EVs, affordable EVs with battery capacities in the range of 55 kWh will be able to serve rural drivers even better than EVs currently serve urban drivers. This rural market offers, per vehicle, a significantly larger opportunity to displace gasoline emissions, and increases in battery capacity will allow for EVs to be more effective in terms of reducing gasoline consumption in rural areas rather than in urban ones. Electric vehicle configurations designed to operate more efficiently at highway speeds would likely be a fruitful avenue for research, even if current battery technology limits their potential immediate use. Additionally, in terms of emissions, as EVs begin to displace longer distance ICEV days it becomes especially important that these EVs draw their electricity from a relatively low carbon grid, as the miles

driven by high-capacity EVs will tend to be more energy-intensive than those driven by the current fleet. This potential new market could also serve as a new use-case for which prototype vehicles could be optimized, as potential EV vehicle days will be much more different between different locations when their battery capacities are 55 kWh versus differences with current capacities.

Chapter 5

Conclusion

Over the past century ICEV technology has had dramatic effects on US travel behavior, the built environment, and society as a whole. As climate change becomes a more pressing policy issue and as alternative technologies improve, basic changes in personal vehicle technology may alter future the travel choices people make, especially with regard to technological choice. The US expends massive amounts of energy towards personal transportation, and new choices and new technologies threaten to greatly disrupt the personal transportation energy system.

Decreasing prices and increasing availability will likely allow for EVs to become more competitive with ICEVs in the marketplace, but the degree to which EVs can penetrate the market, and their performance under widespread use once they do, remains unknown. With a new model that considers both vehicle mechanics and representative driving behavior, we show that the prospects for EV technology to replace a significant percentage of POV energy consumption are good. Range constraints do still significantly limit the number of vehicles that can be replaced with current battery capacity, but even still on a given day 87% of vehicles could be replaced by an EV on only one charge. With full adoption, current technology would be able to reduce US gasoline consumption by 61% without requiring alterations to travel behavior or mid-day charging, but in certain areas this potential is even greater.

As many have suggested elsewhere, we find that current EVs perform especially well in cities, allowing for greater adoption potential and reduction of gasoline use

than in the US on average. We find that the suitability of EVs to different metropolitan areas varies slightly both in terms of performance and demand, but that these variations are too small to differentiate technological targets between cities. Performance variations are driven largely by climatic differences and their associated effects on HVAC auxiliary use, and demand side differences are driven largely by differences in daily driving distances and vehicle ownership. These differences can have significant effects on vehicle range—we show the range can differ by over twenty miles depending on climate and driving style—suggesting that average range is not the best measure of a vehicle's capability to meet daily driving demands. Of the urban areas studied, many of the best performing markets in terms of adoption potential and EV energy efficiency come from cities in the southern and western United States such as Miami, Phoenix, and Los Angeles.

Despite these differences between trips and locations, the effects of continuing increases in battery specific energy promise to have similar effects across cities—increasing the number of ICEV days that could be replaced by EVs and increasing the typical energy use of EVs once they are on the roads. Our study of the effects of increasing battery specific energy provides concrete numbers to evaluate battery specific energy targets. For the test case technology of the 2013 Nissan Leaf, we show that the ARPA-E target battery specific energy will allow for the portion of vehicle days that can be covered on one charge to increase from 87 % to 97.9%, and it will allow for an additional 20% increase in the amount of gasoline consumption that can be electrified, from 61 % to 81% of current demand.

We find that the effects of technological improvement are especially distinct between urban and rural areas. Vehicles in rural areas tend to be driven farther and faster on a day to day basis than vehicles in cities. Current EV technology, with limited range and poor performance on highway trips, is especially growth-constrained in rural areas because of these limitations. Increases in battery capacity will weaken the range constraint and mitigate the effects of poor highway efficiency on vehicle adoption potential in rural areas, however. With current battery capacities, EV usage potential in rural areas is especially constrained by limited range, but as batteries

gain capacity the greater per-vehicle-day energy use in rural areas will mean that EVs are used more—and displace more gasoline consumption—in rural areas rather than urban ones, even if they continue to perform less efficiently over the types of driving most common there.

These results suggest that this urban/rural distinction is the primary differentiation that should drive vehicle technology development, and that especially the rural component should be considered for improvement if the overall goal is maximizing emissions savings. For example, current EVs might benefit more from slight improvements in regenerative braking efficiency than decreases in drag at highway speeds, as their primary current use is expected to be during stop and go driving at lower speeds. However, with larger batteries, performance at highway speeds will become more important, and greater overall energy savings are to be had from technology improvements targeted to reducing energy consumption for rural drivers.

Because current battery capacity constraints limit the type of driving behavior to short and moderate distance vehicle days, which tend to have similarly distributed energy requirements across the US, there is not much of a pressing need to develop specific types of EVs for specific types of driving behavior. However, improved battery technology will expand the EV market from a common niche one to a broader one, where different EVs will benefit from catering to different markets. EV adoption has the most to gain by improving performance in rural areas with longer driving distances, currently types of use for which EVs perform worse when compared to ICEVs. This finding makes intuitive sense, as the use-cases in which ICEVs are used most heavily are the ones that most heavily shaped ICEV technology's evolution over time.

These results also raise many interesting questions about EV policy going forward. If the policy goal is emissions reduction, it is logical to target policies towards increasing EV adoption in use cases where they will supplant the greatest amount of gasoline consumption. But, these policies should also consider the additional electric energy consumption of EVs, as heavily used EVs will likely use more energy per mile than lightly used ones, as we have found. The trade-off between these two ef-

fects is complex and should be examined further, particularly in light of variations in the carbon intensity of the electric grid across the US. Our analysis shows that the final answers to many important questions about EV policy will involve complex tradeoffs. For example, deciding whether subsidy should be allocated to decreasing battery costs over time–allowing for longer-range vehicles to be cost competitive with ICEVs,or to more targeted direct purchase subsidy—potentially increasing adoption level of existing vehicles, requires an understanding of how current vehicles perform across typical use and of how increased battery capacity will alter typical EV use.

Our analysis suggest that EV adoption and EV subsidy, while likely a net benefit to the energy and emissions landscape of the US, should still be explored critically in order to maximize the effectiveness of policy interventions. The results presented in this thesis argue that such analysis requires a detailed model of both vehicle performance and travel demand, such as the one presented here, in order to appropriately capture the complexities of the problem of technology comparison and technology choice.

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